Annual Forecast of Photovoltaic Power Generation Based on MLP Artificial Neural Networks

Pronóstico Anual de Generación de Energía Fotovoltaica Basados en Redes Neuronales Artificiales MLP

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Abstract

The intermittency of solar energy resources presents a significant challenge in balancing power generation and load demand. To enhance system consistency, forecasting photovoltaic solar energy is crucial. Among numerous techniques, Artificial Neural Network (ANN) is an efficient tool that can help simplify this problem and predict photovoltaic power generation based on various inputs such as weather data and panel characteristics. In this paper, we present the results of an annual forecast of photovoltaic power generation based on Multilayer Perceptrons (MLP), which provides valuable insights into the potential of MLP ANN for accurate and reliable prediction of photovoltaic power generation, thereby improving the efficiency and reliability of photovoltaic systems. The results were obtained based on data collected over a year and validated with data from the following year. Mean Squared Error (MSE) was utilized to quantify the error between the predicted and measured photovoltaic solar energy generation. The analysis demonstrated that this annual forecast of photovoltaic power generation is highly accurate.

Photovoltaic energy forecasting, ANN, MLP

Resumen

La intermitencia de los recursos de energía solar presenta un serio desafío para equilibrar la generación de energía y la demanda de carga. Para mejorar la consistencia del sistema, es crucial pronosticar la energía solar fotovoltaica. Entre numerosas técnicas, la red neuronal artificial (ANN) es una herramienta eficiente que puede ayudar a simplificar este problema y predecir la generación de energía fotovoltaica en función de varias entradas, como datos meteorológicos y características del panel. En este documento, presentamos los resultados de un pronóstico anual de generación de energía fotovoltaica basado en perceptrones multicapa (MLP) que otorga información valiosa sobre el potencial de las MLP ANN para el pronóstico preciso y fiable de la generación de energía fotovoltaica, lo que puede ayudar a mejorar la eficiencia y la fiabilidad de los sistemas fotovoltaicos. Los resultados se obtuvieron en base a los datos recopilados durante un año y fueron validados con datos del año siguiente. Para cuantificar el error entre la generación de energía solar fotovoltaica predicha y medida, se utilizó el error cuadrático medio (MSE). El análisis mostró que este pronóstico anual de generación de energía fotovoltaica es muy exacto.

Predicción de Energía Fotovoltaica, ANN, MLP

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Introduction

The generation of energy from renewable sources, such as solar energy, has become one of the main strategies for reducing greenhouse gas emissions and mitigating climate change. Photovoltaic energy is one of the most promising technologies in this regard, as it harnesses solar light to produce electricity in a clean and sustainable manner (IEA, 2021). However, the generation of photovoltaic energy is influenced by numerous factors, such as climatic conditions, geographical location, the tilt, and orientation of solar panels, among others. This makes predicting the amount of energy that will be generated in a specific period a complex task (Almasad, 2023). This is where artificial intelligence (AI) comes into play (Gupta, 2022), and in our case, artificial neural networks, specifically MLP models. These networks have been successfully used in predicting photovoltaic energy generation, as they can learn from historical data and forecast the amount of energy that will be generated in a future period (Sharkawy, 2023).

The ability to forecast photovoltaic energy generation largely depends on the time horizon considered for the prediction. The temporal prediction scale can vary based on the forecasting purpose, ranging from periods of a few seconds to several years. Long-term photovoltaic energy forecasting is primarily used to assess the technical and economic feasibility of photovoltaic plant projects (Iheanetu, 2022), thereby enabling the planning of energy distribution. Annually forecasting photovoltaic energy generation becomes a valuable tool for planning such energy generation. This forecast enables energy planners and investors to anticipate the amount of energy that will be generated in a specific year, aiding them in making informed decisions regarding the implementation of solar projects and the integration of solar energy into existing electrical grids.

In recent years, various models based on artificial neural networks have been developed to predict solar energy generation. These models utilize historical data of solar radiation, temperature, and other environmental variables to train the neural network and achieve an accurate estimation of solar energy generated in a future period (Singla, 2021) and (Sudharshan, 2022).

Among the most common models are those based on MLP and recurrent neural networks (RNN), which have demonstrated high accuracy in predicting photovoltaic energy. Among the most recent studies, we find (Asiri, 2023), who present a methodology for regional-level photovoltaic energy forecasting using machine learning models such as MLP and Support Vector Machines (SVM), along with climatic data. They validated their model with real photovoltaic energy production data and achieved a mean absolute error of 3.8% for one-day-ahead prediction.

In (Phan, 2022), a novel solar energy generation forecasting model is introduced, based on a deep learning framework and data preprocessing and postprocessing techniques. The proposed model utilizes a Convolutional Neural Network (CNN) to extract relevant features from historical data and a Recurrent Neural Network (RNN) to capture temporal relationships within the data. On the other hand, (Ncir, 2022) introduces a novel configuration of an artificial neural network model to enhance maximum power point (MPP) tracking in photovoltaic panels. In this study, a model is proposed that combines an Artificial Neural Network (ANN) with a maximum power point tracking algorithm based on a Proportional-Integral-Derivative (PID) controller.

Hybrid models of ANN and highly sophisticated ones can also be found, such as (Liang, 2023), who present a novel hybrid machine learning approach for efficient short and medium-term photovoltaic generation prediction. This approach combines a Fourier-based Characteristic Decision Tree (FCDT) analysis technique to extract relevant features from historical data, a Particle Swarm Optimization (PSO) algorithm based on another interactive swarm optimization algorithm called (IWBOA) to fine-tune model parameters, and a Linear Kernel Support Vector Regression (LSSVR) model for prediction.

In this work, we present the annual generated energy prediction of a solar farm using a simple MLP ANN without utilizing atmospheric parameters. The decision to employ a basic neural network instead of more advanced architectures was contingent on the specific objectives of our problem and the amount of available data.

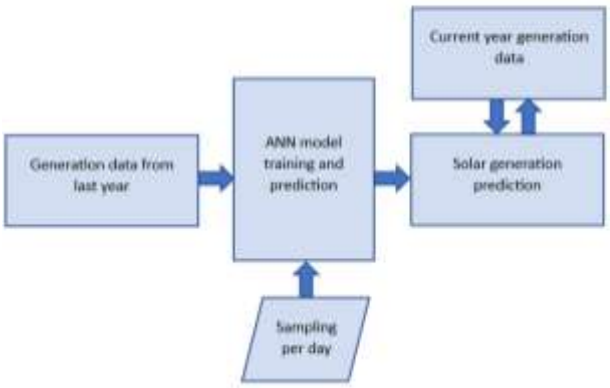

Figure 1 Model Used for Photovoltaic Solar Energy Prediction

In our case, we demonstrate that a simple neural network is adequate for addressing the annual solar energy forecasting issue, particularly when dealing with a restricted dataset such as generated energy. Furthermore, the ANN can be computationally more efficient than advanced networks, which could be crucial for scaling to a real-time application. As discussed in the previous paragraph, a CNN, MPP with FCDT, IWBOA, LSSVR, and other techniques might be necessary to handle larger and more complex datasets.

Methodology

The process of predicting photovoltaic solar energy generation begins with the acquisition of historical data. Once obtained, missing data errors are corrected to minimize their impact on the results of photovoltaic production prediction. Finally, the development of the MLP ANN model for prediction is undertaken.

Figure 1 shows the model employed for photovoltaic solar energy production prediction. The forecasting process consists of two main stages. In the first stage, the model is trained using only historical production data measured during the year 2021 at the solar plant. Once the model is trained, historical data from the year 2022 is used for comparison and validation of the forecast.

To quantify the error of the predicted data, a comparison was made with observed data from the same period one year later. Differences between forecasted and observed values were calculated, i.e., the mean squared error (MSE).

The forecast results for all output combinations were compared based on the MSE provided by

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

Data Acquisition

Energy generation data were collected from the solar energy field situated at the University Center of Tonalá (CUTONALA) during the years 2021 and 2022. The field comprises 1560 solar panels with a maximum generation capacity of 499 KWp. In Graph 1, a plot of the obtained data for the daily photovoltaic energy production in the month of February 2022 can be observed.

Description of the MLP Model

The prediction problems of univariate time series can be modeled using multi-layer perceptrons, or MLPs. A model is required that learns from the set of previous observations to predict the subsequent value in the sequence within a dataset of univariate time series, which comprises a single series of observations with a temporal order.

Graph 1 Data obtained from the monitoring of photovoltaic solar energy generation for the month of February 2022

Before modeling a univariate series, training data must undergo preprocessing. The MLP model will learn a function that transforms a series of previous input observations into an output. As a result, the sequence of observations needs to be divided into distinct examples so that the model can learn from them. To learn a one-step prediction, we can split the sequence into input/output patterns, or samples, where *N* time steps serve as input, and one time step serves as output.

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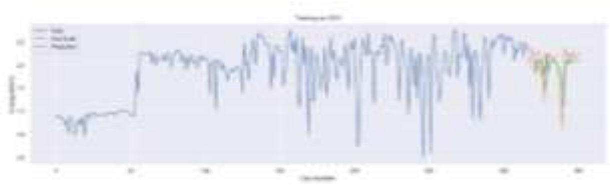
A basic MLP model consists of an output layer for making predictions and a single hidden layer with nodes. Using the Mean Squared Error (MSE) loss function, the model is adjusted and optimized using *Adam*, a variant of stochastic gradient descent. Additionally, the Rectified Linear Activation (ReLU) function is employed in the hidden layer. The input dimension is determined by the number of time steps *N*.

During training, the model is fitted for 50 epochs to find the optimal set of parameters. The best model, which achieved the lowest error on the validation set (Graph 2), was selected. This validation set constitutes 10% of the total training set. Choosing this model enables the acquisition of a more generalizable model capable of making accurate predictions on previously unseen data.

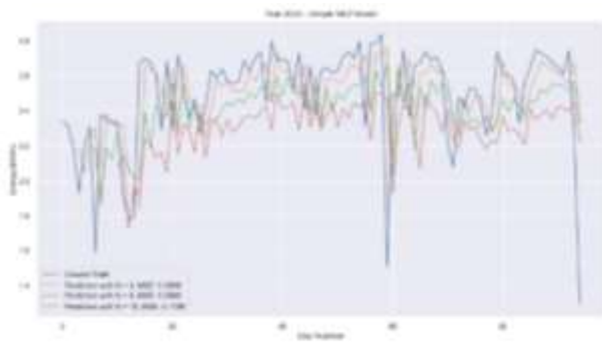
For model evaluation, the data from the year 2022 were used. The following time step sizes were chosen for utilization and evaluation: N = 3, 5, 10. Table 1 displays the results for each of these N sizes. Similarly, Figure 4 illustrates the patterns and trends learned by the model applied to the 2022 data. It can be observed that the time step size N=3 corresponds to the model with the lowest error.



Graph 2 Data series throughout the year 2021 (blue). The MLP model learns patterns over the days, making accurate predictions (green) for the validation set (orange)

Results

A model was evaluated using data from the year 2022, considering three different time step sizes: N = 3, 5, 10. The evaluation results are presented in Table 1, indicating that the model with the smallest error corresponded to the time step size N=3. Furthermore, Graph 3 illustrates the patterns and trends learned by the model when applied to the 2022 data. These findings suggest that the model with a time step size of N=3 is the most suitable for making accurate predictions using future data.



Graph 3 Data series throughout the year 2021 (blue). The MLP model learns patterns over the days, making accurate predictions (green) for the validation set (orange)

As depicted in Graph 3, the time step size is crucial for such prediction; however, the energy prediction trend for the year 2022 remains consistent and close to the actual data, regardless of the chosen time step size.

Conclusions

It can be stated that the annual photovoltaic energy generation forecast based on MLP artificial neural networks is an efficient and accurate technique for predicting long-term solar energy production. The reviewed studies demonstrate that the use of data preprocessing techniques and the inclusion of meteorological variables as additional inputs could significantly enhance the model's accuracy.

N	MSE
3	0.0809
5	0.0865
10	0.119

Table 1 Three-time step sizes were selected for utilization and evaluation: N=3, 5, 10. The model with the lowest error for each N value is shown in bold

The choice of the presented neural network architecture is relevant due to its low complexity, significant reduction in training time, and the potential for online implementation. Once trained, our MLP network has proven to be efficient, achieving predictions with lower MSE than reported values. In conclusion, the application of MLP artificial neural networks for photovoltaic solar energy generation prediction is a valuable and promising tool to enhance the efficiency and profitability of our solar farm. Ultimately, it contributes to the energy transition towards renewable and clean sources.

For future work in annual photovoltaic energy generation prediction, the incorporation of advanced data preprocessing techniques is considered to enhance the quality of data used in model training. Exploring the utilization of other deep learning techniques, such as convolutional and recurrent neural networks, is also on the agenda to achieve higher accuracy in photovoltaic generation prediction. Additionally, there are plans to include atmospheric data to improve the predictive capability of the model.

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