UNCERTAINTY ANALYSIS AND FORECASTING OF PV POWER PRODUCTION

Abstract

In today's time, the ecological condition and the energy supply has become critical around the world. The important reason for the growth and application of renewable energy sources is the limitation of non-renewable sources. The most ideal non-renewable energy source is solar energy. The important feature in solar energy consumption patterns is photovoltaic power generation, but the output of photovoltaic power plant is irregular and changes frequently. The current work introduces an empirical ground framework for the analysis of uncertainty and forecasting of photovoltaic (PV) power generation. The energy system has momentarily affected by the photovoltaic (PV) generation, when PV infiltration rises to a very huge level since this source has high inconsistency and uncertainty, to analyse our data smoother we developed a method to remove the periodic component. We can regulate the ambiguity of PV data by discarding the periodic effect of the sun in the sky. To determine predictable low-frequency components in the system operation we have used the least squares method. The least square method can be applied to valuation the probabilistic characteristics of PV generation at many sites on the earth concerning the different solar radiation due to changing solar position, PV generation has distinct probability distribution at different locations on the earth. The nature of the solar position is deterministic and periodic. By observing the data precisely to characterize the uncertainty we can abolish the effect of periodicity. In power generation the forecasting of the output of photovoltaic power is essential and the forecasting is necessary for timely electric power distribution and to boost the authenticity of electrical energy system operation, this problem can be solicited with

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the help of artificial neural network (ANN) and the wavelet decomposition (WD). To address the voltage-current relationship a hybrid model is created which is based on an artificial neural network (ANN) and wavelet decomposition (WD), the climatic variables and solar irradiance are the input for this hybrid model. Wavelet decomposition is used to separate the required useful information from the disturbance in the PV power plant output. Based on decomposed output (in WD) models are created with the artificial neural network and then the output of the artificial neural network model is reconstructed in the forecasted photovoltaic plant power output. Here in this approach, we compare the traditional forecasting method which is based on an artificial neural network (ANN). Based on this we can analyse the discrepancy of renewable energy sources with different characteristics (i.e., non-stationary) and ambiguous components. In this approach, the nonlinear PV behaviour is captured by the AI technique and wavelet transform shows the impact on ill-behaved of photovoltaic time series data.

Keywords: Photovoltaic (PV), PV power generation, Power prediction and forecasting of PV power, ANN and WD in PV power

I. INTRODUCTION

Photovoltaics (PV) continues to the interest of utility engineers and researchers, despite overall high prices and low efficiency. Electric power generation is a relatively new and growing industry, in many latest technological applications. Of these, the photovoltaic cell is possibly one of the costliest alternatives. The output of the photovoltaic power plant shows the one-day periodicity because the solar irradiance, which is collected at the Earth's surface and has different effects due to the rotation and revolution of the Earth. The traditional power prediction approach cannot ensure accuracy in forecasting results so we approach the effective strategy to reduce the flexible characteristics.

PV generation has a momentous effect on the energy system when PV infiltration rises to a huge level. As this renewable source has good inconsistency and ambiguity. Photovoltaic generation happens only in the light (i.e., daytime) as there is a need for solar irradiation and its production is simply changed by the ecological situations since the photovoltaic output depends on sunstroke. Due to ecological conditions (time and location) the abundance and nature of the solar illumination are predictable variables. But some climatological conditions like fog and clouds are less anticipated. So, the system operators cannot control the output of photovoltaic generation. Though the output of the photovoltaic power system is periodic and has a random probability distribution pattern that may be analysed statistically but not predicted accurately due to its dependency on the weather as it depends on weather and solar radiation and characteristics.

Intermittence causes different issues to run and dispatch the energy grid. Depending on the surrounding condition the prediction of the output power of photovoltaic systems is very difficult to work and it may vary significantly from one location to another. Using an accurate annual power demand, forecasting allows the shares sale department to make sure plans for regular power supply, and scheduling adjustments are made. In practical applications, the best effective method is that which is based on insolation but the drawback is that it uses a huge number of climatological data to settle different mathematical equations and their realization is cost-effective. The various details of the photovoltaic power plant which is used for the analysis are described below.

Table- 1 PV Power Plant Description

Item	Data
Longitude	79.4304' E
Latitude	28.3670' N
Altitude	268m
Azimuth	0'
Tilt	45'
Mounting disposition	Flat roof
Field type	Fixed tilted plane
Installed capacity	100Kw
Technology	Multi-crystalline silicon
PV module	DESERV 3M6-325

II. PV POWER PRODUCTION ANALYSIS

In a partially recognizable environment, the solar forecasting is a data analytics problem that includes the two-pattern finalization and prediction the power production of the solar panel is observed and we have taken the power production output data for two years for the analysis of uncertainty. Firstly, a typical power production curve is measured by using the power output which is shown in figure 1.

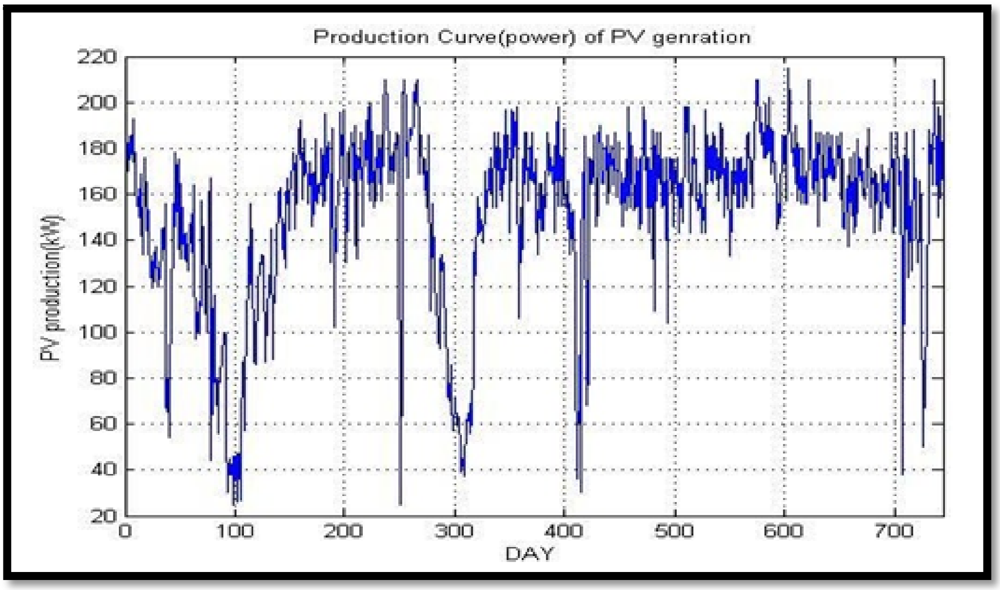

Figure 1: A two-year PV generation production curve

The corresponding probability density function curve of PV production is shown in figure 2. The Earth's trajectory around the sun can be decisive to the great extent of accuracy in the absence of meteorological aspects. Because of Earth's trajectory, we can calculate the position of the sun in the sky. We can estimate the photovoltaic (PV) production in our approach. Now to obtain the amplitude spectrum of PV generation data in the frequency domain we apply the Fast Fourier Transform (FFT) to the photovoltaic generation data in fig.1. Fig.3 shows the magnitude spectrum of fig.1. This amplitude spectrum also implies that there is a periodic component present in the data.

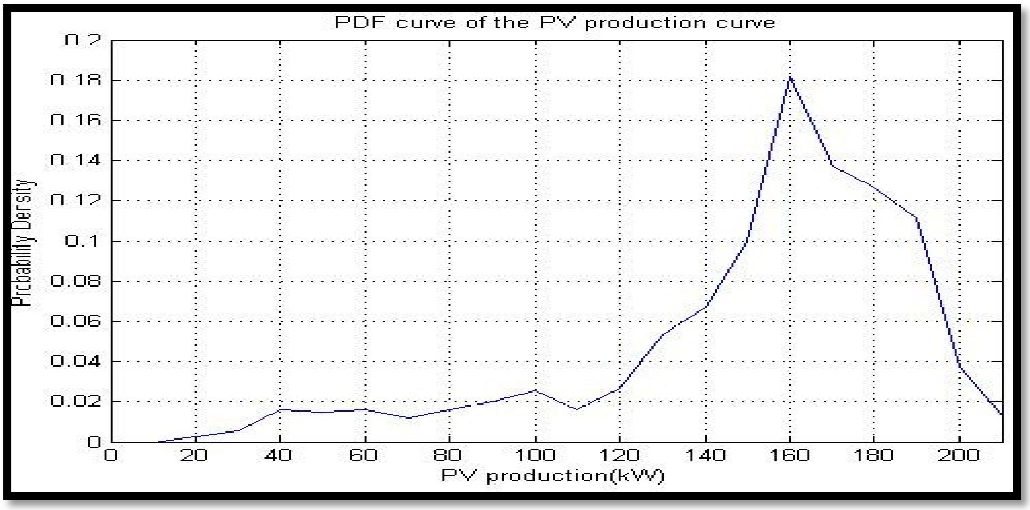

Figure 2: Plot of PDF of the PV production data of Fig.1

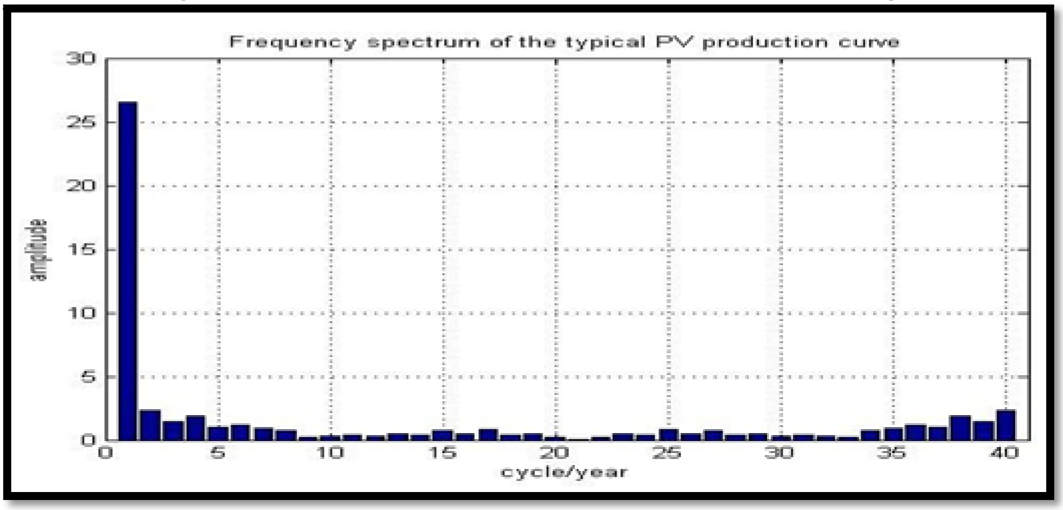

Figure 3: Frequency spectrum plot of Fig.1 data

III. DETERMINATION OF UNPREDICTABLE COMPONENTS

θs is the angle of elevation for a certain site and solar time, the solar elevation angle is defined as the angle between the centroid of the sun and the skyline. We can calculate the variation in the extra-terrestrial solar irradiance and this solar irradiance is almost corresponding to $\sin(\theta s)$. It is mandatory to remove the cyclical variation in the frequencies of PV generation about 1 cycle / year in the assessment of variability in photovoltaic generation. The least square method is applied to remove this temporal variation and the photovoltaic production is supposed to be direct function of $\sin(\theta s)$.

$$P = a \sin \theta s + b \quad (1)$$

Where a and b are the variables. Let Y be the estimated photovoltaic output, we can calculate a and b as

$$\boldsymbol{a} = \frac{\boldsymbol{n}\cdot\sum^{n} \boldsymbol{xy} - \sum^{n} \boldsymbol{x}\boldsymbol{\Sigma y}}{\boldsymbol{n}\cdot\sum^{n}\boldsymbol{x}^{2} - (\boldsymbol{\Sigma}^{n}\boldsymbol{x})^{2}} \quad (2)$$

$$\boldsymbol{b} = \bar{\boldsymbol{y}} - \boldsymbol{a}\bar{\boldsymbol{x}} \quad (3)$$

Where X' and Y' are the anticipated values of X and Y and n is the samples number.

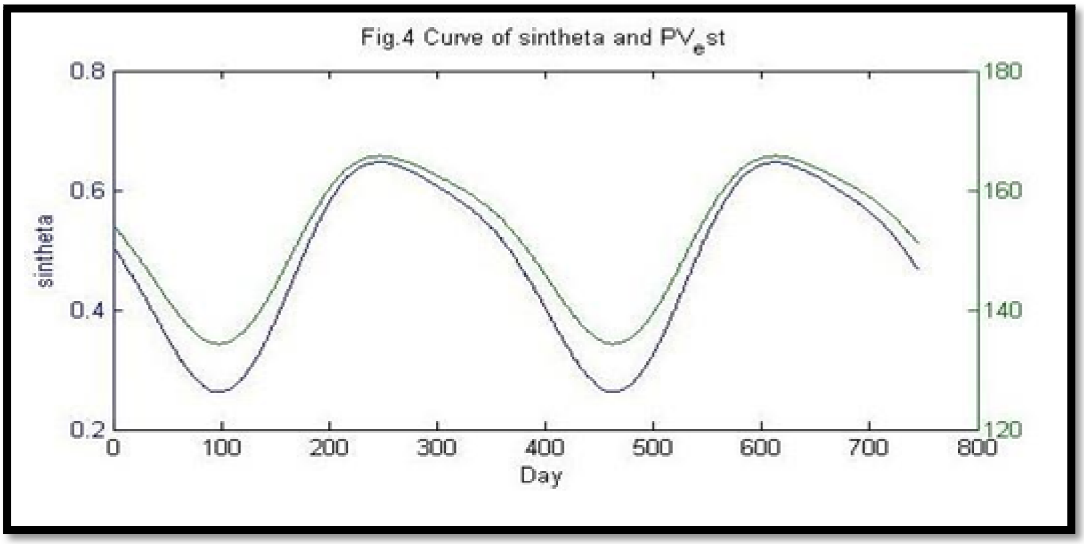

Fig.4 Curve of sintheta and $PV_{e}st$

Figure .4 shows the PV production in the absence of climate factors on sunny days. If we do not consider the weather factors like sunny days, rainy days, storm, fog etc. we get the power production shown in the above figure 4. The constraint is what left of the linear model. It is evaluated to be the incalculable component of photovoltaic power generation in accordance to uncertainty. A significant aspect to consider to study is that the deepest frequency periodic element in photovoltaic production is the yearly insolation contrast. This periodic component happens because of the sun's position in the sky in a year. In this study we have developed an approach to remove this periodic component, in a way that make the following study of the data simple. This technique remarks the connection between photovoltaic power production and fluctuating position of sun and distributes the photovoltaic data into predictable and unpredictable portion.

$$\boldsymbol{\varepsilon} = Y' - (aX' + b) \quad (4)$$

In equation 4, the cyclic effect of change in position of sun is pull out from the photovoltaic generation data. By using the least square method, the magnitude spectrum in the frequency domain and the probability density function curve of the incalculable component of photovoltaic production is shown in Figure 5 and in figure 6.

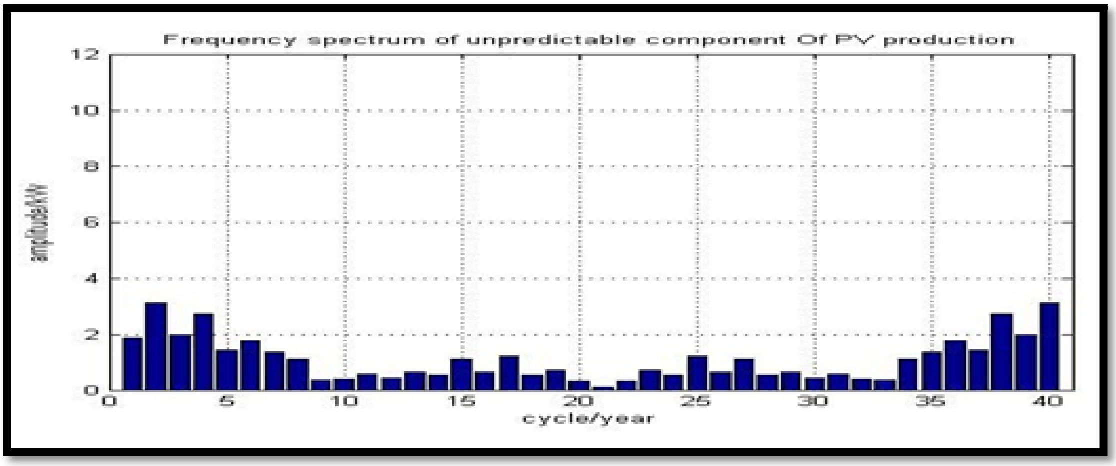

Figure 5: Frequency spectrum of unpredictable components of PV production

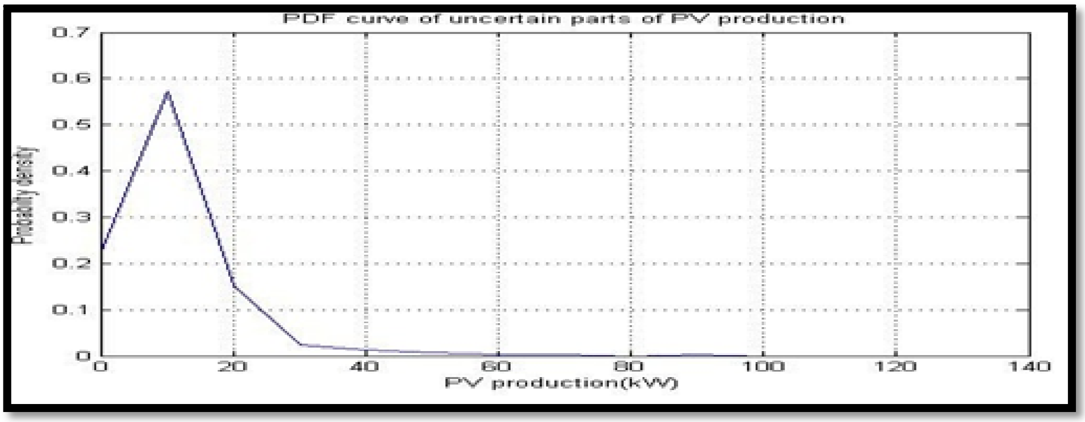

Figure 6: PDF curve of uncertain parts of PV power production

With the help of figure 6 we can see that the after separating the effect of change in sun's position the uncertainty is still very large. The photovoltaic power generation uncertainty has a presiding factor that is time-to-time change in meteorological conditions.

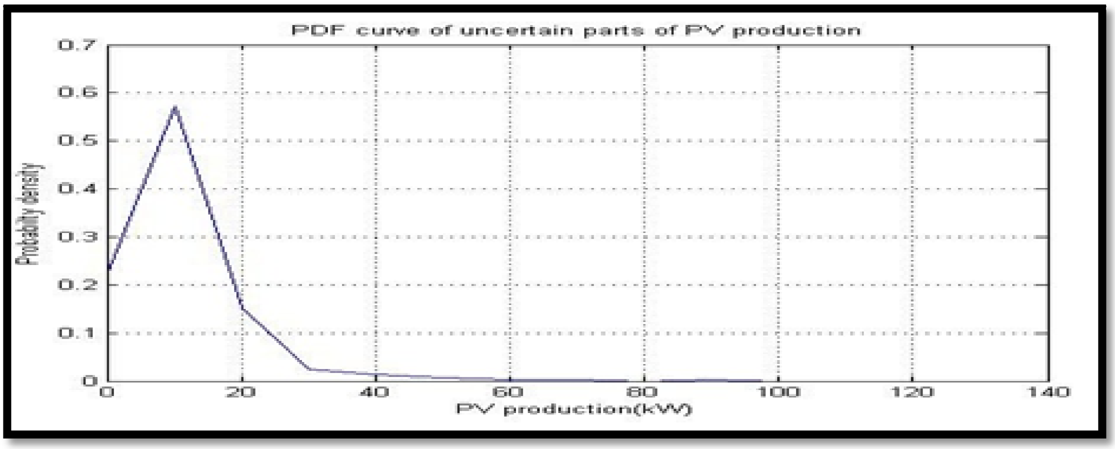

Figure 7: PDF curve of uncertain parts, after filtering the periodic elements

To compare the previous result, we need another consequence that is acquired by processing the yearly cyclic elements of the photovoltaic generation which is shown in figure 3, and the probability density function curve is shown in figure Table 2 compares the coefficient of variation (CV) and the standard deviation of photovoltaic production for individual cases. The conclusions show that photovoltaic production has little and foreseeable change in different weather conditions. The coefficient of variation is defined as the ratio of standard deviation to the expected value of photovoltaic production.

Table 2: Comparison of the Standard Deviation And Coefficient Of Variation

	Fig 2	Fig4	Fig6	Fig7
Standard deviation	0.0520	10.7681	0.0855	0.1223
Coefficient of variation (%)	0.0342	7.0778	0.0562	0.0804

IV. FORECASTING OF PV PRODUCTION

This susceptibility power utilities to work with PV power because the grid planning and balancing become very difficult to perform. Some errors are associated with PV forecasting and for efficiently integrating this solar energy into the grid we need to reduce this error and for reducing this error we evolve a reliable algorithm. These all are challenges that play a very important role in PV power forecasting. So, the technique that predicts PV output is the merger of wavelet transform (WT) and artificial intelligence (AI) to make use of the interactions of photovoltaic systems with solar isolation and temperature data in a linear model. Artificial intelligence techniques capture the photovoltaic behavior in the exceptional way.

1. **Wavelet transform:** Now we apply the wavelet transform in our data and the scalogram plot is obtained. In wavelet transform the scalogram is defined as the absolute value of a signal in the continuous wavelet transform (CWT) plotted as a function of time and frequency. Better time localization for short-span high-frequency incident and better frequency localization for small frequency lengthier span, scalogram is used. Figure 8 shows the scalogram plot and figure 9 shows the contour plot. If we want better time localization for short-duration high-frequency incident and better frequency localization for low- frequency lengthier period incident we use the scalogram curve. The contour plot shows the wavelet spread in time and frequency preserving the energy in the analysis stage.

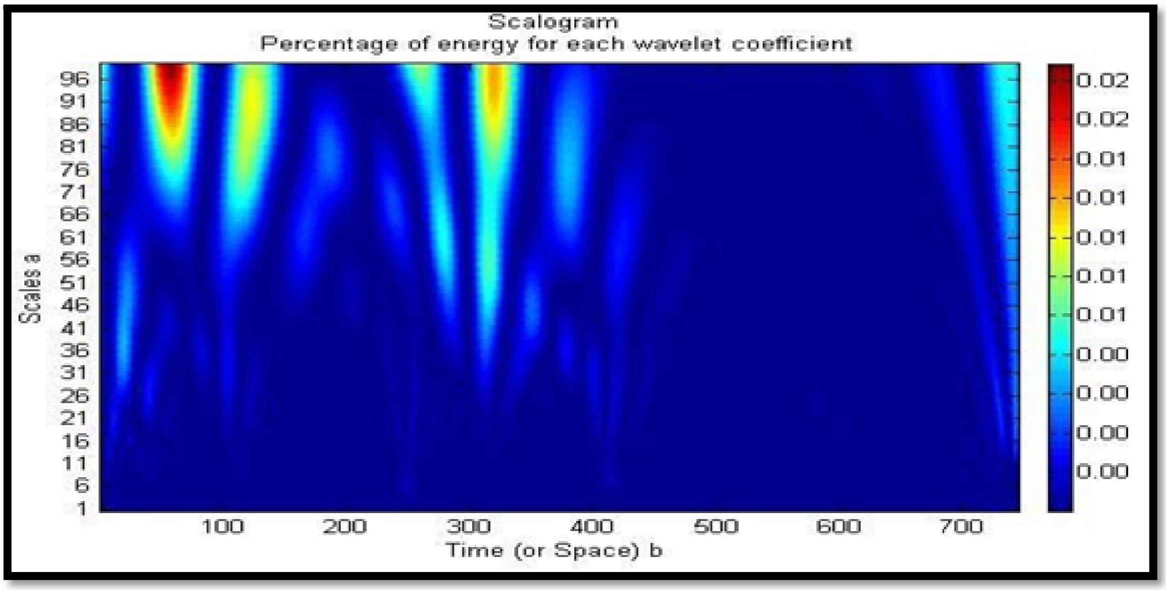

Figure 8: Scalogram of the percentage of energy of each wavelet coefficient.

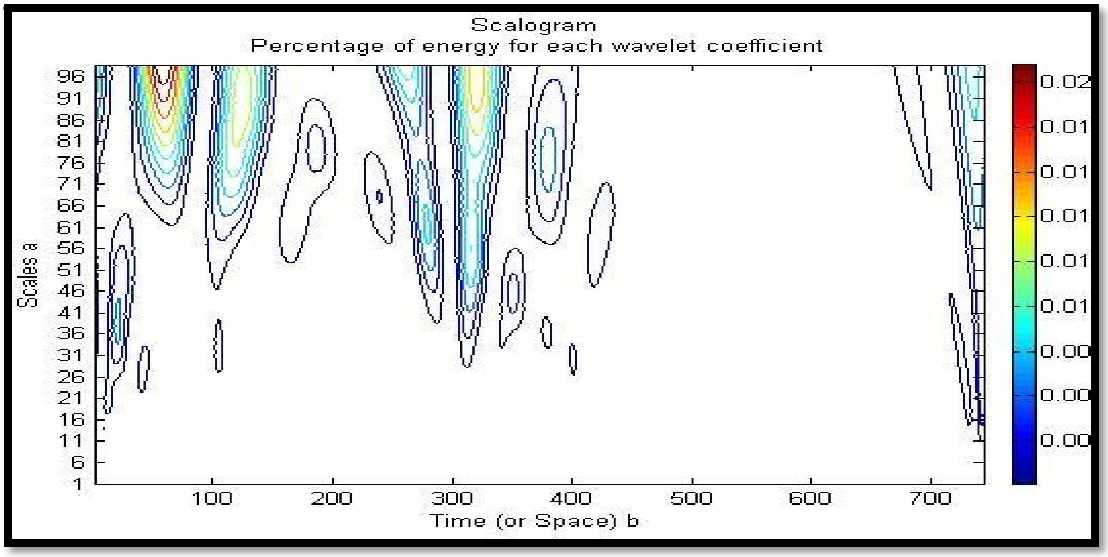

Figure 9: Contour of percentage energy for each wavelet coefficient

To obtain the decomposition i.e., analysis and reconstruction synthesis filter for the b-spline by orthogonal wavelet specify three vanishing moments in the synthesis and five vanishing moments in the analysis wavelet.

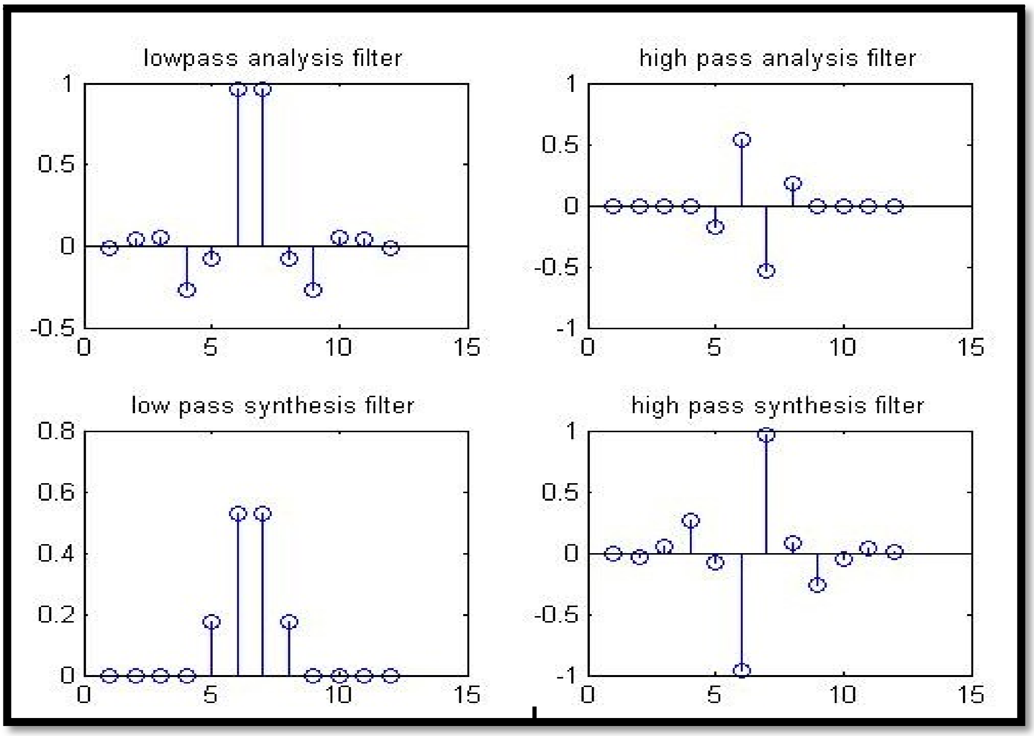

Figure 10: The analysis and synthesis components of continuous wavelet component of signal x (n)

There are various vulnerabilities, spikes, and various non-stationarities in the photovoltaic power data. The tool which is used to manage these spikes is the wavelet transform (WT). So, by the wavelet transform, we can improve the error in PV power forecasting. The wavelet transform (WT) is of two types, the first is the continuous wavelet transform (CWT) and another is the discrete wavelet transform (DWT). Hence by discrete wavelet transform (DWT), we have decomposed our PV power production into approximation and detailed coefficient at level one. Then we reconstructed the power output by using these coefficients and then we are having compared the graph obtained.

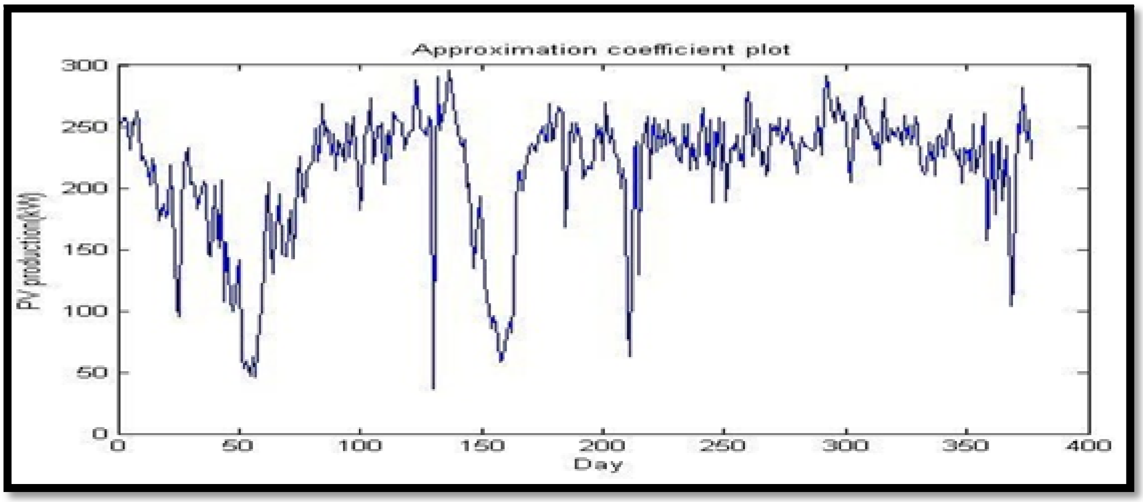

Figure 11: Approximation coefficient plot.

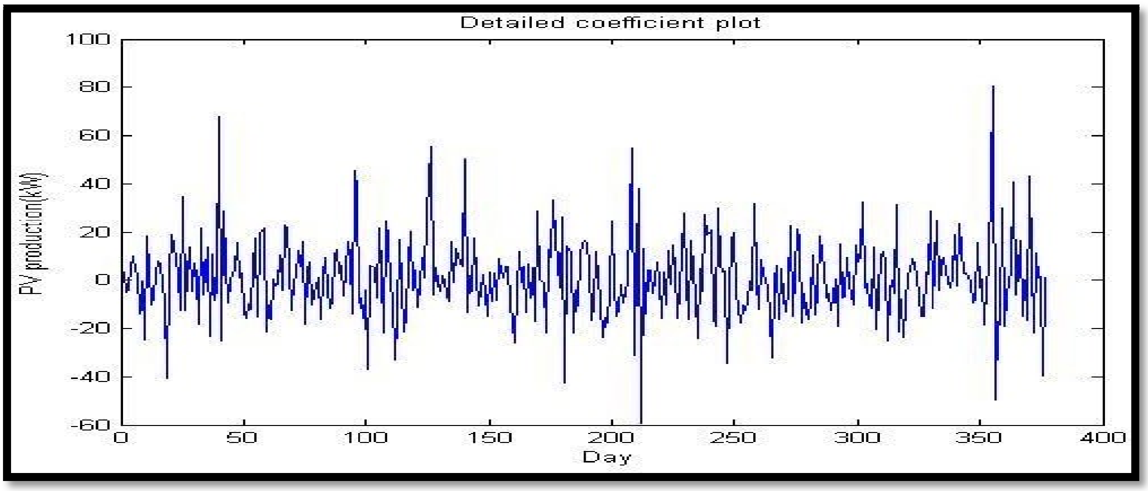

Figure 12: Detailed coefficient plot

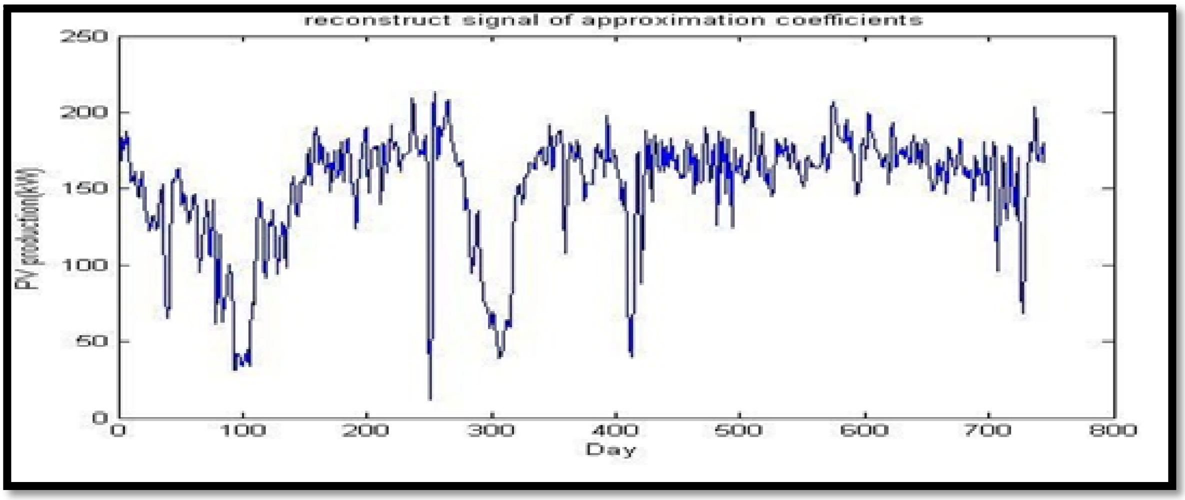

Figure 13: Reconstruction plot

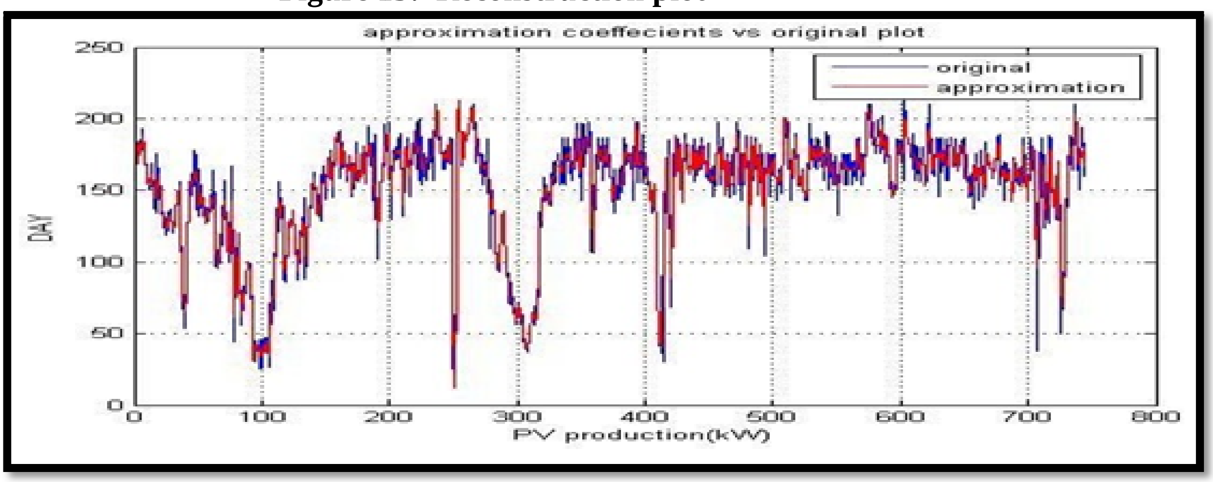

Figure 14: Comparison between approximation and original PV

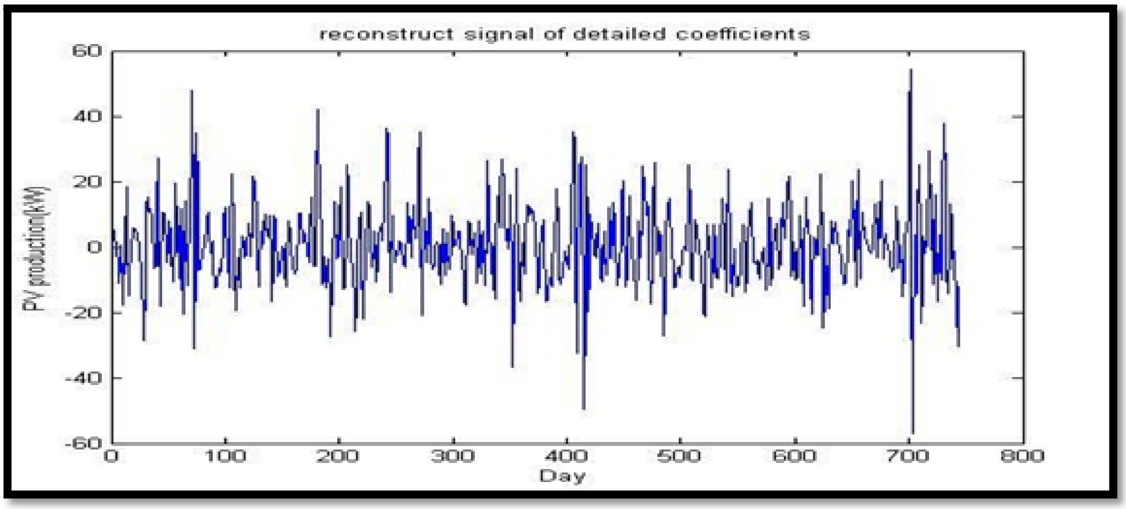

Figure 15: Reconstruction of detailed coefficients

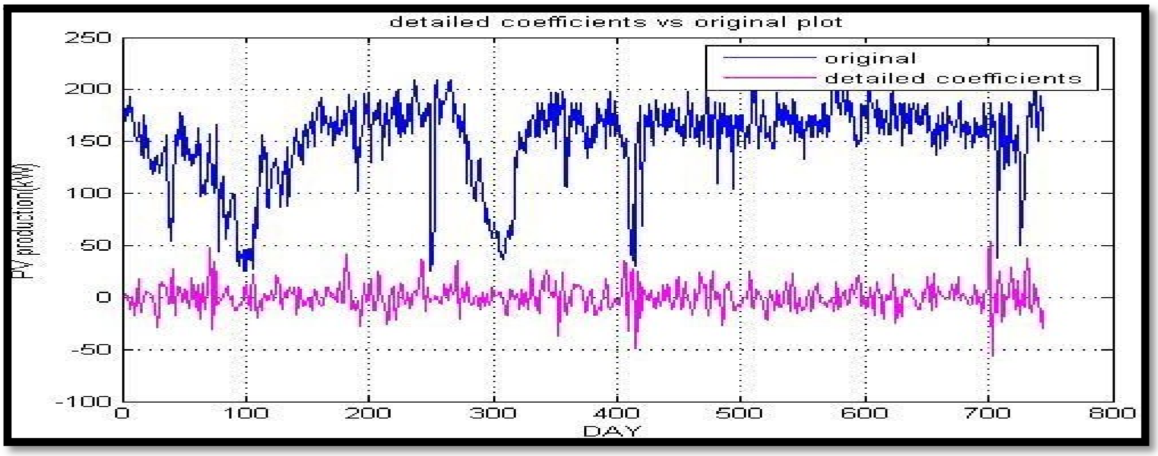

Figure 16: Comparison between original and detailed PV

2. **Wavelet decomposition:** wavelet transform is used to analyze nonlinear and non-motile time series signals, and this WT is much more likely to be a Fourier transform. To break a signal into individual scale layers with separate levels of resolution the wavelet transform technique is used. The WT technique is constructed on a square-integrable function and the group theory depiction, because of this reason the decomposition of a signal into different levels is possible. The WT (wavelet transform) is appropriate for analysing a signal with the changeable frequency and time resolution, such as the photovoltaic power plant output.

   The wavelet decomposition decomposes the signal into its explicit smoothed layers. A signal for the photovoltaic power plant output can include shrill boundaries and changes in locations caused by variations of the sun's emission, this signal has periodicity and some random properties. With the help of WD, we can decompose the photovoltaic power plant output into two parts. The first one is the flattened form of the signal and the second one comprises the detailed form of the signal. So, by the use wavelet decomposition technique, we can remove the disturbance in the earliest signal and can analyse them individually.

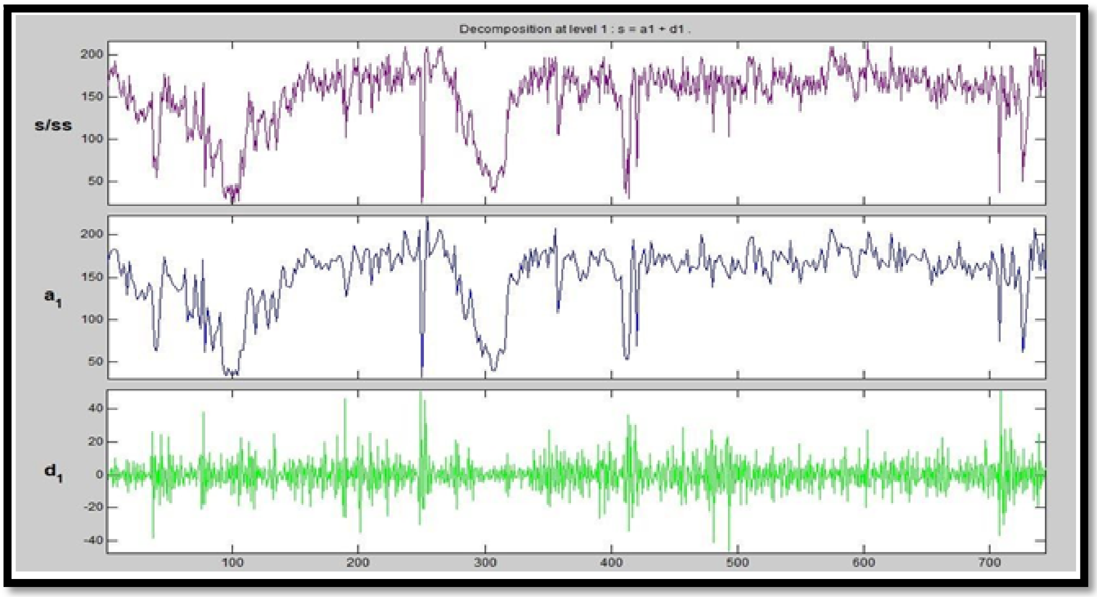

Figure 17: Decomposition of PV production at level 1.

Let us consider a signal which is discrete in the time domain, for the photovoltaic power plant output this discrete time signal is to be decomposed into one smoothed layer and detailed layers. By Wavelet decomposition technique, the decomposed signals at scale 1 are S1(n) and Dt1(n), where S1(n) and Dt1(n) are the smoothed version and detailed version for the input signal X(n) respectively in the form of WT coefficients.

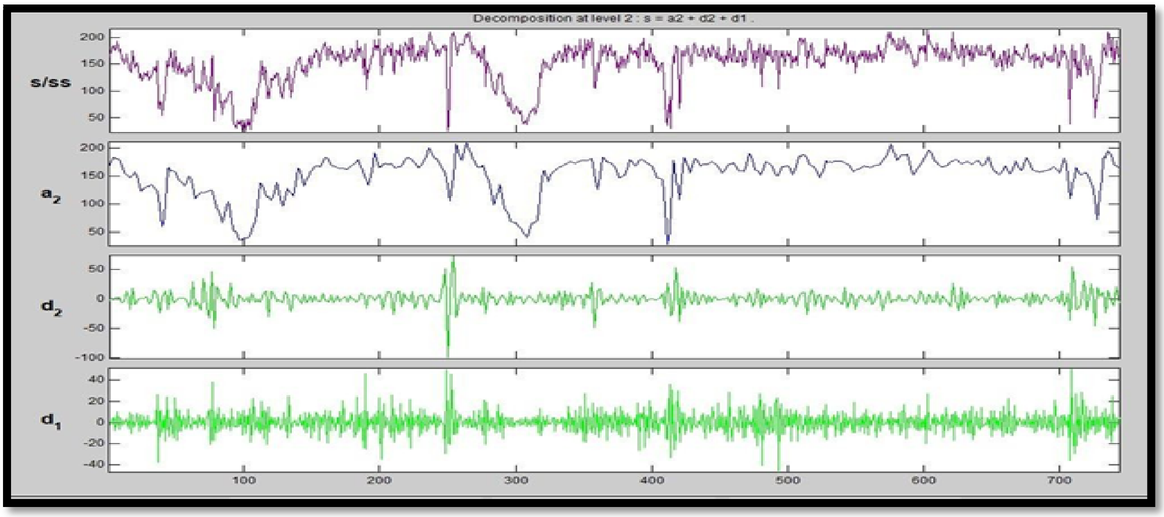

Figure 18: Decomposition of PV production at level 2

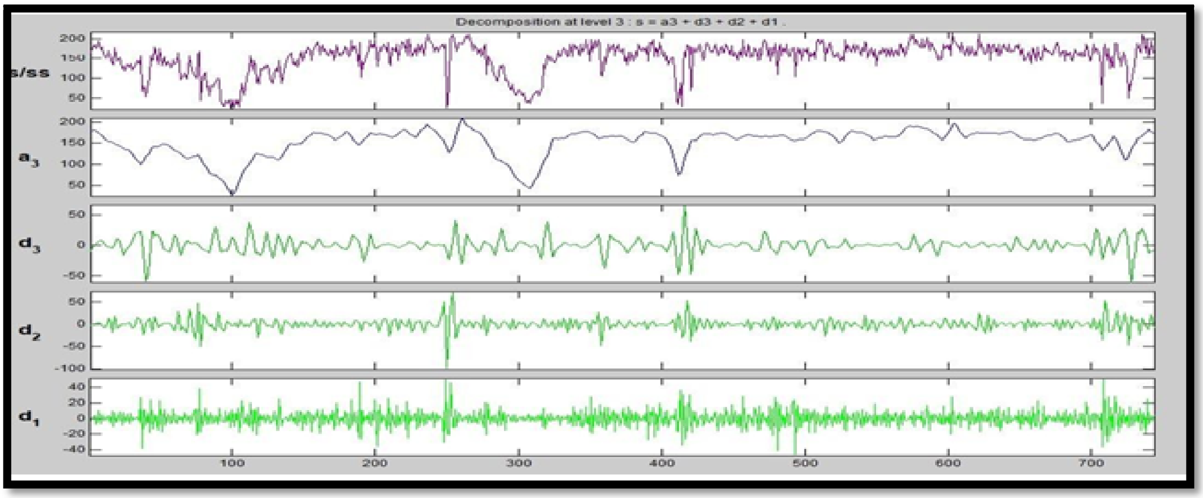

Figure 19: Decomposition of PV production at level 3

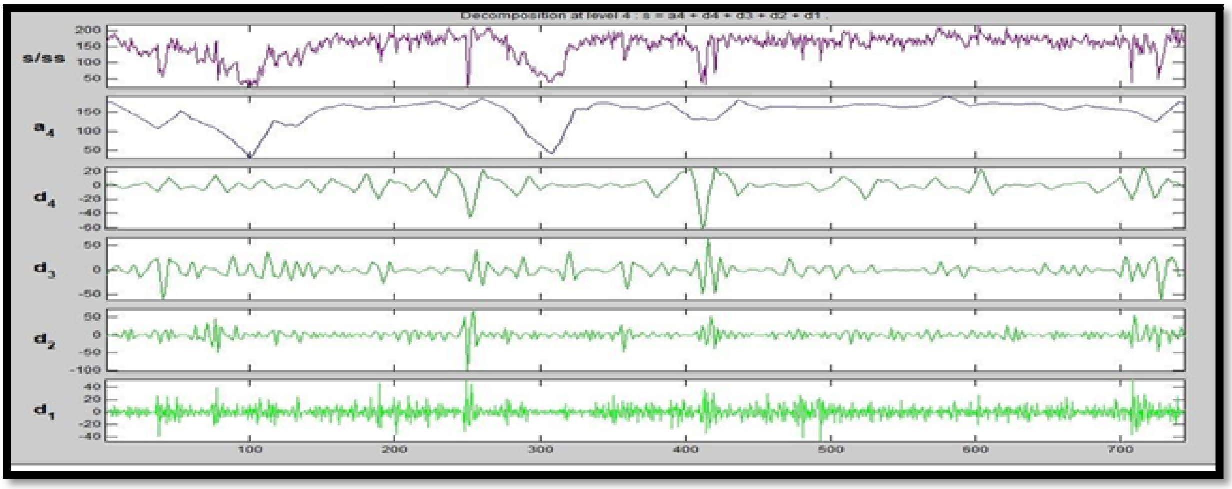

Figure 20: Decomposition of PV production at level 4

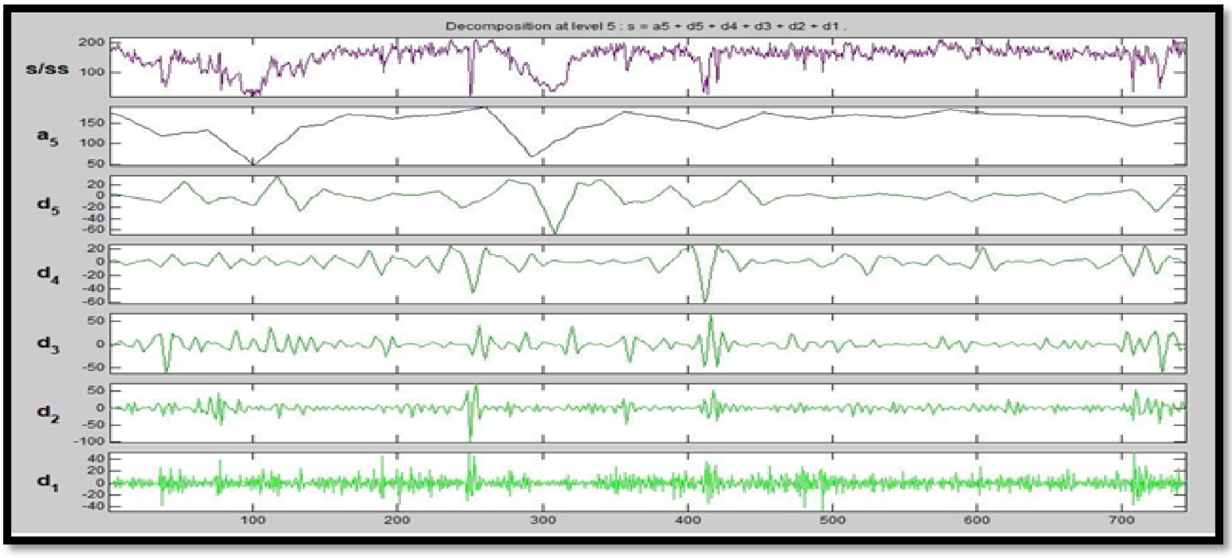

Figure 21: Decomposition of PV production at level 5

Table 3 Various Layers of Wavelet Decomposition (WD)

Sequence of Reconstructed Signals	Description	Meaning
S5	The smoothed signal at the 5th layer	Reflects change trend of the photovoltaic power plant output, close to tentatively calculated solar irradiance
Dt5	The detailed signal at the 5th layer	Show composition and alteration in rules of a high-frequency portion of the signal
Dt4	The detailed signal at 4th layer	
Dt3	The detailed signal at 3rd layer	
Dt2	The detailed signal at 2nd layer	
Dt1	The detailed signal at 1st layer	

3. **Power prediction:** In scientific perception, solar emission is a feature that governs the exact effect of photovoltaics on power generation. The intensity of the sun directly consequences the yield of a PV cell. PV array received solar emission or sun’s radiation which is effect by the number of clouds in the sky, sun position, and the array installation angle. For the PV system, the output time series data has a certain autocorrelation function except this the output of the PV system is also affected by the meteorological condition. These all occurred due to power output data of power plant containing photovoltaic plant information, and typical examination of the consequence of arbitrarily installation site and the functioning time on photovoltaic degeneration can be ignored. That’s why we use an artificial neural network to implement output forecasting modelling for photovoltaic power plants.

   According to the formation of the forecasting model.We have to train the approximation coefficients (S5, S4, S3, S2, S1) and detailed coefficients (Dt5, Dt4, Dt3, Dt2, Dt1) obtained from the wavelet decomposition of our PV production output. High-frequency information (detailed coefficients Dt3, Dt2, Dt1) at different layers are considered as disruption interferences for implementing the approach that’s why they are not used. We carried out a 5-layered wavelet decomposition for the photovoltaic power plant output along with the comparison between two layers that are detailed layer and the approximation layer.

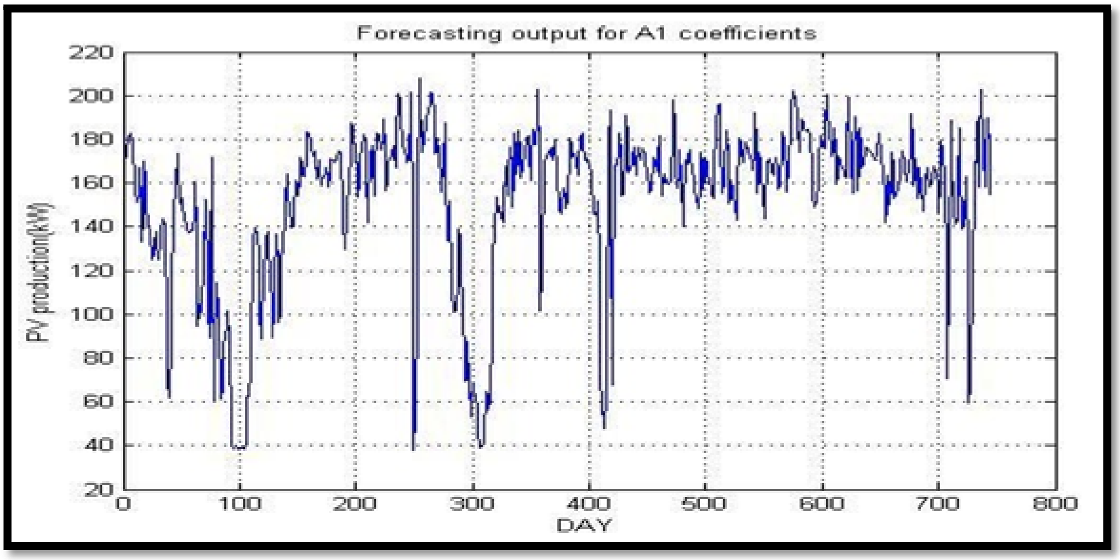

Figure 22: Forecasting result of S1 coefficients

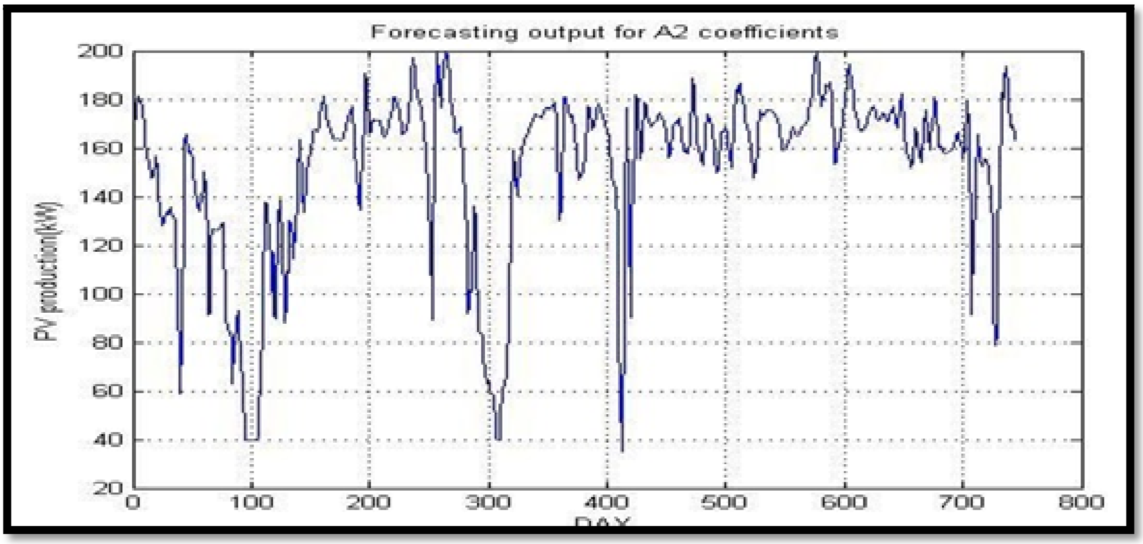

Figure 23: Forecasting result of S2 coefficients

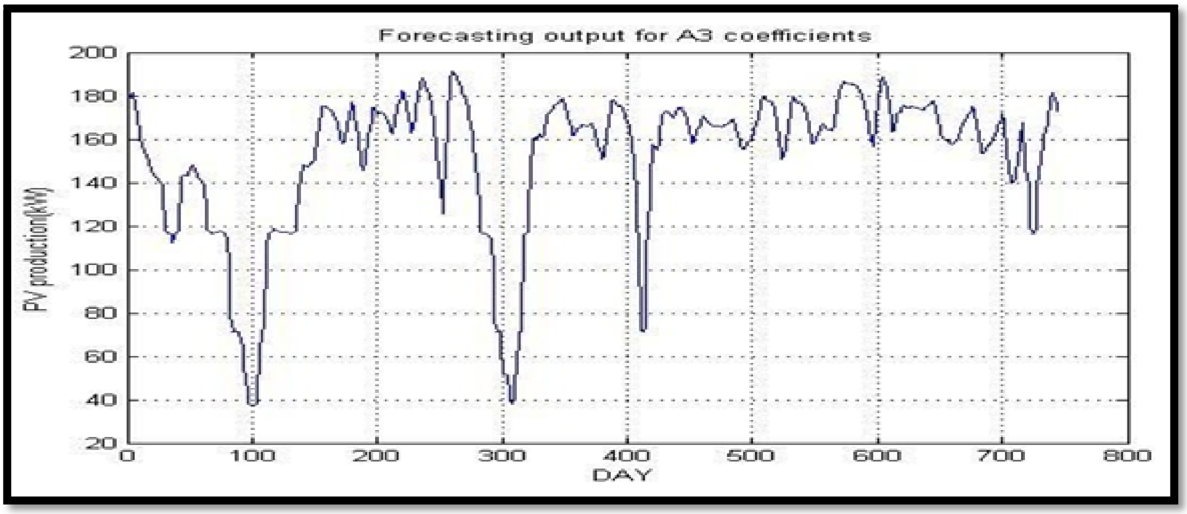

Figure 24: Forecasting result of S3 coefficients

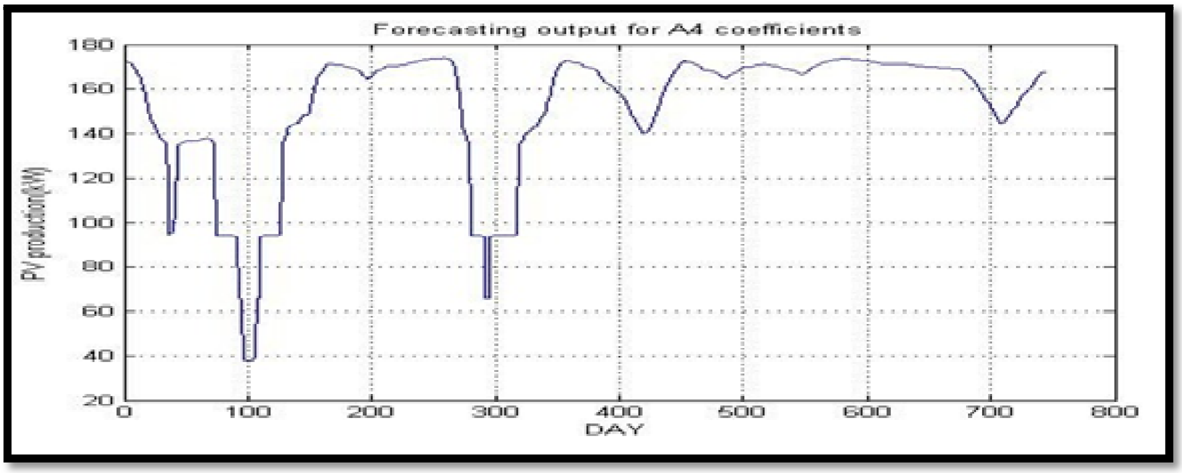

Figure 25: Forecasting result of S4 coefficients

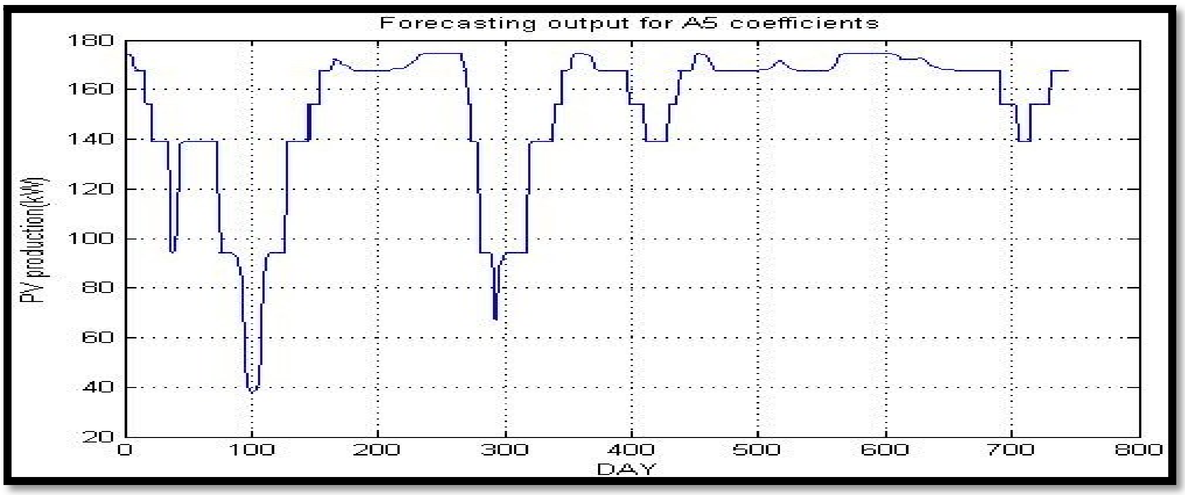

Figure: 26 Forecasting result of S5 coefficients

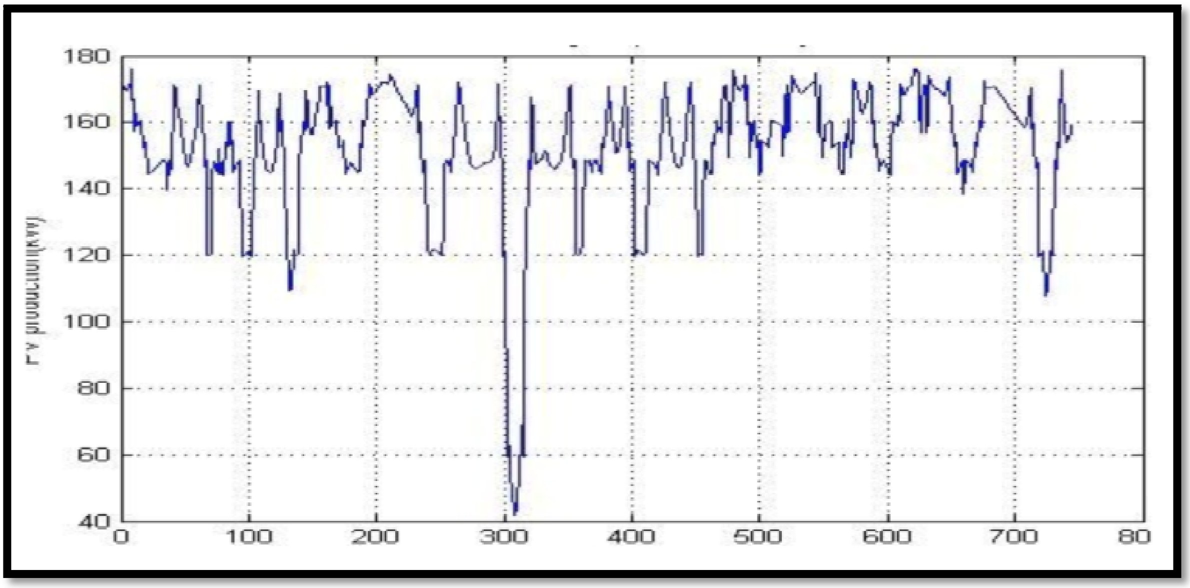

Figure 27: Forecasting result of S5 coefficients

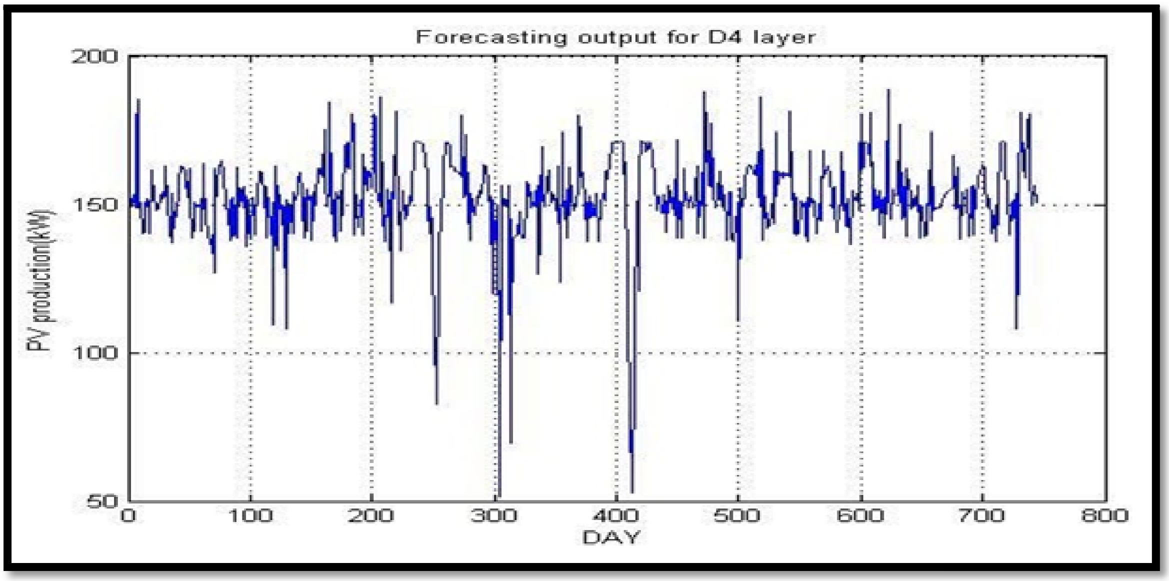

Figure 28: Forecasting result of Dt4 coefficients

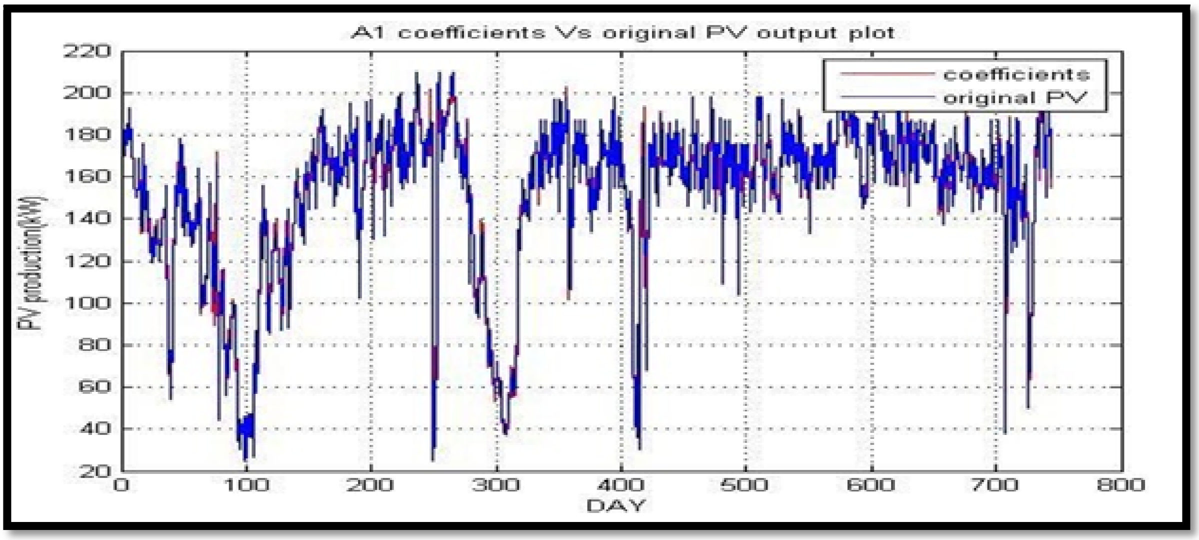

Figure 29: Comparison of earliest PV signal and forecast S1 coefficients

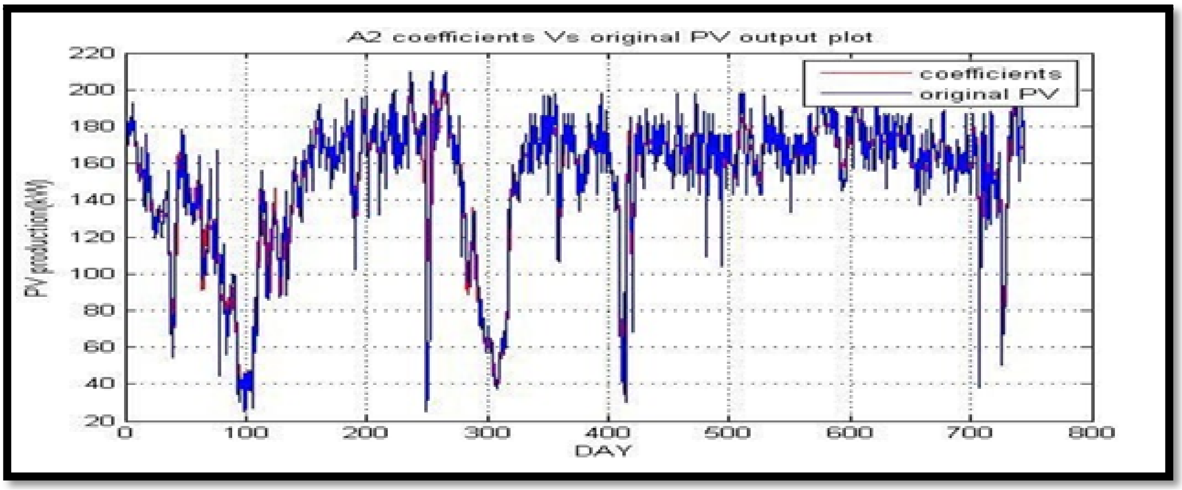

Figure 30: Comparison of earliest PV signal and forecast S2 coefficients

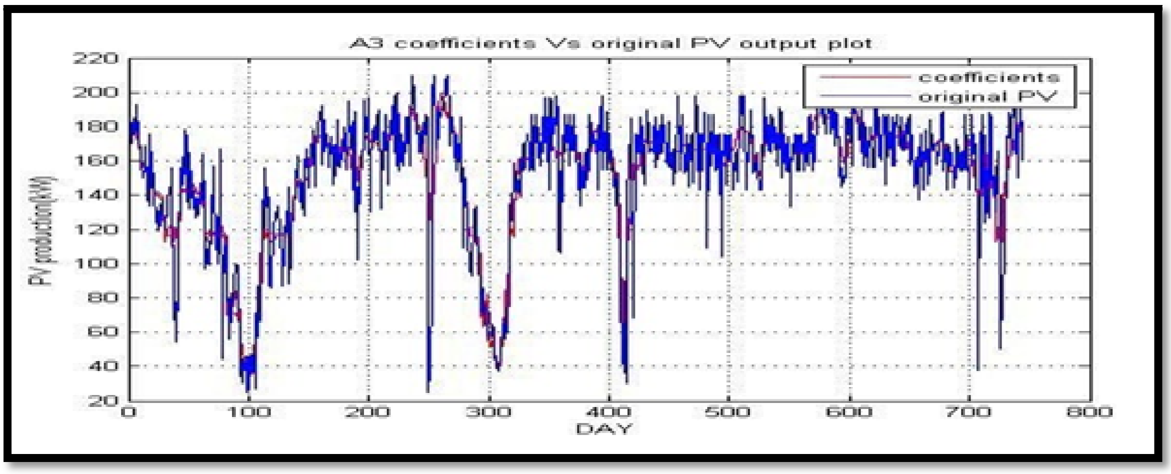

Figure 31: Comparison of earliest PV signal and forecast S3 coefficients

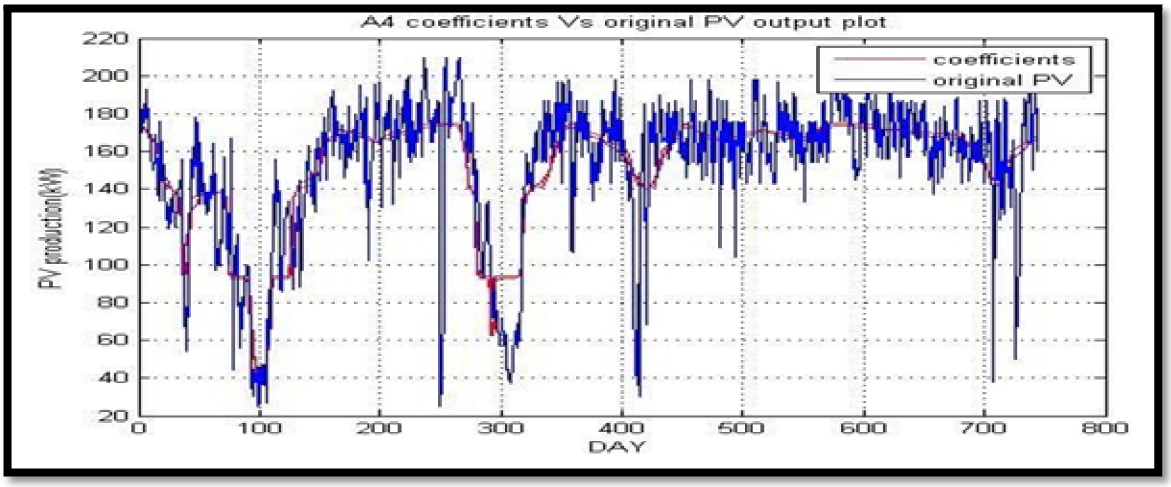

Figure 32: Comparison of earliest PV signal and forecast S4 coefficients

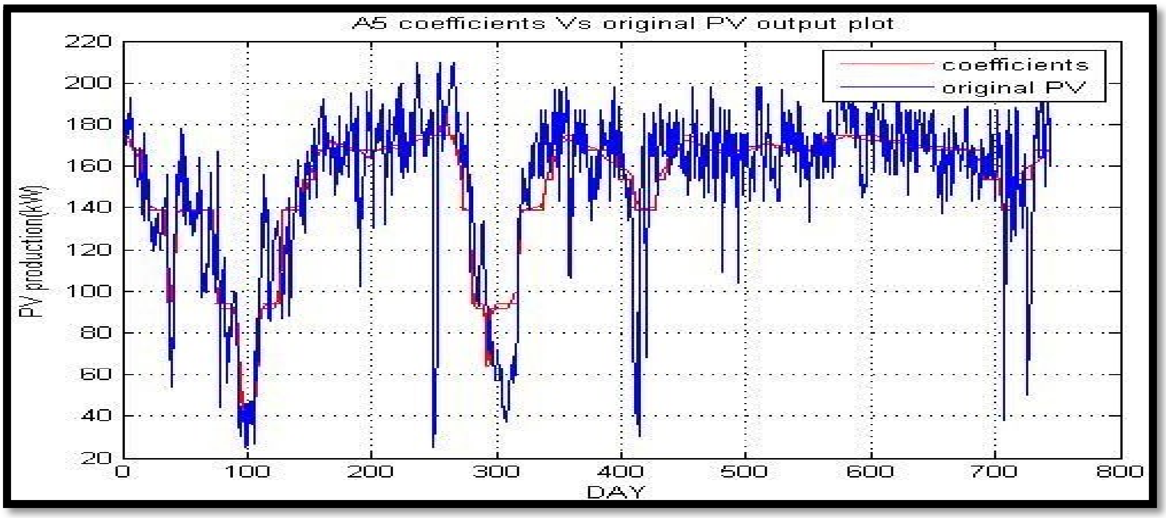

Figure 33: Comparison of earliest PV signal and forecast S5 coefficients

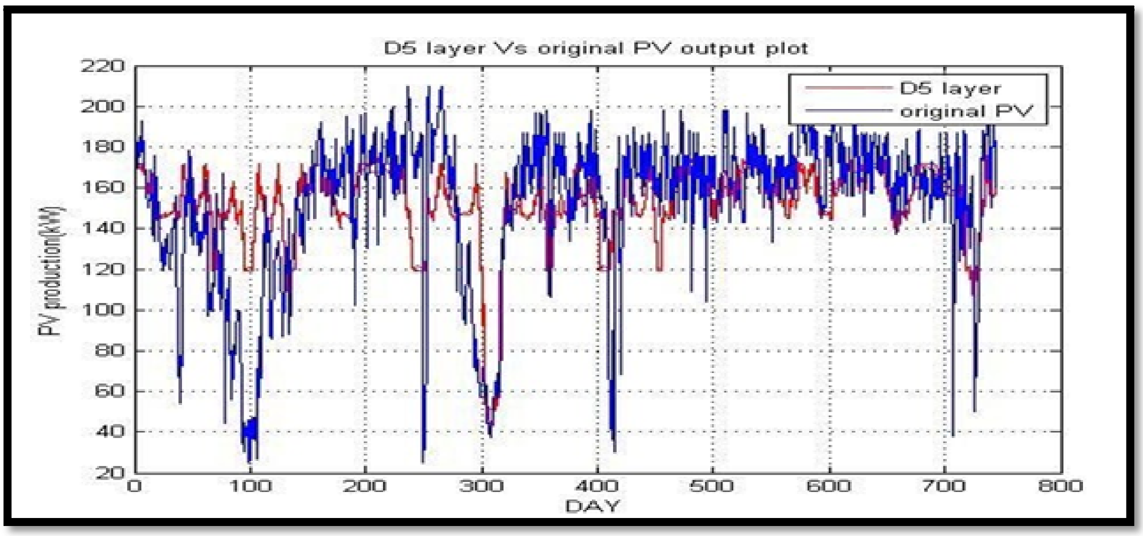

Figure 34: Comparison of earliest PV signal and forecast Dt5 coefficients

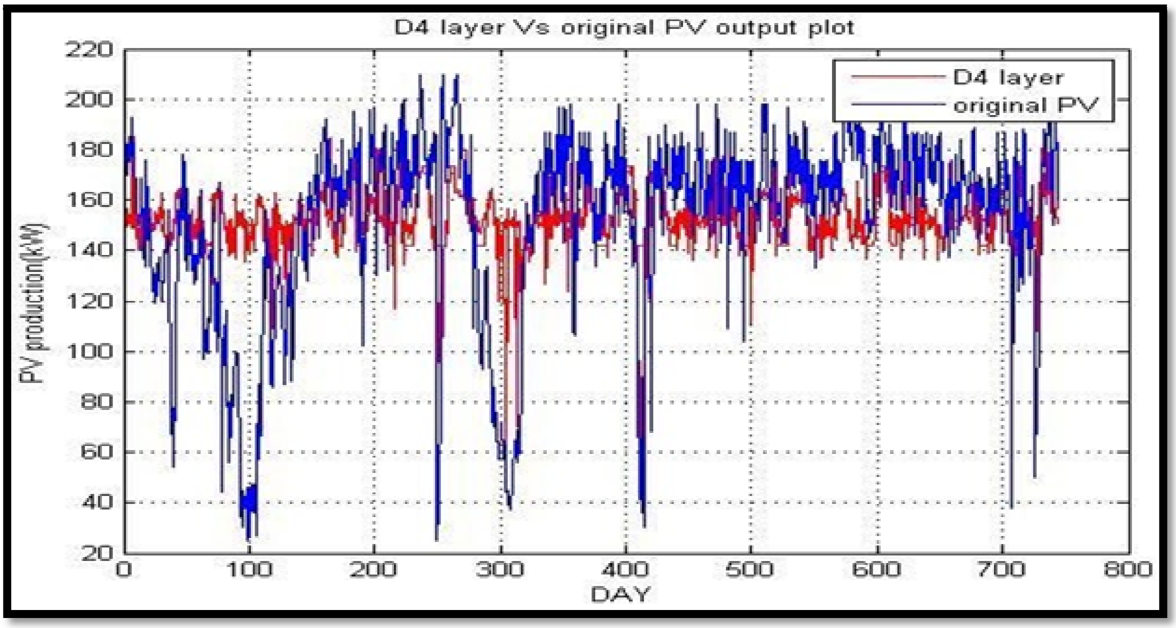

Figure 35: Comparison of earliest PV signal and forecast Dt4 coefficients

$|Pn(j)-Pf(j)|$
$MAE =$
$j=1 \quad * 100\%$ …… (6)
$caP*n$

MAPE = 1
n
n
$\sum \quad |$
$j=1$

$Pn(j)-Pf(j)$
$Pn(j)$

$| * 100\%$ …… (7)

Where Pn(j) is power count at time j; Pf (j) is the forecasted power at time j; n is the samples count; Cap is the capacity of running mean.

The calculation of mean running capacity in PV power forecasting is decided by the initial power of the photovoltaic inverter, installed capacity of the PV system, and operation time. Factor Run(j) is defined to express the working condition of the photovoltaic power plant at time j. When the measured power Pn(j) is elevated than PS, the earliest power of the PV inverter, then Run(j) is considered as 1, concluding that the photovoltaic plant is running, otherwise, Run(j) is considered as 0, conclude that the photovoltaic power plant is not running, as explain by the equation (8)

$$Run(j) = \{1, \text{ if } Pn(j) \geq Pz$$
$$Run(j) = \{0, \text{ if } Pn(j) \leq Pz \qquad \ldots\ldots (8)$$

The relation between the Cap and Run(j) is shown in Equation (9)

$$Cap = \frac{\sum_{j=1}^{n} Run(j)}{n} * Pc \qquad \ldots\ldots (9)$$

where Pz is the beginning power of the PV inverter and Pc the is installed size of the PV system.

Error/ Layer	S1	S2	S3	S4	S5
RMSE (%)	11.14 %	15.73%	19.35%	24.29%	24.10%
MAE (%)	8.33%	11.20%	13.78%	17.47%	17,46%
MAPE (%)	6.43%	9.38%	12.12%	16.34%	16.25%

The above table shows the error results obtained during the forecasting of PV production output comparing between wavelet decomposition of power output in five layers and the trained output obtained by using artificial neural networks. In the table, it can be observed that the error is escalating with the level of decomposition on the PV power production.

A novel probabilistic model of photovoltaic generation is developed depending on the ecological conditions that influence PV behavior. The Forecasting is based on the ANN and WD. Because of the non-stationary and periodic behaviour of photovoltaic power plant output, the wavelet transform technique is followed to find out the multi-scale decomposition of output photovoltaic power and the detailed and smoothed signal occurs. Using the ANN at different layers the forecasting model is implemented. In the end forecasting result of the output of the photovoltaic power plant is obtained by reconstructing the forecasting result at different signal layers. Here in this proposed method, it is shown that the artificial neural network technique has excellent forecasting precision and less algorithm convergence time as compared to traditional methods. Solar power is the best solution due to its adequate availability in our country and an abrupt initiative should be taken to install a solar thermal power plant in India for obtaining the necessary experience in its design, installation, procedure, and management.

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