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Irradiance And Temperature Forecasting for Predictive Control of Modular Cascaded PV Inverters

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ABSTRACT

Solar radiation data is needed by engineers, architects and scientists in the framework of studies on photovoltaic across modular cascaded PV inverters. A stochastic model for simulating global solar radiation is useful in reliable power systems calculations. The main objective of this paper is to present an algorithm to predict hourly solar radiation in the short/medium term, combining information about cloud coverage level and historical solar radiation registers, which increased the performance and the accuracy of the forecasting model. The use of Artificial Neural Networks (ANN) model is an efficient method to forecast solar radiation during cloudy days by one day ahead. The results of three statistical indicators - Mean Bias Error (MBE), Root Mean Square Error (RMSE), and t-statistic (TS) - performed with estimated and observed data, validate the good performance accuracy of the proposed three indicators.

Keywords: Forecasting model, Neural networks, Solar radiation

Introduction

Due to over population and industrialization, the demand for electrical power is increasing more and more. Fossil sources also depleting day by day. In order to achieve the power demand renewable energy sources are the best alternative. Among all renewable sources Solar energy is most popular and having more abundance all over the globe and as well as pollution concern also PV system is the best alternative in renewable sources. After development of new power electronic devices it is becoming easy to establish large scale PV generating systems. There are mainly two types of generating systems in PV. One is small scale PV system and another one is large scale PV system. Small scale PV systems are mainly used in Distributed Generating systems (DG).The problem with PV DG system is for designing this system high voltage gain need to be required [1-4]. In order to achieve this high gain we are choosing Grid connected PV system that is large scale Grid connected PV system In Grid connected PV system Power Electronic devices such as converters and inverters are main parts along with PV panels. Converters are used for stepping up the voltage which is produced by PV panels. Voltage source inverters are needed for conversion of DCAC supply and for getting MPPT or stabilizing the DC voltage. Cascaded Modular Multilevel Inverters having so many advantages like improved

Waveform quality and less THD etc. For interfacing Large scale PV system with Grid the main medium we require is this Cascaded Modular Multilevel Inverters [5]. Thus, Large scale PV systems with Cascaded Modular Multilevel Inverters are facing some severe problems like mismatch of MPPT power values of each Module, Thermal gradient, dirt etc. In this entire system the input for grid is given by Cascaded Multilevel inverter which converts DC output from DCDC converter to AC supply for each phase of grid. If the output of Inverter is mismatch to the grid requirements, then active power flow will get disturbs [6-7].

Research Motivation

The issue of partial shading in photovoltaic (PV) power generation systems has been well-investigated by many researchers [1-6]. A standard solution has involved incorporating bypass diodes within the PV array, but it has been recognized that this scheme alone reduces the power generated by the system [7-10]. Since the cost of power switching devices is steadily falling, the current trend is to replace the bypass diodes with power electronic converters, so that all series connected panels in an array can generate power corresponding to their respective levels of irradiation. Many such schemes have been proposed, based on either continuous or differential power processing approaches [10-14]. An example of the former is illustrated where one or several series and/or parallel chained PV panels are connected to a DC-DC converter forming a PV and converter integrated module [10]. Connecting multiples of such modules in series can raise the voltage levels sufficiently to enable transformer-less grid connection. Several well-known DC-DC converter topologies have been considered for such a scheme [10, 11]. However, the shortcomings of this scheme are twofold; firstly, the operating point of each of these modules is constantly changing in response to a system disturbance even though it may be, for example, due to the variation in light intensity level experienced by the other modules in the chain [12]. The other drawback is that the full power generated by each of these PV modules flows through their respective converters, causing additional power loss [10, 12]. The above shortcomings can be alleviated by using differential power processing scheme, which has been investigated by various researchers [10-14].

Impact of Solar Irradiance and Ambient Temperature

With the rapid advancement of power electronic technologies, PV inverter systems [1] have been widely applied to harvest energy from solar energy systems, grid connected applications etc. The application of inverter leads to an increase in the utilization of solar energy sources and shares a significant amount in total electricity demand [2]. Nevertheless, researchers reported PV inverter as the most unreliable device in the PV system. The studies [3-7] says that the Grid connected PV inverter is the weakest among all in terms of reliability due to the power semiconductor switches. Factors such as quality control, adequate design, Electrical component failure, and other manufacturing factors influence the reliability of PV inverter. A survey [8] taken from industries concluded that power electronics switches are the critical components. The major failures in power electronic switches are due to thermomechanical failures. Reported wear out, bond wire liftoff, etc., are the most occurring failures in switches [9, 10]. Environmental conditions lead to power cycling and thermal cycling of the switch, which are the major causes for failure. Hence reliability evaluation of power electronic switch is needed.

The reliability performance of the PV inverter is affected by environmental factors like solar irradiance, ambient temperature (also called Mission Profile). Environmental condition varies from location to location. Regions near the equator receive relatively high average solar irradiance and average ambient temperature all over the year. Similarly, regions far from the equator receive relatively low average solar irradiance and average ambient temperature all over the year.

Unbalanced Load Across Control of Modular Cascaded PV Inverters

For stability study, to analyze the stability of a system including a power converter and constant power loads. We need to analyze the system stability from the ac side [6]. The method considers a stability study for an ac and dc distribution system connected together via a power converter Power systems deliver energy to loads that perform a function. These loads range from household appliances to industrial machinery. Most loads expect a certain voltage and, for alternating current devices, a certain frequency and number of phases. The parameters considered for the unbalanced load. Unbalanced load makes the lines / phases to carry different current magnitudes, and sum total of these at neutral point is not zero. Load in each phase is different, carrying its own current. Neutral in this case carries the net unbalanced current. For our analysis we have considered resistive load of different magnitude for each phase. The parameters and type of loads used during the simulation are being depicted in the figures above. The mixed load analysis help us to make sure that the system is being modeled efficiently for various loading conditions.

Irradiance And Temperature Forecasting For Predictive Control Using AI

Solar Photovoltaic (PV) systems represent key and transformative technology at the forefront of the global shift towards sustainable energy solutions. These systems harness the renewable radiation of the sun, converting it into clean electricity. Their importance cannot be overstated as they play a fundamental role in mitigating climate change, reducing dependence on finite fossil fuels, and providing access to clean energy sources for both developed and developing regions. Solar PV systems are not only a key component of the renewable energy portfolio, but also a symbol of our commitment to a greener and more sustainable future for generations to come.

The main difficulty in solar energy production is the volatility and intermittency of photovoltaic system power generation, primarily stemming from unpredictable weather conditions. Variations in irradiance and temperature can have a profound impact on the quality and reliability of electricity production from solar PV systems. Since solar irradiance is intricately linked to the efficiency of solar power harvesting, its accurate prediction serves as a crucial indicator of power production potential. For large-scale solar plants, any power imbalance within the PV system can lead to significant economic losses. Therefore, precise solar irradiance prediction, coupled with the appropriate modeling of PV system behavior, has emerged as a vital necessity to mitigate the impact of uncertainty and control energy costs. Furthermore, it facilitates the seamless integration of PV systems into smart grids, a growing trend driven by the increasing adoption of PV technology.

Numerous studies were undertaken to develop models and algorithms that predict solar irradiance based on various routinely measured meteorological parameters, such as temperature and humidity, to address these challenges. These advancements in accurate solar irradiance forecasting and the sophisticated modeling of PV systems have now become the cornerstone of modern smart grid development, supporting the expansion of Renewable Energy Sources (RESs).

The importance of Artificial Intelligence (AI) methods in predicting, modeling, and fault detection in PV systems cannot be overstated in today's energy landscape. AI has emerged as a transformative force in addressing the inherent challenges associated with solar energy production. Through the utilization of advanced machine learning algorithms and data analytics, AI techniques can ingest vast datasets, including historical weather patterns, system performance data, and real-time measured parameters, to provide highly accurate solar irradiance predictions. This precision in forecasting enables PV systems to optimize their energy capture, adapt to changing weather conditions, and maximize their overall efficiency. Moreover, the AI-driven modeling of PV systems goes beyond mere prediction by providing a comprehensive understanding of how these systems behave under various operating conditions. These models allow for the fine-tuning of PV system parameters, such as PV array orientation and tracking mechanisms, to achieve ultimate performance. Additionally, AI-based modeling helps to identify potential issues and areas of improvement, contributing to system longevity and reducing maintenance costs. In fault detection, AI technologies offer real-time monitoring and anomaly detection capabilities. By continuously analyzing the performance data from PV systems, AI algorithms can swiftly identify deviations from expected behavior, such as PV module failures, inverter malfunctions, or shading issues. The early detection and identification of these anomalies is crucial in preventing downtime, reducing energy losses, and ensuring the overall reliability of the PV system.

Proposed Artificial Neuro Networks Predictive Modeling

Neural Networks

Neural networks are a computational method that uses an enormous group of artificial neurons. These neurons are inexactly equivalent to axon in a biological brain. Neural networks are used in various fields such as machine learning, image processing, signal processing, and computer science, controlling power electronics converters that interface the PV systems [11] and modeling energy sources [2]. They consist of three parts: neurons, activation functions, and bias. The neurons can be either input neurons, output neurons, or hidden neurons. Fig. 4a shows a simple feed-forward neural network with one hidden layer. Fig.1 shows the FNN with input from a sliding window [12]

Forecasting allows for predicting the required future steps for different application areas, such as commercial and industrial fields. This is mandatory for to make the necessary decisions to improve the future situation and avoid the worst outcomes that could affect the desired situation. Forecasting is divided into two types: qualitative and quantitative forecasting. Time series forecasting is the most prominent of these methods. Indeed, time series are predicted by mathematical forecasting through time-specific historical data. The historical data are analyzed and strategic decision-making is performed for the future. For this type of prediction, the analysis must be thorough and evidence-based to ensure that the future outcome is achievable.

Nowadays, most technologies use artificial intelligence (AI) because of its efficiency. Among AI techniques, those based on neural networks (NN) are being employed to address many problems, including prediction problems. The working principle of NNs is based on an interconnected processing element that depends on biological neurons equivalent to pieces that carry information and transmit it to other cells in a series of networks.

According to fig.1 the artificial neurons consist of three levels: the first level is the input, which consists of a number of nodes where each node represents one of the inputs, and the second level is the hidden level, and its number varies from one network to another according to the level of input and output. The last level is the output level, which is the result or the goal to be reached. All the previous levels are connected to each other through the nodes and contain a group of nodes that receive inputs and outputs called the level, and each node carries weights that enhance the strength of the neural connection.

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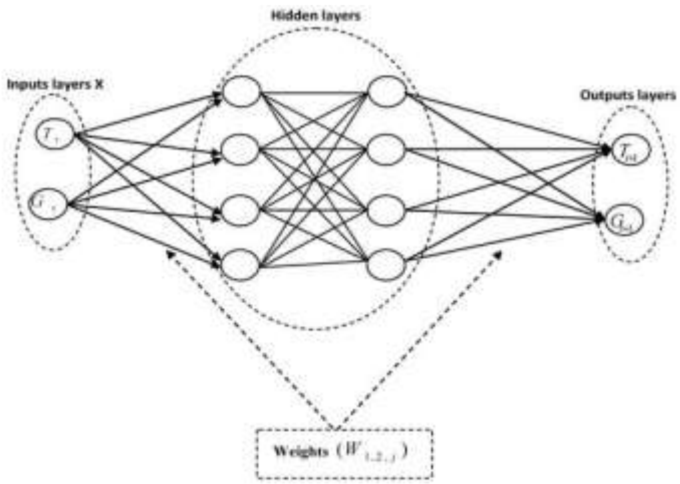

Fig.1 Neural network architecture

The NN-based prediction technique of the temperature and the irradiation (T and G) follows these steps:

Step1: Data assembly, pre-processing, data conversion, and normalization. The data set used to predict the temperature and solar radiation reflected on the PV under study was obtained from the Department of Systems Engineering and Automation at the Vitoria School of Engineering of the University of the Basque Country.

Step2: Statistical analysis.

Step3: Neural Network objects design.

Step4: Network training; the algorithm of Levenberg Marquardt has been used for the training of the network. This choice has been justified by the fact that this algorithm typically requires more memory but less time. The training automatically stops when the generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The Mean Squared Error is the average squared difference between outputs and targets. Lower values are better, as zero means no error. This algorithm is also improving the regression, R, and it is the value measuring the correlation between outputs and targets. A unit, R, value indicates a close relationship, while 0 denotes a random relationship.

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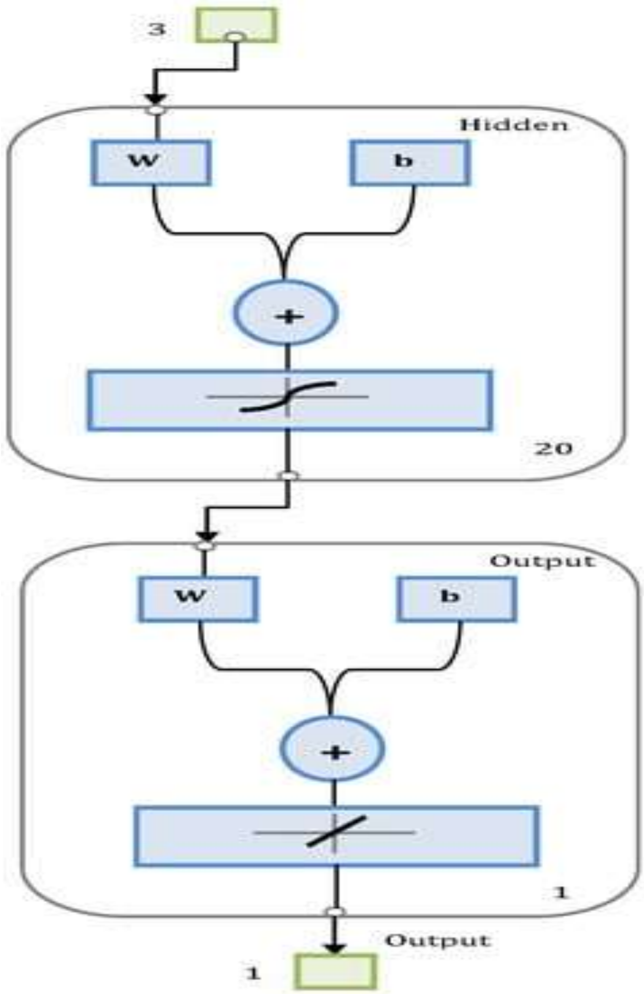

Fig.2. The neural network architecture.

Step 5: Simulation of network response to new entries.

Step 6: Approval and testing.

The sample data process is divided into three phases: A reasonable result can be achieved by adjusting the ANN weights during the training phase. The second phase involves determining the minimum point of error. In the third phase, the accuracy of the ANN is evaluated.

After presenting the proposed forecasting technique, the following section focuses on the suggested MPPT-based control of the DC-DC chopper integrated to extract the maximum available power independently of the meteorological conditions.

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Result And Analysis

Furthermore, AI-driven insights are indispensable for the integration of PV systems into smart grids. These systems require precise forecasting, adaptive control mechanisms, and seamless coordination with other energy sources to ensure grid stability and reliability. AI plays a pivotal role in enabling this integration by providing real-time information on the expected power output from PV systems, allowing for grid operators to make informed decisions about load balancing and energy distribution.

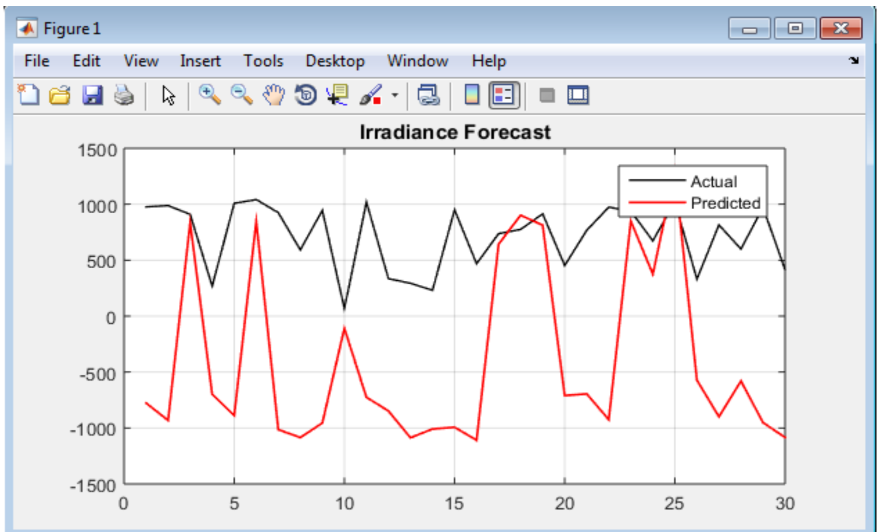

Fig 3. Actual and Predicted result.

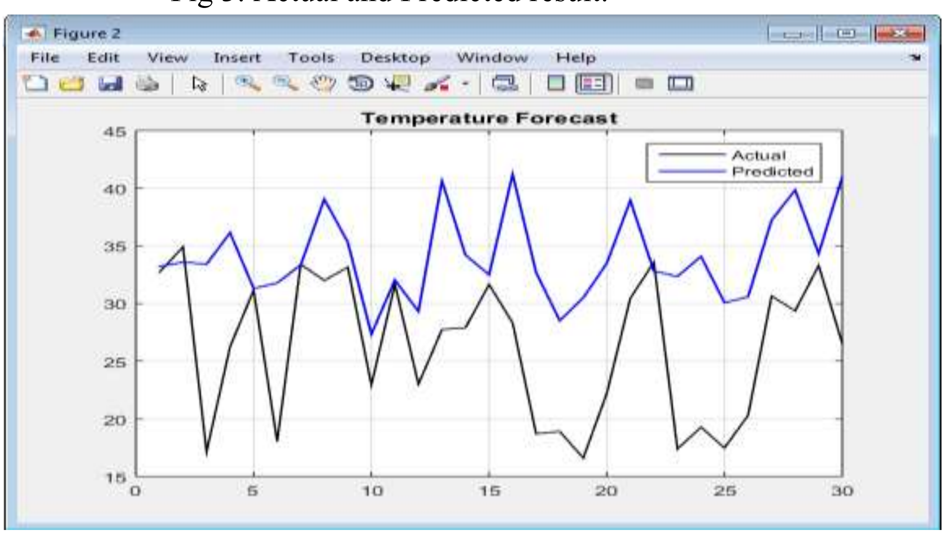

Fig 4. Temperature Actual and Predicted result.

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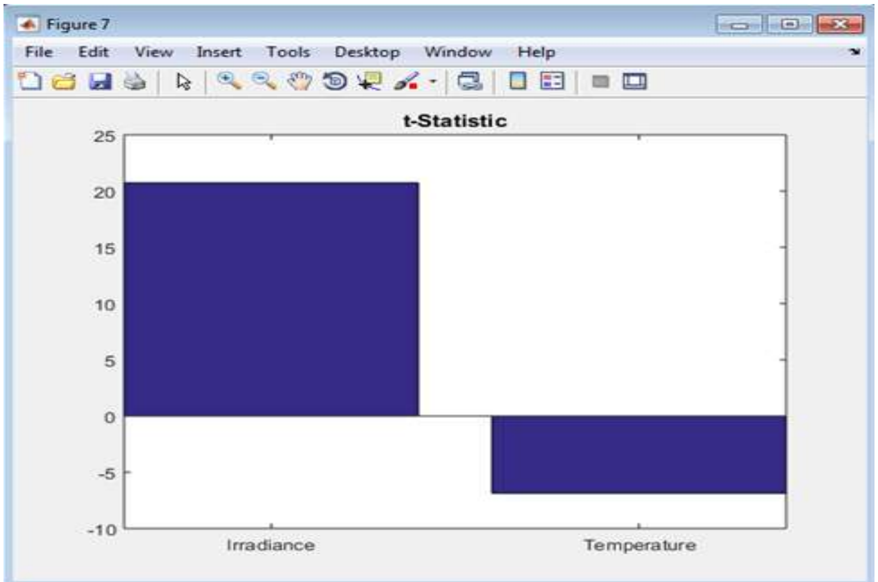

Fig 5.T statics.

Conclusion and Future Work

This paper presented a deep learning neural network algorithm and was implemented to predict short-term solar irradiance. The data was cleaned, and anomalies such as wrong readings were removed and the data normalized to be ready for training. Then, the network was implemented to train the data and predict the future samples. The results were presented and were compared to other methods such as NN. All other predictive models exhibited lower accuracies and more bias error than deep learning neural network. Deep recurrent neural networks have potential in big-data applications, renewable energy forecasting, and predictive modeling. Solar irradiance time series can be treated as big data if the sampling rate and volume are high.

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