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Solar Prediction in Multi-Area Networks Using Shallow Neural Network

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Abstract-
In the worldwide electric energy grid, power system operation depend heavily on the accuracy of solar energy forecasts. Thus, it is essential to guarantee that consumers receive a steady and consistent power supply. But because solar energy data is erratic, simple statistical and machine learning techniques are unreliable for predicting. Performance evaluation criteria, weather classification, predicting horizon, and other aspects all affect how well solar irradiance performs. As a result, it offers research on models for forecasting solar irradiance that use shallow neural networks. More than a thousand records of solar energy output are included in the dataset, together with meteorological data covering a full year. Various indicators are used to evaluate these models' performance. The model of the type that was chosen has a mean absolute error (MAE) of 0.24 and a mean square error (MSE) of 0.14.

Keywords*: Solar Forecasting, Artificial Neural Network, Shallow Neural Network, Solar Prediction etc.*

I. Introduction

Globally, photovoltaic energy has grown remarkably as a result of rising energy consumption. This renewable energy source serves major consumers' demands in the industrial and residential sectors. Because of its unique ability to reduce CO_2 emissions, photovoltaic (PV) energy generation is positioned as a growing and powerful weapon in the fight against change in climate.

A relevant concern pertains to the sporadic and unstable character of energy production in PV systems. The amount and quality of solar radiation have a big influence on photovoltaic energy production. Even though solar panels use solar radiation to generate electricity during the day, the amount of energy produced varies greatly because of variations in the weather.

The photovoltaic system may become unbalanced as a result of this instability, which also affects the integrated electrical grid's stability. These unanticipated variations can result in substantial swings in power generation in large-scale solar facilities, especially those that are connected to the grid. This can cause problems with power quality and supply disruptions. In addition to the difficulties related to technology and system stability, solar generation's instability has financial ramifications. Large solar farms usually run on long-term contracts for electricity supply; any unexpected change in output can result in contract violations and significant losses in money.

By 2030, the total PV power capacity could surpass 1700 GW worldwide. However, weather circumstances such as bright, cloudy, and rainy days; abrupt changes in the weather; snowy days; and other weather types greatly impact the forecast ability of solar PV output, posing issues for system administrators. From now on, accurate and dependable PV power output is necessary for efficient grid operation. Because electric power systems need precise forecasting models to plan their operations, commercial electric power firms are facing challenges in providing safe and dependable electricity to their customers. In addition to time, the economy, and social and environmental variables also influence the patterns of power use.

Forecasting solar irradiance helps with energy storage system scheduling, energy transmission optimization that lowers energy loss, and integration of solar PV facilities into the electrical grid. Additionally, it lowers reserve capacity and cost generation, reducing disruptions to the electrical energy system and facilitating the prediction of PV power generation. Academics and corporations have become increasingly interested in solar irradiance forecasts over the years since solar energy is a renewable resource that can be used to power entire countries.

Several solutions have been suggested to address this problem. The application of short-term forecast models is one of these fixes. With the use of these models, solar energy generation may be tracked and predicted in relation to relevant weather and other variables. These models help optimize solar plant operations and lessen the negative consequences of generation volatility by using machine learning techniques to produce more accurate projections. The search for technological solutions is essential to mitigating the adverse effects of this instability, guaranteeing the effective assimilation of solar energy into the electrical grid.

Although there has been a lot of research done recently to create novel models that can forecast meteorological factors related to photovoltaic power, one crucial step that is sometimes missed is the preliminary examination of the data before it is used. This study offers a thorough grasp of the traits and trends in the data, producing insightful knowledge that can be used to improve forecast models and provide more consistent and accurate outcomes.

The forecasting of solar irradiance for photovoltaic systems (PHV) using image-based models for GHI forecasting is covered in the literature that is currently available. When applied to the task of estimating solar irradiance in a certain region, this approach works wonderfully. The ability to capture cloud motion is made possible by the great temporal and geographical precision of sky photographs. Unlike empirical approaches, image-based algorithms guarantee the accuracy of GHI forecasting by extracting cloud information from the sky image collection. Nevertheless, restricted access to picture datasets, pricey image capturing hardware, and costly image processing are the disadvantages of image-based models. Forecasting PV power and solar irradiance can be done in four different ways: physically, using statistical models, artificially intelligent techniques, and hybrid approaches. Using a dynamic atmospheric model, the NWP model calculates the solar irradiance and physical state. Additionally, the NWP model integrates meteorological and geographic data. Physical models are widely used to predict atmospheric dynamics, but a significant drawback is their complexity. This issue arises because handling large datasets with physical models takes more time and more computer power. As a result, it is thought to be useless to estimate short-term solar irradiation using physical models. The literature claims that a number of additional statistical models, such as dynamic systems with linked autoregressive features and autoregressive moving averages, have been applied.

The main objective of this paper is to estimate and assess daily solar radiation using an ANN model's inputs. Test and training datasets from Indian cities are used. All ANN models use backpropagation techniques. These statistical metrics were calculated to evaluate the performance of the proposed models like mean absolute error etc.

The structure of the paper is as follows: A broad overview of the effects of solar forecasting use is given in Section II. Section III provides a brief overview of system architecture. The results are presented in Section IV. Finally, Section V discusses the conclusion.

Ii. Impact of solar forecasting

Based on their predicting horizon, solar energy forecasting models can be categorized. Future demands for power generation and consumption must be known to a power generation operator. For solar irradiance forecasting to be used effectively for a variety of purposes, including the operation of PV power plants, the types of forecasting horizon used are crucial. There are three main types of forecasting horizons: medium-term, long-term, and short-term. Furthermore, a fourth kind known as "extremely short-term forecasting" was included in a small number of investigations.

- Intra-hour forecasting, also known as now casting, is a very short-term forecasting horizon that extends from one minute to many minutes in advance.
- Analysing sales and purchase agreements between various companies, rotating reserve control, and optimal unit commitment all depend on short-term forecasting horizons. They can be scheduled one or more hours in advance, as well as one day or one week. As a result, they improve grid security and facilitate the design of an integrated photovoltaic energy management system.

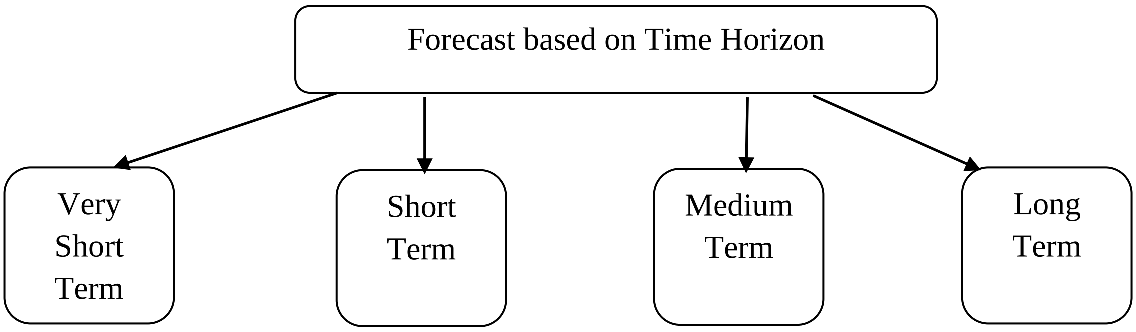

Fig 1: Classification of Solar Power Prediction [1]

- Medium-term forecasting horizons, which range from one month to one year ahead of time.
- Long-term forecasting spans ranging from one year to ten years. It is not the best option for long-term forecasting, though, as it is unable to predict long-term weather changes. Nevertheless, it is regarded as the most effective model for developing timetables, estimating expenses, and selecting site strategy.

Weather Classification

It is well known that solar radiation is the primary factor that determines PV power potential. The availability of solar irradiance is influenced by a number of meteorological input variables, including pressure, wind speed, temperature, relative humidity, cloud types, and aerosol index. This observation suggests that weather variations are the primary factor influencing the accuracy of solar irradiance forecasting models. This outcome shows how important weather classification is to the longevity and efficacy of forecasting algorithms. Numerous studies indicate that the primary component at play during the pre-processing step of short-term solar irradiance forecasting is weather classification. One significant obstacle to weather classification is said to be the dearth of data available for model training.

Data Description

It makes use of open source data on Indian city data. The system consists of a solar forecasting database containing more than 33000 values for several characteristics such as temperature, wind speed with date and time etc. The main objective of this effort is to use a shallow network to forecast the solar data.

Model Performance Metrics

In particular, a comparison between predicted and actual sun irradiance is used to evaluate overall performance. Models can be adjusted to reach a desired level of precision thanks to the metrics that are employed, which will give feedback on forecasting accuracy: a lower score denotes more exact forecasting. These are:

- Mean Absolute Error (MAE): Equation (1) illustrates this measure, which shows the mean of the absolute errors between the actual and expected GHI values and gives each data inconsistency an equal weight distribution.

$$MAE=\frac{1}{N}\sum_{i=1}^{n}|G_{ai}-G_{pi}| \quad (1)$$

Where n is the total number of data points, and G_{ai} and G_{Pi} stand for the actual and expected GHI values, respectively.

- Mean square error (MSE): Equation (2) illustrates this metric, which is the mean computation of square discrepancies between the amounts of solar irradiance that are predicted and actual. Thus

$$MSE = \frac{1}{N}\sum(G_{pi}-G_{ai})^2 \quad (2)$$

Optimization of Input Features

By choosing the right inputs in terms of amount and kind, forecasting can be enhanced. Large parameter sets have the potential to severely distort forecasts, and inputs with weak correlations or redundancies will make computations even more difficult. Therefore, the selection of appropriate input features depends heavily on optimization approaches. The literature describes a wide range of strategies for PV models, such as grid-search, PSO, ant colony optimization (ACO), chaotic artificial bee colony algorithm (IA) etc. Although every algorithm has advantages and disadvantages, genetic algorithm (GA)-based optimization is the most well-known and effective method for enhancing weights. It is also useful for combination with ANN. By adjusting the input weights, Tao and Chen increased the back propagation neural network (BPNN) model's forecast accuracy.

Iii. System architecture

This work's primary goal is to investigate solar forecasting and prediction using a model of shallow neural networks. Shallow neural networks have one or two hidden layers, at most. Fig 2 shows the structure of shallow neural network, it has different inputs with one hidden layer and one output.

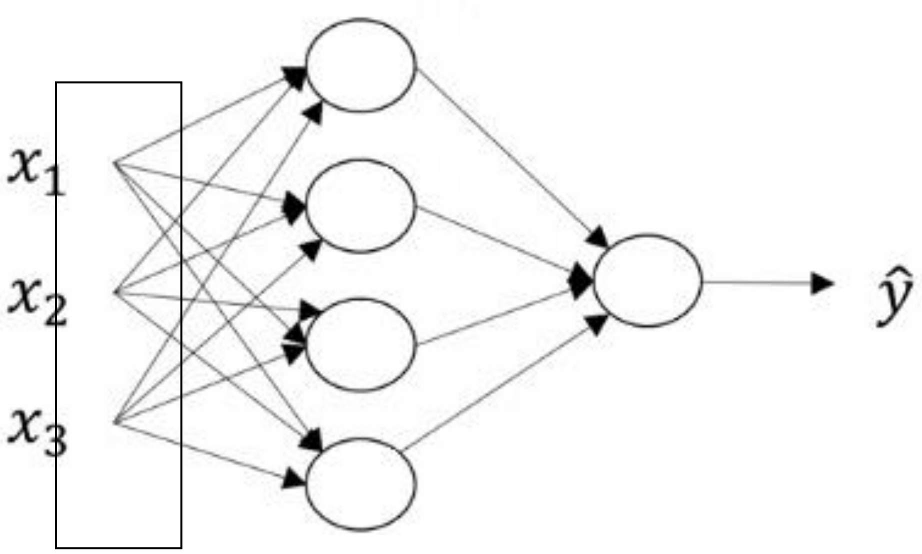

Fig 2: Architecture of Neural Network

The Neuron

The neuron is the fundamental unit of a neural network. It takes an input, produces an output, and then sends that output along as an input to the layer above. You can think of a neuron as the combination of two pieces:

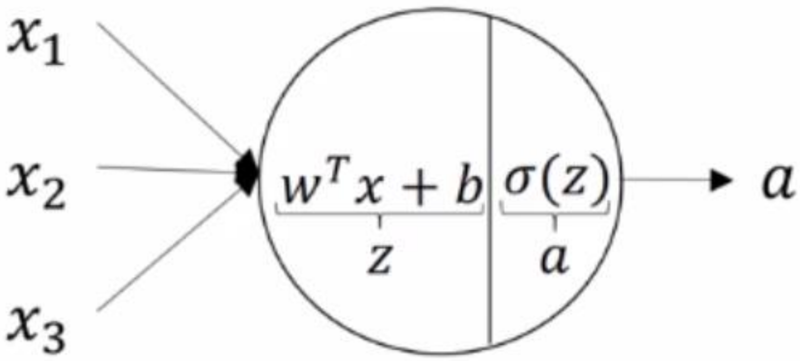

Fig 3: Neuron Structure

1. Using the inputs and weights, the output Z is computed in the first section.
2. The second section activates Z to release the neuron's ultimate output, A.

The Hidden Layer

The aforementioned two computations are carried out by different neurons that make up the hidden layer. Although it is constructed using multiple hidden layers, a shallow neural network is an artificial neural network. Now that it is aware of the computations that take place in each layer. Another name for them might be the forward-propagation equations.

$Z[1] = W[1]^T X + b(1)$

$A[1] = \sigma\ (Z[1])$

$Z[2] = W[2]^T A[1] + b(2)$

Y= A [2] = $\sigma\ (Z[2])$

1. The intermediate output Z [1] of the first hidden layer is computed by the first equation.
2. The first hidden layer's final output, A [1], is computed using the second equation.
3. The output layer's intermediate output, Z [2], is computed using the third equation.
4. The output layer's final output, A [2], which is also the neural network's overall final output, is calculated using the fourth equation.

It uses activations functions to strengthen the network and improve its performance in various conditions. The neural networks acquire non-linear features as a result of these activations functions. A neural network's weights are initialized at random. We must adjust these weights in order to use the neural network to make accurate predictions. We update these weights using a technique called Gradient Descent.

Tool Used

Python is a popular language for machine learning, and there are lots of machine learning libraries available for it.

Iv. Results & discussion

More than a thousand records of solar energy generation are included in this collection, together with meteorological data for a full year. CSV files were used to store the dataset. Kilowatt-hours are used to measure daily production (kWh). The following weather variables were also available: Wind direction in degrees (°), temperature outside in degrees Celsius (°C), wind speed in kilometres per hour (km/h), and adjusted irradiation in watts per square meter (W/m^2). A timeline including the date and time is displayed with these data.

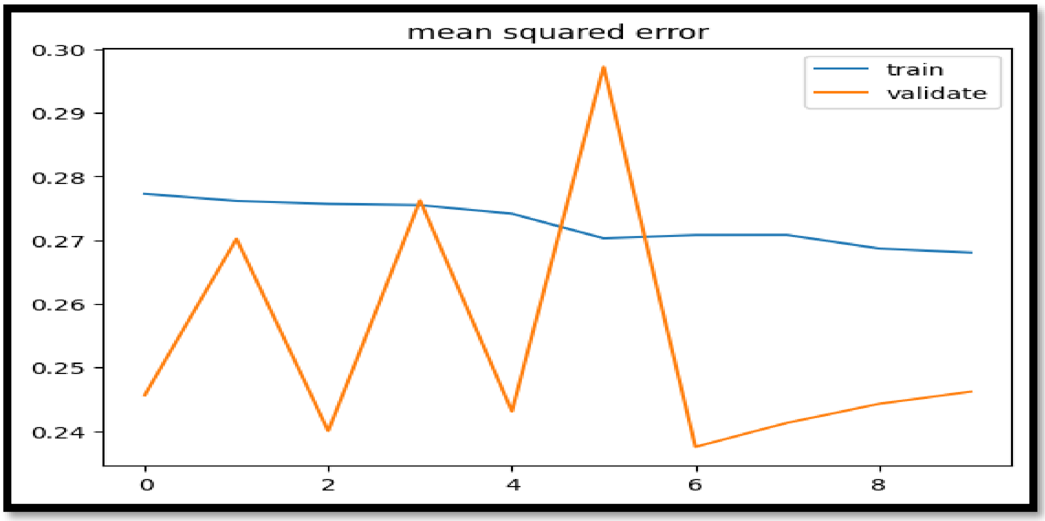

Fig 4: MSE Performance using Neural Network

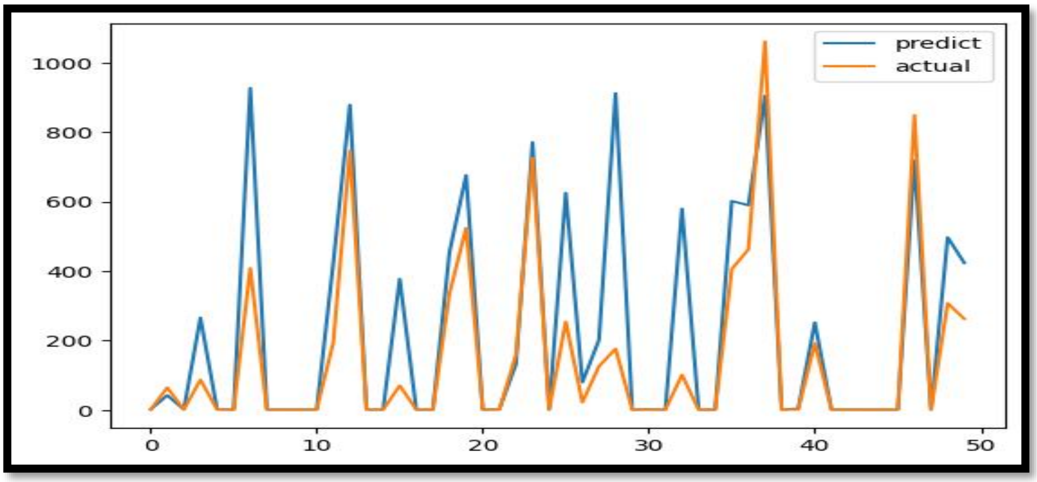

Fig 5: Solar Prediction Output using Neural Network

Table 1: Performance Comparison of System

Model	MAE	MSE
MLP (ANN)	48.1	11500
SNN (ANN)	0.24	0.14

Table 1 shows the performance comparison of system. In this work, it presents the solar prediction using shallow neural network which is a part of ANN with single hidden layer. Hence, it shows better MAE and MSE value as compared to MLP-ANN model.

sV**. Conclusion**

Forecasting using solar radiation is useful now a days and beneficial for climate change concept. This work uses SNN, a component of ANN, to deliver the solar prediction result. The corresponding architecture, advantages, and disadvantages of these models are also included. Furthermore weather classifications, input feature assessment measures all of which have an impact on predicting model accuracy are discussed. The forecasting horizon is seen to be the most important component for increasing forecasting model accuracy. The average solar irradiance forecasting model's performance. As the forecasting horizon gets longer, it gets worse. As a result, depending on the forecasting horizon chosen, forecasting models should be taken into consideration. A single learning model can only be used so often. Our results demonstrate that hybrid models, which combine several models to increase accuracy, are better than simple deep learning models. The selected model's mean square error (MSE) is 0.14 and its mean absolute error (MAE) is 0.24. When comparing the results to the MLP-ANN model, the MAE and MSE values are favourable.

Refferences

[1]. Chengfu Wang, Hongbin Sun, Jun Liang, (2014), "The study of Unit Commitment Considering Wind Forecasting Power" International Conference on Power System Technology, pp. 2614-2617.

[2]. Gianni Goretti, Aidan Duffy, (2017), "The Impact of Power Curve Estimation on Commercial Wind Power Forecasts - An Empirical Analysis" IEEE, pp. 01-04.

[3]. Jie Yan, Yongqian Liu, (2013), "An Integration of Enhanced Wind Power Interval Forecasting into Reactive Power Dispatching" IEEE, pp. 01-06.

[4]. Jie Yan, Yongqian Liu, (2014), "A robust probabilistic wind power forecasting method considering wind scenarios" IEEE, pp. 01-06.

[5]. Menglin Li, Ming Yang, Yixiao Yu, (2020), "Wind Power Probabilistic Forecasting Based on Wind Correction Using Weather Research and Forecasting Model", IEEE Student conference on Electric Machines" Systems, pp. 619-624.

[6]. H. J. Lu, G. W. Chang, (2018), "Wind Power Forecast by Using Improved Radial Basis Function Neural Network", IEEE, pp. 01-05.

[7]. Man XU, Zongxiang LU, Ying QIAO, (2013), "Study on the Adaptability of Day-Ahead Wind Power Forecast System For On-Site Use", IEEE, pp. 01-05.

[8]. Ankita Singh, Gurtej K, (2016), "Short Term Wind Speed and Power Forecasting in Indian and UK Wind Power Farms", IEEE, pp. 01-05.

[9]. Jyothi Varanasi, M.M. Tripathi, (2016), "Artificial Neural Network Based Wind Power Forecasting in Belgium", IEEE, pp. 01-06.

[10]. Sheng-Hong Wu, Yuan-Kang Wu, (2020), "Probabilistic Wind Power Forecasts Considering Different NWP Models", IEEE International Symposium on Computer, Consumer and Control, pp. 428-431.

[11]. Jie Yan, Hao Zhang, (2017), "Forecasting the High Penetration of Wind Power on Multiple Scales Using Multi-to-Multi Mapping", IEEE Transactions on Power Systems, pp. 01-09.

[12]. Shen Yang-Wu, Mao Xun, (2019), "Load Frequency Control Strategy for Wind Power Grid-connected Power Systems Considering Wind Power Forecast", IEEE conference on Energy Internet and Energy System Integration, pp. 1124-1128.

[13]. Eddie Yatiyana, Sumedha Rajakaruna, and Arindam Ghosh, (2017), "Wind Speed and Direction Forecasting for Wind Power Generation Using ARIMA Model", IEEE, pp. 01-06.

[14]. Xinpeng Zheng, Xiaoxia Qi, Hongda Liu, (2018), "Deep Neural Network for Short-Term Offshore Wind Power Forecasting", IEEE, pp. 01-05

[15]. Sumit Saroha, S.K. Aggarwal, (2019), "Wind Power Forecasting Using Wavelet Transform and General Regression Neural Network for Ontario Electricity Market", Recent Advances in Electrical & Electronic Engineering, pp. 1-11.