Prediction-of-Solar-Photovoltaic-Power-Generation-Based-on-MLP-and-LSTM-neural-networks

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1 General Introduction

The global demand for electric power is increasing exponentially due to population growth, contemporary lifestyle, and the industrial revolution. This energy is largely provided by fossil energy sources. However, the depletion of this type of energy and its environmental problems (emission of CO2, global warming, etc.) have incited the international community to look for other forms of energy. Recently, solar photovoltaic (PV) power became the most popular renewable energy alternative since PV systems are carbon-free, have low maintenance costs, and have a long presumed life. Many countries are switching to large-scale PV power integration on their power systems. In Tunisia, the goal is to develop a PV installation of 937 MW by the end of 2023 according to the National Agency for Energy Management [1].

Photovoltaic output power depends strongly on weather conditions (solar irradiance, temperature) and therefore it varies randomly in time. This power fluctuation affects the stability, reliability, and planning of power grids. It can affect, also, the energy management system in microgrids where the main goal is to keep the balance between energy supply and the loads at minimum cost [2]. To overcome these problems, photovoltaic output power forecasting has become crucial.

Depending on the application, photovoltaic output power, forecasting is performed based on different forecasting horizons (long-term , medium,short-term,and very short-term solar forecasting) [3].
Very short-term forecasting methods, giving forecasts from 1 min to an hour ahead. These methods are used by power system operators for real-time dispatch of active and reactive power.
Short-term forcasting methods, providing forecasts from one to 6 h ahead. Forecasted values are used for load trading, reserves purchasing, unit commitment, and power curtailment in order to ensure grid stability in terms of frequency

and voltage.
Long-term forecasting methods, providing forecasts from 6 h ahead to 3 days ahead and beyond. Such methods are used for economic dispatch and unit commitment optimization activities.

Various techniques are used to forecast PV output power. The authors in [4] provide a comprehensive review of the theoretical forecasting methodologies for both solar resources and PV power. These methods can be classified into four different techniques such as physical techniques, statistical techniques, Artificial Intelligence techniques (AI), and hybrid methods [5].In the realm of literature, various statistical methods have been employed to predict PV power, including models like Auto-Regressive Moving Average (ARMA),Auto-Regressive Integrated Moving Average (ARIMA), and Autoregressive Moving Average with Exogenous Inputs (ARMAX). [6], [7].

Numerous studies are dedicated to exploring AI methodologies, such as Artificial Neural Networks (ANN) and fuzzy logic, among others.Recent breakthroughs in AI technologies have given rise to innovative Deep Learning (DL) approaches aimed at surpassing the constraints inherent in conventional Machine Learning (ML) methodologies. DL techniques have more advantages than physical and statistical ones since they are characterized by unsupervised feature extraction, dominant generalization ability, and capability training on big data [8]-[9]-[10].For the purpose of enhancing the precision of PV power predictions, hybrid forecasting approaches can be employed. Within this framework, the researchers mentioned in [10] have devised a short-term PV power prediction method by amalgamating the Empirical Mode Decomposition (EMD) technique, the Sine Cosine Algorithm (SCA), and the Extreme Learning Machine (ELM) technique. The objective of this study is to predict the output power of a photovoltaic generator (PVG) using AI techniques. For short-term prediction, not only ML techniques (Simple Regression Tree, Polynomial Regression, Gradient Boosted Trees, Linear Regression, and Random Forest) are used but also DL techniques were applied (MLP).Regarding long-term forecasting, the utilization of a Deep Learning technique known as Long Short-Term Memory (LSTM) is employed.

The dataset has been sourced from the Research Center of Energy, situated at the Borj Cedria Science and Technology Park, with coordinates at Latitude: 36.717^{o} and Longitude: 10.427^{o}. The dataset spans from January 1st, 2005 to December 31st, 2020, encompassing four input parameters: solar radiation, ambient temperature, wind speed, and sun height. Additionally, it includes one output variable, which is photovoltaic power.

To fine-tune the hyperparameters of both Machine Learning (ML) and Deep Learning (DL) algorithms, a Grid Search Cross-Validation (GSCV) technique was employed. Specifically, for each combination of hyperparameters within the grid, Cross-Validation (CV) was utilized to identify the most suitable architectural configuration for the predictive model. This approach aids in identifying the optimal hyperparameter set that enhances the model's performance while guarding against overfitting, wherein the model excels in training data but struggles with unseen data. To assess the effectiveness of each prediction method, the following metrics are employed: Mean Absolute Error (MAE),Mean Square Error (MSE), and the coefficient of determination (R_2).

The master's thesis report is structured into three chapters as outlined below: Chapter one is dedicated to the state of the art of interconnected photovoltaic systems and their prediction techniques. It provides an in-depth exploration of cutting-edge developments in the field of interconnected photovoltaic systems, accompanied by a comprehensive assessment of advanced forecasting methodologies.

Chapter two focuses on forecasting photovoltaic solar power one hour ahead by exploring seven ML approaches (simple regression tree, polynomial regression, gradient-boosted trees, linear regression,random forest,multi-layer perceptron (MLP) and Long Short-Term Memory (LSTM)).

In Chapter three, the experimental phase unfolds, delving into meticulous measurements and assessments to gauge precision. The focus extends to scrutinizing the performance intricacies, employing rigorous analysis techniques. This section serves as a critical juncture, where empirical data intertwines with insightful evaluations, offering a comprehensive understanding of both the experimental process and the ensuing results.

References

[1] A.S. Saidi, " Impact of large photovoltaic power penetration on the voltage regulation and dynamic performance of the Tunisian power system" Energy Exploration & Exploitation, vol. 38, no. 5, pp. 1774-1809, 2020.

[2] Y. Guan, B. Wei, J. M. Guerrero, J. C. Vasquez, and Y. Gui, "An overview of the operation architectures and energy management system for multiple microgrid clusters," iEnergy, vol. 1, no. 3, pp. 306–314, 2022.

[3] A. Mellit, A.M. Pavan, " A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste Italy," Solar Energy, 84 (5), pp. 807-821, 2010.

[4] C. Wan, J. Zhao, Y. Song, Z. Xu, , J. Lin, Z. Hu, "Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management," Journal Of Power and Energy Systems, vol. 1, no. 4, pp. 38-46, , December 2015.

[5] M.K. Behera, N. Mayak, "A comparative study on short-term PV power forecasting using decomposition based optimized extreme learning machine algorithm," Engineering Science and Technology, vol. 23, no. 1, pp. 156-167, 2020.

[6] S. Safi, A. Zeroual, M. Hassani, " Prediction of global daily solar radiation using higher order statistics," Renew. Energy, 27 (4), pp. 647-666, (2002).

[7] J. Contreras, R. Espínola, F.J. Nogales, A.J. Conejo, " ARIMA models to predict next-day electricity prices," IEEE Trans. Power Syst., vol. 18 no. 3, pp. 1014-1020, 2003.

[8] A. Youssef, M. El-Telbany, A. Zekry, "The role of artificial intelligence in photo-voltaic systems design and control: A review," Renew. Sustain. Energy Rev., vol. 78, pp. 72–79, October 2017.

[9] H. Wang, Z. Lei, X. Zhang, B. Zhou, J. Peng, "A review of deep learning for renewable energy forecasting," Energy Convers. Manag. vol. 198, 111799, October 2019.

[10] M.N. Akhter, S. Mekhilef, H. Mokhlis, Z.M. Almohaimeed, M.A. Muhammad, A.S.M. Khairuddin; R. Akram, M.M. Hussain, " An Hour-Ahead PV Power Forecasting Method Based on an RNN-LSTM Model for Three Different PV Plants" Energies, vol. 15, no. 6, 2243, 2022.