Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

EVALUATION OF PHOTOVOLTAIC MODULES OF RENEWABLE ENERGY FORECASTING USING ARTIFICIAL NEURAL NETWORKS

Dr.K. Uma Maheswari[1], Dr.A. Nagaraju[2], Dr.M. Sreevani[3]

Associate professor, Department of Mathematics, Srinivasa Ramanujan Institute of technology[1]
Assistant professor, Department of Mechanical Engineering, JNTUA[2]
Assistant professor, Dept of Humanities & Sciences, SKU College of Engineering &technology[3]
Andhra Pradesh India[1,2,3]

ABSTRACT

Over 1.5 billion people worldwide lack electricity, with many of them living in places far away from the centralized generation. Most of them reside in Asian and African developing countries. The availability of electricity to such places is a continuing global development problem that should be discussed. Some projects have been initiated by the developing nations for electrification, but most of them are not feasible. This examines the sustainability of rural areas and then develops measures to improve how these projects' sustainability can be measured. Moreover, the global energy scenario changed due to drastically reducing fossil fuel reserves worldwide. Even though a PV module-based energy system is known to be maintenance-free, its performance depends on many factors including the effect of shading and orientation of the PV module, solar insolation, tilt angle, temperature of the PV module, performance ratio, and weather conditions. In this paper a solar energy forecasting model based on artificial neural networks is proposed, the intensity of solar radiation is predicated over 24 hours, six months ahead of the solar Azimuth angle.

Keywords: Wind power forecast, Solar power forecast, Artificial Neural Network, and Performance.

I. Introduction:

A project is a significant, short-term, goal-oriented activity that involves a diverse set of skills and resources. It also refers to a collection of individuals who collaborate in a temporary organization to accomplish a goal. As half of their project work, they must construct any machine or building using mechanical principles. The most popular traditional energy sources are coal, oil, and gas. Hydro and renewable sources of energy, on the other hand, play a critical role in developing countries like India, wherein solar energy is abundant and ample [10]. Energy is divided into two types: commercial and non-commercial. Commercial energy is dominated by electricity, with oil products and coal coming in second and third. Industrial, agriculture, transport, and commercial expansion all impact commercial energy in today's globe [6, 7]. Firewood, cow dung, agricultural waste, renewable power, animal-powered vehicles, and wind energy are examples of non-commercial energy. Solar energy, wind energy, geothermal energy, tidal energy, and hydroelectric power are examples of renewable energy sources that may be gathered without generating hazardous pollutants.

Mainly the forecasting of these renewable energy sources plays a vital role in power generation at markets. The ANN is the simple biological algorithm of the brain; they are implemented in widespread applications with different artificial intelligence algorithms that test and train data predicated. [3] ANN learns from the data by training them to approximate and estimate the function of the relationship between the input and output variables.

ANN could provide forecasting for the unstable generation of solar and wind power when the data is valuable. The ANN is considered a color box because it does not provide a sufficient qualitative and quantile understanding of the relationship between the real and predicate values. In this paper mainly the ANN model has used the most feed-forward neural networks sometimes called the single hidden layer network and the performance is compared with other modules. [5] .

II. LITERATURE SURVEY :

Ghassoul (2001) demonstrated a positional tracking system using a Siemens micro–PLC S216. The scheme had never been used before, and the testing specifications had never been made public. In (Sungur 2008) proposed a dual-axis tracking system that used the method to calculate the Sun's azimuth and solar altitude angles over one year. The dual-axis tracking system, which a PLC controlled, had been designed and installed. In the two-axis sun tracking system, 42.6 percent more energy was obtained.

The system used no unusual amounts of energy. (YOUSIF 2012) introduced an industrial automation tracking system based on four sensors mounted on the solar panel frame to track the position of the Sun. An ATmega16L microcontroller controlled the system. The power output gain for the solar tracking panel with two axes was 31.5 percent higher than the fixed solar panel. (Wang and Lu, 2013) proposed a simple response to the requirements of a hold Sun tracker using a single dual-axis A.C. motor to follow the Sun. With only a single tracking motor, V Sundaram Siva Kumar and S Suryanarayana suggested a dual-axis tracking system to implement and develop a simple and effective control method. Their primary goal is to increase power gain by precisely solar tracking. This paper successfully developed, built, and tested a dual-axis sun tracking system and got the highest result.

III. Theoretical analysis of solar and wind energy:

a) Wind Power Energy

Factors of the Wind model on which the production of electricity is dependent are

a) Output curve of power b) Velocity of sound c) Height of Hub

$P_{wind} = P_{RE} * (i_w - i_{wci})/(i_{wr} - i_{wci})$ if $i_{wci} < i_w < i_{wR}$

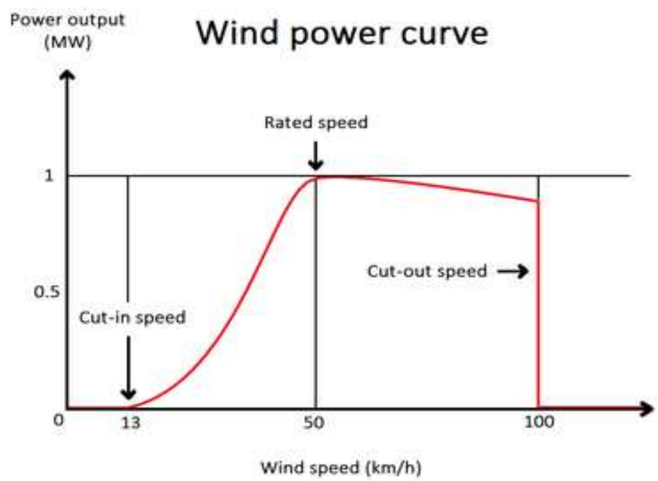
$P_{wind} = P_{RE}$ if $i_{wr} < i_w < I_{wef}$

$P_{wind} = 0$ if $i_w < i_{wef}$ and $i_w > i_{wef}$

Were

i_{wi} = cut in wind velocity, i_{wR} =Rated wind speed, i_{wef} = Cut off wind speed

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025



A permanent magnet synchronous generator (PMSG) produced by the wind energy conversion makes up the proposed hybrid renewable energy generation system. With the aid of the wind generator, which would be a rotating rotor of a PSMG winds generator to produce AC electrical energy, the WECS converts the wind potential energy into kinetic energy. [8-9]

$$P_W = 1/2\ A\ C_p\ (\lambda, \beta)\ *\ (V_w)^3$$

Where P_w =Generated Kinetic energy
A= Swept Area
Cp =Coefficient of rotor power
λ = tip speed ratio
β = pitch angle
Vw= wind speed velocity.

b) SOLAR PV SYSTEM:

The solar PV system converts solar radiation into direct current (DC) electricity; the number of panels connected to the array determines the system's rating.

N_{series} = Vmax DC/ Vmax P and $N_{parallel}$ = Imax DC / Imax P.

i. Single-axis sun tracker:

Single-axis trackers have only one degree of freedom, which serves as a rotating axis. Single-axis trackers' rotation axis is usually aligned with the true North meridian. With powerful tracking algorithms, they may be aligned in any cardinal direction. Single-axis trackers can be implemented in a variety of ways. Horizontal single-axis trackers, horizontal single-axis trackers with slanted modules, vertical single-axis trackers, tilted single-axis trackers, and polar-aligned single-axis trackers are some of the options. When modeling performance, the module's orientation about the tracker axis is critical. In tropical places where the sun rises quite high at noon yet the days are short, the horizontal type is utilized. The vertical kind, on the other hand, is employed in high latitudes where the sun does not rise very high yet summer days can be extremely lengthy.

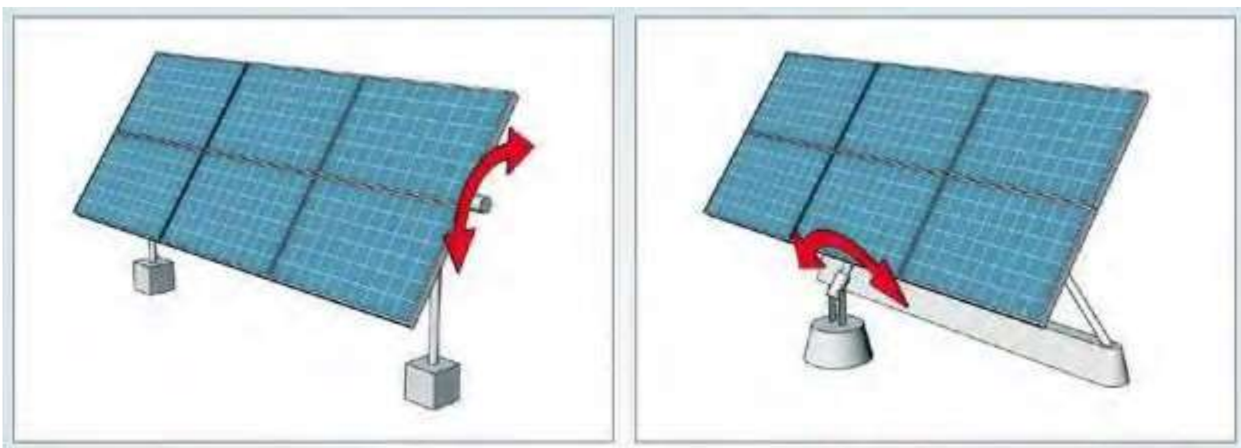


Fig:1. Horizontal and tilted single-axis solar panel

ii. Dual-axis sun tracker:

Dual-axis trackers have two degrees of freedom that serve as rotational axes. These axes are usually perpendicular to one another. A main axis is defined as an axis that is fixed about the ground. A secondary axis can be defined as an axis that is referenced to the primary axis. Dual-axis trackers come in a variety of configurations. The orientation of their principal axes about the ground is used to classify them. Tip-tilt dual-axis trackers and azimuth-altitude dual-axis trackers are two typical implementations. When modeling performance, the module's orientation about the tracker axis is critical. Modules on dual-axis trackers are usually aligned parallel to the secondary axis of rotation. Dual-axis trackers can angle themselves to be in direct touch with the Sun no matter where it is in the sky.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

Fig:2. Dual-axis solar panel

iii. Latitude and longitude:

The Earth's surface is defined as the angle founded by the equatorial region and the single sentence passing through at that point and through the Earth's core. Lines and areas of similar latitude detect groups on the Earth's crust concurrent to the equator and one another. The angle created by a compared meridian and another meridian intersecting with a point on Earth's surface. All connections are large ellipses that intersect at the north and south poles.

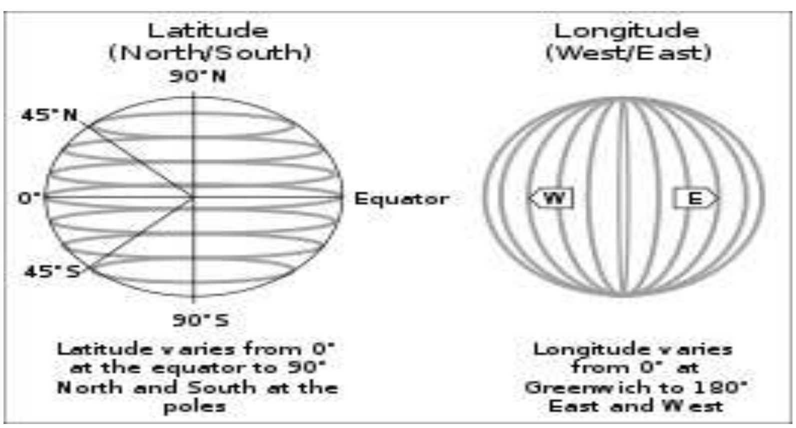


Fig: 3. Latitudinal and Longitudinal axis

iv. Solar zenith angle:

The solar zenith angle is the angle found by the sun rays and the lateral orientation. It is linked to the photo-voltaic altitude angle, established by the Sun's rays and the horizontal distance.

v. Solar azimuth angle:

The solar azimuth angle is the azimuth angle of the Sun. The Sun's position along the local horizon is specified by the horizontal coordinates, while the solar zenith angle stipulates the Sun's maximum height in the sky.

vi. Performance ratio:

The performance ratio of a PV system is typically calculated by computation and analysis of the ratio of solar panels.PR is also known as a performance metric, it determines the efficiency of the PV system converts irradiance into AC energy,[8]

$$PR = \frac{Yf}{Yr}$$

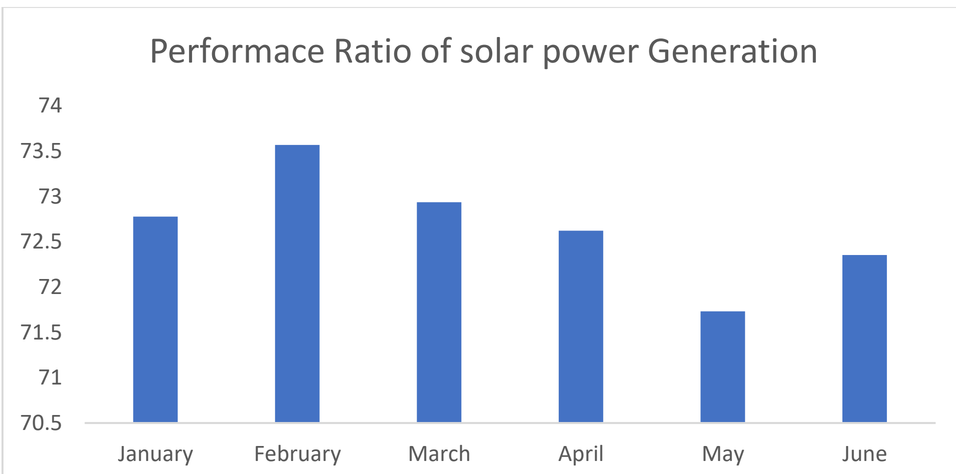


Fig .4: PR ratio of Solar power Generation

The value of PR is affected by the ambient thus the PR change that the values are usually greater in the winter than in summer because there is a temperature change, the PR value is highly independent of both specific and independent of module orientations, If the PR is low in location the high solar radiation will occur. If the 100% of the PR value is very close, the more efficient system is operating, however, the real-life value of 100% cannot be achieved because of unavoidable losses.

IV. FORECASTING VARIABLE GENERATION MODELS

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, April : 2025

Forecasting models are ceaselessly improved to bring about more accurate forecasts of solar and wind power. The models that use both non-learning and learning approaches are described in this section.

a) Non-learning approach Models:

The above model describes the connection between the real and predicted solar irradiance from the various weather conditions. The connection can be used to forecast future plant outcomes.[10]

b) Learning Approach Models:

AI methods are used to learn the relationship between the real and predicted weather conditions and the power that output generated as a historical time series. The Al methods are the algorithms that can describe the nonlinear and highly complex relationship between input data and output power instead of an explicit statistical analysis.

V. The architecture of ANN:

The architecture of ANN consists of three layers, The first layer is the input layer. It contains the input neurons that send information to the hidden layers. The layer of hidden performs the computations on input data and transfers the output to the output layer. There are some types of Neural network architecture such as single-layer feed-forward networks, Multilayer feed-forward Networks, and Single nodes with their feedback. The below figure consists of 20 Inputs of Temperature, wind speed, and solar Azimuth, three layers the Input layer, the Hidden layer, and the output layer. In the hidden layer consisting of 32 neurons and 64 neurons (one side and another side), the output layer generated the power.

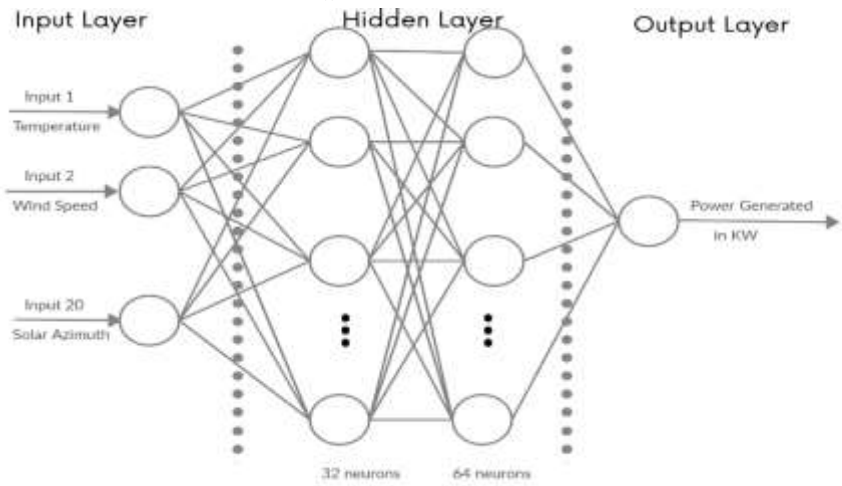


Fig .5: Flow chart of ANN Architecture

VI. CONCLUSION:

. The Presence of each module has been reasoned out and placed very carefully. Dual-axis tracker aligns with the sun's route, tracks the sun's movement cost-efficiently, and includes an excellent performance upgrade. The investigation outcomes clearly show that dual-axis tracking is good enough for the fixed-axis system. The proposed method is price effective collectively as an angle adjustment in fixed-axis hunter provided notable power increase among the system. The ANN model output performs the RSME, Performance ratio, performance of ANN depends on how well is tested and trained and the quality of the data used. The ANN contains 12 weather variables with hourly step size forecasts that performed better than real and neural networks. The normalized input data does not improve the performance but only removing the night hours slightly improves the performance model.

- Correlation is high between Zenith and the angle of incidence of 0.71.
- Hence, we conclude that the model produces a more accurate forecast than cloudy hours of solar Azimuth vs the real and predicated generation data.

REFERENCES:

[1] Kandil SA, Mohamad MA, Ahmad GE. Effect of local meteorological conditions on the PV module performance. In: 2nd World Renewable Energy Conference. Reading, UK, 1992, pp. 467–72.

[2] Duffie JA, Beckman WA. Solar engineering of thermal processes. New York: John Wiley and Sons; 1991.

[3] Fordham M, et al. Photovoltaics in buildings: a design guide. Report No. ETSU S/P2/00282/REP, Department of Trade, and Industry, ETSU, UK, 1999.

[4] Klein SA et al. TRNSYS 14.2: a transient system simulation program. Madison, USA: Solar Energy Laboratory, University of Wisconsin; 1994.

[5] Ahmad GE, Hussein HMS, El-Ghetany HH. Theoretical analysis and experimental verification of PV modules. Renewable Energy 2003;28:1159.

[6] A. Botterud, J. Wang, V. Miranda, and R. J. Bessa, “Wind power forecasting in US electricity markets,” The Electricity Journal, vol. 23, no. 3, pp. 71–82, 2010.

[7] M. Abella and B. Chowdhury, “Solar Power Probabilistic Forecasting by Using Multiple Linear Regression Analysis,” in IEEE Southeastcon Proceedings, Ft. Lauderdale, FL, 2015.

[8] M. Lange and U. Focken, Physical Approach to Short-Term Wind Power Prediction. Springer, 2006. [4] B. Ernst, B. Oakleaf, M. L. Ahlstrom, M. Lange, C. Moehrlen, B. Lange, U. Focken, and K. Rohrig, “Predicting the wind,” IEEE Power Energy Mag., vol. 5, no. 6, pp. 78–89, 2007.

[9] T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning, 2 Edition. Springer-Verlag New York, 2009. [6] J. Kleissl, Solar Energy Forecasting, and Resource Assessment. Elsevier, 2013.

[10] R. H. Inman, H. T. C. Pedro, and C. F. M. Coimbra, “Solar forecasting methods for renewable energy integration,” Prog. Energy Combust. Sci., vol. 39, no. 6, pp. 535–576, Dec. 2013.

[11] “Global Energy Forecasting Competition 2014, Probabilistic solar power forecasting.” [Online]. Available: http://www.crowdanalytix.com/ contests/global-energy-forecasting-competition-2014.

[12] “Many fields have seconds in their units e.g. radiation fields. How can instantaneous values be calculated?” [Online]. Available: http://www.ecmwf.int/en/many-fields-have-seconds-their-units-egprecipitation-and-radiation-fields-how-can-instantaneous.

[13] E. Lorenz, T. Scheidsteger, J. Hurka, D. Heinemann, and C. Kurz, "Regional PV power prediction for improved grid integration," Prog. Photovoltaics Res. Appl., vol. 19, no. 7, pp. 757–771, 2011.