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Predicting Solar Energy Generation for Efficient Grid Integration

Yaser Pakzad Jafarabadi
Edward E. Whitacre Jr. College of Engineering
Texas Tech University
Lubbock, USA
Yaser.pakzad@ttu.edu

Afshin Balal
Department of Electrical and Computer Engineering
Texas Tech University
Lubbock, USA
Afshin.balal@ttu.edu

Ali Rezaei
Department of Electrical and Computer Engineering
University of Genova
Genova, Italy
rezaei.ila@gmail.com

***Abstract*—Solar power is an abundant and renewable energy source that has received great attention recently because of its potential for mitigating climate change and reducing reliance on fossil fuels. Accurate forecasting of solar power generation is crucial for efficient energy management and grid integration. This paper proposes using Long Short-Term Memory (LSTM) models, a recurrent neural network (RNN) type, for solar power forecasting. We present a comprehensive study on applying LSTM models to forecast solar power generation, considering various input features, model architectures, and performance evaluation metrics. the result indicates the efficacy of LSTM models in accurately predicting solar power output, providing valuable insights for renewable energy stakeholders, utility companies, and policy-makers.**

Keywords—Solar Radiation, Deep learning prediction, Solar Systems, LSTM

I. Introduction

As a clean energy source, solar power has emerged as a promising alternative to traditional fossil fuel-based energy generation. With the increasing global focus on sustainable development and the urgent need to mitigate climate change, solar power has gained significant attention in recent years [1, 2]. Harnessing energy from the sun not only reduces greenhouse gas emissions but also offers long-term energy security and economic benefits. Integrating solar power into the existing energy grid presents opportunities and challenges [3, 4]. One of the critical challenges is accurately forecasting solar power generation, which is vital for efficient energy management, grid stability, and optimal resource allocation. Accurate solar power forecasting enables utility companies, energy traders, and policymakers to make informed decisions about grid operations, load balancing, and the integration of solar power into the electricity market [5, 6]. Additionally, solar power forecasting aids in integrating solar energy into wholesale electricity markets, enabling efficient market participation and trading of renewable energy. Solar energy's inherent variability and intermittency pose unique challenges for forecasting solar power generation. Factors such as weather conditions, cloud cover, shading, and seasonal variations significantly impact solar power output. Traditional forecasting techniques, such as statistical and numerical weather prediction models, often struggle to capture the nonlinear and complex relationships in solar power generation data [7]. Moreover, the dynamic nature of solar power makes short-term and long-term forecasting challenging tasks [8]. Several approaches have been employed in the past for solar power forecasting, ranging from statistical methods to machine learning techniques. Numerous statistical techniques, including ARIMA, have been employed. While these methods can capture specific patterns in solar power data, they often fail to account for complex nonlinear relationships and seasonality [9]. Furthermore, traditional statistical models may struggle to adapt to changing conditions and handle large datasets efficiently. The potential for enhancing solar power forecasting accuracy has been demonstrated through ML/DL techniques such as SVM, RF, and ANN. While these methods can capture nonlinear relationships, they may lack the ability to handle long-term dependencies and capture time series patterns effectively [10]. This limitation becomes particularly significant when dealing with data exhibiting complex temporal dynamics, such as solar power generation. This paper's primary objective is to explore the application of Long Short-Term Memory (LSTM) models for solar power forecasting. LSTM models, as a type of recurrent neural network (RNN), have shown remarkable performance in capturing long-term dependencies in time series data. We aim to investigate the effectiveness of LSTM models in accurately predicting solar power output based on various input features [11, 12]. Additionally, we seek to provide insights into the impact of different model architectures, training parameters, and evaluation metrics on the forecasting performance

II. Methods

Forecasting the performance of solar power installations requires meteorological data by following the below steps:

A. Data Collection and Preprocessing

To conduct our solar power forecasting experiments, we collected a comprehensive dataset consisting of historical solar power generation data and relevant meteorological variables. The solar power generation data was obtained from solar power plants with accurate and reliable monitoring systems. The meteorological variables included measurements such as solar irradiance, ambient temperature, wind speed, humidity, and cloud cover. The data collection process ensured that the temporal alignment between the solar power generation and meteorological variables was maintained. Prior to model training, Preprocessing was done on the gathered data to make sure it was good quality and appropriate for LSTM modeling. This involved handling missing values, correcting outliers, and normalizing the data to a common scale [13, 14]. Missing values were either imputed using appropriate techniques or discarded based on the extent of missingness. Outliers were identified and treated to prevent them from adversely affecting the model's performance. Normalization techniques, such as min-max scaling or z-score normalization, were applied to ensure that all input features were on a comparable scale, preventing any single feature from dominating the model's learning process [15].

B. Feature Selection

Feature selection is a crucial step in building an accurate LSTM model for solar power forecasting. Variables that exhibited strong correlations with the target variable (solar power generation) were given priority, as they were likely to provide valuable information for forecasting. Additionally, variables with high feature importance scores obtained from feature ranking algorithms, such as random forest or gradient boosting, were also considered for inclusion. Domain knowledge and understanding of the physical relationship between weather features and solar power generation guided the selection of appropriate input features [16, 17].

C. LSTM Model Architecture

The design of the LSTM model architecture played a vital role in capturing the temporal patterns and dependencies in the solar power generation data. The architecture comprised multiple LSTM layers, allowing long-term dependences to be modeled. Additionally, dense layers could be incorporated to enhance the model's ability to learn complex relationships. Hyperparameter tuning was performed to optimize the architecture, including the number of LSTM units, the learning rate, and the batch size [18].

D. Training and Evaluation

The training set was used to optimize the model's parameters through an iterative process, leveraging techniques such as backpropagation and gradient descent. The validation set was employed to monitor the model's performance during training and to prevent overfitting. Early stopping was applied to halt training when the validation loss ceased to improve significantly, thus avoiding unnecessary training and reducing the risk of overfitting. Once the model was trained, it was evaluated on the test set to assess its performance in forecasting solar power generation. Evaluation metrics, such as mean absolute error (MAE) was calculated to quantify the accuracy and reliability of the forecasts [19]. Comparative analysis with other forecasting models, such as traditional statistical methods or alternative machine learning approaches, was conducted to assess the superiority of LSTM models in solar power forecasting.

III. Long Short-Term Memory (LSTM)

LSTM was specifically designed to overcome the limitations of traditional RNNs, such as the vanishing gradient problem, which hinders the ability to capture long-term dependencies in sequential data. LSTMs incorporate memory cells, input gates, forget gates, and output gates to selectively retain or discard information over time. The memory cells allow LSTMs to store and access information for extended periods, enabling the capture of long-range dependencies. The gates, controlled by activation functions, regulate the flow of information into and out of the memory cells. The input gate determines the relevance of new information, the forget gate decides which information to discard from the memory cells, and the output gate determines the output based on the current input and the memory cells' content [20]. By utilizing this sophisticated architecture, LSTMs are capable of effectively capturing temporal dependencies in sequential data, making them particularly well-suited for time series forecasting tasks. The ability to retain long-term memory allows LSTMs to capture complex patterns, non-linear relationships, and seasonal variations, which are crucial aspects of solar power generation forecasting [21]. LSTM models offer several advantages for time series forecasting, making them a suitable choice for solar power prediction [22, 23]:

a) Capturing Long-Term Dependencies: LSTMs can effectively capture and model long-term dependencies in time series data. This is particularly valuable in solar power forecasting, where previous observations at different time intervals may have a significant impact on future power generation [24].

b) Handling Nonlinear Relationships: Solar power generation is influenced by various factors, such as weather conditions and environmental variables, which often exhibit nonlinear relationships. LSTMs, with their ability to model complex non-linear patterns, can capture these relationships and improve forecasting accuracy [25].

c) Handling Temporal Dynamics: Solar power generation exhibits temporal dynamics, such as daily and seasonal variations. LSTMs can capture these dynamics by considering the sequential nature of the data, enabling accurate modeling and forecasting of solar power output over time.

d) Adaptability to Changing Conditions: LSTMs are inherently adaptive and can adjust their model parameters dynamically as new data becomes available. This adaptability allows them to handle changing weather patterns and evolving solar power generation dynamics [26].

e) Handling Large and Multivariate Data: Solar power forecasting often involves large datasets with multiple input features, such as weather variables, time of day, and historical power generation [27]. LSTMs can efficiently process and model these multivariate time series data, considering the dependencies among different input features [28].

By leveraging these advantages, LSTM models have the potential to improve the accuracy and reliability of solar power forecasting, aiding in the efficient integration of solar energy into the existing power grid and facilitating the transition towards a sustainable energy future [29, 30].

IV. Results and Discussion

The results were obtained using Python and MATLAB software with a comprehensive dataset of historical solar power generation data and associated meteorological variables. The dataset spanned one year and encompassed various weather conditions, capturing the variability and seasonality of solar power generation. Fig. 1 shows the solar radiation over one year.

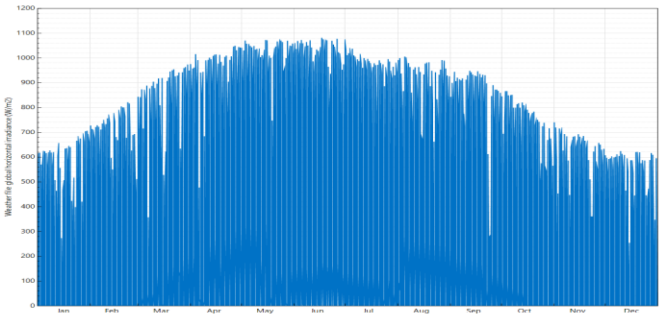

Fig. 1. Solar radiation

According to Fig. 1, solar radiation is higher at around 1100 $\frac{w}{m^2}$ during May. In addition, Fig. 2 indicates the wind speed in the same year.

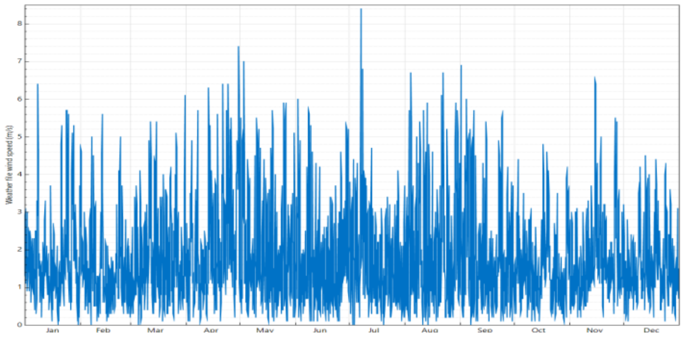

Fig. 2. Wind speed

Also, Fig. 3 depicts the ambient temperature in the same year, showing that the highest temperature goes up to 45° C.

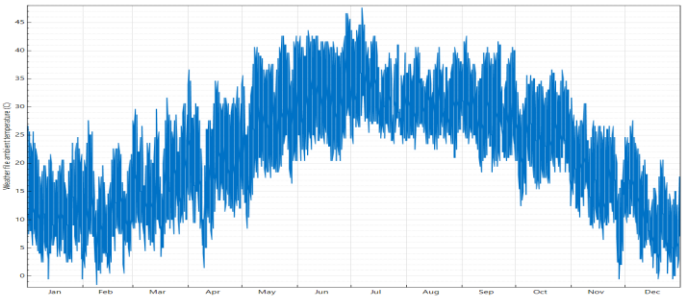

Fig. 3. Temperature

And finally, Fig. 4 shows the yearly solar output power.

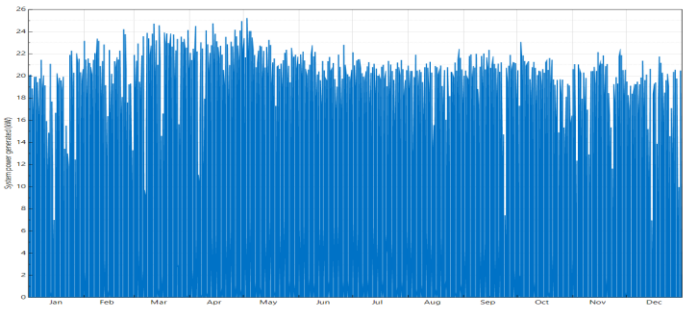

Fig. 4. Extracted solar power

Now, by simulating the target value and weather variables, the LSTM model can predict the output extracted power. The performance of the LSTM models for solar power forecasting was evaluated using standard evaluation metrics, including mean squared error (MSE) and coefficient of determination (R-squared). These metrics provided quantitative measures of the forecasts' accuracy, precision, and goodness-of-fit compared to the actual solar power generation values.

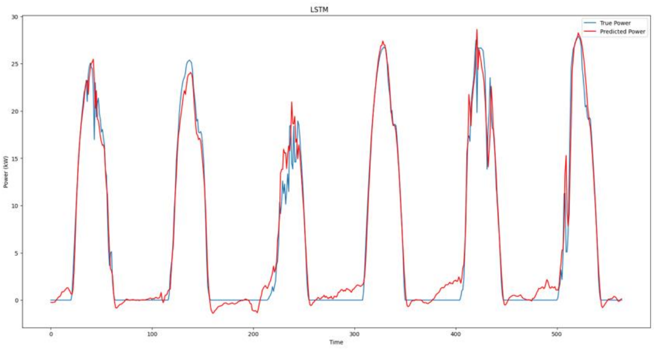

Fig. 5. Power prediction using LSTM

According to the result, long-short term memory method can predict the true power with a very high accuracy as it can be seen from Fig. 5 even during cloudy days such as day 3. The accuracy of the model is up to 98.45% in this paper.

V. Conclusion

This paper investigated the application of LSTM models for solar power forecasting. The experimental results highlighted the effectiveness of LSTM models in accurately predicting solar power generation by capturing complex temporal patterns and nonlinear relationships. Comparative analysis with traditional methods demonstrated the superior performance of LSTM models in solar power forecasting tasks. According to the result using LSTM, the accuracy of 98.45% were achieved.

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