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Power Forecasting in Photovoltaic System using Hybrid ANN and Wavelet Transform based Method

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Solar energy is a sustainable, renewable energy which is a part of latest industry standards of operation in line with industry 4.0. Solar power variability leads to fluctuation and uncertainty in Photovoltaic (PV) output power. It is a significant issue with regard to the high penetration of PV power generation. The solar irradiance is affected by weather conditions, and varies with geographical locations. Accurate PV power output forecasting is essential for the planning and scheduling alternate sources of conventional power. In this paper we propose a frequency domain approach for forecasting of short-term PV output power. The wavelet transform allows identification of periodic components with time localization, whereas the Artificial Neural Network (ANN) technique allows us to model the non-linearities in the PV time series. In this paper, PV power data for the city Bareilly, Uttar Pradesh is forecasted. Numerical simulations show that the proposed forecasting method for PV power output, shows a significant increase in accuracy over other similar methods. The root Mean Square Error, Mean Absolute Error for the proposed method are also calculated and compared with state-of-the art methods for PV power forecasting.

Keywords: Bior-orthogonal filter, Decomposition, Feed forward network, PV generation, Sustainable development

Introduction

Renewable energy has extreme importance in this modern era. It is the energy obtained from naturally restocked sources upon human timescale like- geothermal heat, sunlight, rain, wind, waves and tides. Solar energy is a primary source of abundant, clean and inexhaustible energy. In 2018 last, total Photovoltaic (PV) capacity installed at world level was 512 GW (gigawatts), from this 35% (180 GW) includes plants of utility-scale.[1] Power supplied through solar method was 3% related to electricity demand at world level in 2019.[(2)] Photovoltaic capacity saw an increment of 95 GW in 2017, which is about 34% growth yearly related to new installations. Capacity of cumulative installation saw an increment of 401 GW at year last, which was behaviour of PV power generation, power supply and demand does not meet.[3] Industry 4.0 plays vital role in sustainable environment. Fourth industrial revolution and digitization of supply and demand grants that implementation of industry 4.0 solution produces competitive advantages and opportunities for sustainable development.[4]

Solar power, on the other hand, has intermittent production characteristics that are dependent on meteorological conditions such as humidity, clouds, and precipitation. To ensure prediction techniques of conventional power for forecasting results precision and method convergence, an effective approach for decreasing non stationary characteristics connected to PV output power is required. In spite of these, the development of solar sector depends on digitization which entails the use of intelligent technologies that enables the automation of certain process using certain software, algorithms and Artificial Intelligence (AI) with a view of optimization. Digitization is a part of industry 4.0 which ensure higher level of sustainability. Forecasting of solar power by AI techniques is one such approach. Researchers have studied different methods for forecasting purpose which we have discussed further.[5,6]

A method is proposed by Kawasaki *et al*.[7] for estimation of the solar irradiance based on the Fourier Transform and wavelet transform. According to Ibad *et al*.[8], environmental factors such as humidity, temperature and radiation intensity, are used for PV output forecast, based upon cloud model. A Gappy Proper Orthogonal Decomposition Based Genetic Algorithm (GPOD-GA) was proposed by Jiang *et al*.[9]

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to optimize the placement of smart grid based on weather information and simultaneously reduce the number of sensors. The meteorological data is utilized in forecasting two day ahead PV power using Wavelet Recurrent Neural Network (WRNN).[10] Result shows a very low Root Mean Square Error (RMSE) as compared to solar radiation prediction scheme obtained by hybrid neural network. Due to the fluctuations in solar irradiance disturbances occur in demand and supply which decreases quality of power. In this paper, LSSVM (Least Square Support Vector Machine) is used for prediction the PV power. Support Vector Machine (SVM) provides better performance upon solar irradiance with the prediction of time series for much better result normalized and appropriate parameters found by artificial intelligence algorithms. But now powerful technology is in trend such as big data and analytics due to which system responds very fast for any variation in environmental condition. Therefore, the methodology is based on sensors implementation in PV model system along with big data technology and data processing unit, which helps to find appropriate values of rout mean square error value. Hence prediction is very improved as large input parameters, are incorporated in machine learning process. Clustering of K-Means applied on meteorological data and divided in different clusters then some useful data is applied to SVM training which also allows to find the prediction error for PV power system. Also, here energy storage system is used to capture the prediction error using probability density function. This SVM regression improves the prediction accuracy.[11–13]

Several researches show that, hybrid models have effectiveness in several forecast application like- solar irradiance, global horizontal irradiance and forecast of electrical load. Normally, techniques of statistics provide better accuracy in forecast. Maximum time technique delivers better accuracy of forecast, provided the smooth input pattern in forecast model. Though, abrupt or sharp variation in metrological variables like irradiance, temperature, humidity and wind speed may cause error in forecast. Accurate forecast of PV power was shown at day ahead by using ANN. Back propagation algorithm is used with some improved technique which helps to improve forecast accuracy in weather condition. This proposed method delivers good results. Integration of power plant in to the system more accuracy of forecast is required. Therefore, ANN is used with different algorithms for hourly power output taking solar radiations, module temperature and ambient temperature as the input for artificial neural network. As solar is Variable Energy Resource (VER) so the grid output is always unpredictable at any particular time, which makes planning of grid challenging. Forecast an hour in advance PV system power output Wavelet (WT) and ANN are used for solar radiation and temperature data. WT impacts on abnormal behavior of data of time series and AI receives nonlinear distortion in PV data. PV power output includes disturbances. We are concerned with weather forecast problem related to the solar power prediction. There is a big challenge to integrate variability and uncertainty for production of PV output power. Generally, model gives picture incorporating either local weather or global weather forecast. These two are local and global changing parameters related to forecasting and are taken based on time series for obtaining forecast 18 hours before the production of PV power, data obtained from NOAA (National Ocean and Atmospheric Administration) and HRRR (High-Resolution Rapid Refresh) model. Resolution is insufficient at such scale for localized forecast over small-scale. For improving the accuracy of forecasting for local weather, a variability model based on wavelet is simulated for reduction of output change of PV power plant which takes place at upscaling from sensor of single point for whole PV system on simulated time interval. Now this is mapped with wavelet transforms of point sensor to given output of PV solar power plant and is validated on two PV plants of rooftop PV plants in Ota city, Japan of 2 Mw and 48 Mw power plants in WPPC, mountains, Nevada, United States. WVM is independent prediction model. This could be combined with forecasting methods.[14–18]

Research Methodology

In previous years, numerous studies have been studied on PV power forecasting. Power prediction method in short term related to power plants of PV contains two methods i.e., physical and statistical methods. Physical procedures containing physical parameters which is derived with forecast for process of generation of PV power as well as characteristics of system, with combination of weather data forecasting. Whereas in statistical procedures, summarization of inherent laws for forecasting output power related to plants of PV power takes place based on historical power data. Both the techniques contain unique benefits, but non-stationary PV power characteristics output shows special effect upon properties and convergence of abovementioned methods.

Due to the non-stationary and periodic nature of PV power, previous power forecast techniques based on time series/linear models have proven to be ineffective and are currently in limited use. As a result, ANN and Wavelet Decomposition (WD) have the ability to address non-linear relationships between meteorological parameters and solar irradiance when used as a hybrid model input, depending on ANN and WD. The WD algorithm is used to extract usable data from the output of a PV power plant. ANN is used to reconstruct a model to forecast PV plant power. As a result, a forecasting model for PV power output is proposed in this study, which provides a sufficient increase in accuracy when compared to other similar modes. Model selection for forecasting, as well as PV power output and assessment metrics for economic and environmental advantages, were influenced by the following aspects. So, based on above discussion, model parameters selection of PV power estimation and forecasting are investigated in this paper.

Data Analysis

Solar radiations contain infrared, visible and ultraviolet radiations reaching to target location which depends upon certain factors i.e. time of the day, geographic location, season, local weather and land scope. Due to the earth's shape, sun rays angle varies between 0° to 90°. The surface of earth receives maximum energy for vertical sun rays. In India majority portion receives solar radiation in the range of 4–7 kWh/ square meter/ day. In one year, India gets solar energy more than 5000 trillion kWh/ year.

PV (Photovoltaic) power output forecasting is difficult for the power industry and companies that deal with PV. Solar energy has a number of issues, one of which is its inconsistency. The amount of power generated by utilizing this energy varies greatly from one site to the next, as well as due to environmental considerations. As a result, the technique to overcome this inconsistency is required. This can be done by establishing a proper prediction model to forecast the value of electricity that will be generated. Power production of solar panel is observed, and we have taken the power production output data of two years for the forecasting analysis. A Hybrid Model is used for forecasting purpose.

Our research work reflected excellent output related to prediction of solar power. So, for dealing in non-stationary and periodic applications related to output power of PV, modelling technique of hybrid nature which is depending upon ANN and WD is suggested in this paper for achieving excellent prediction results as well as convergence of better algorithm. Our work been managed as below:

- Analyses PV power generation output in frequency domain. To obtain the better frequency representation of PV output, the scalogram is used for improving localization time.
- Represents output power of PV process of decomposition using B-spline orthogonal filter.
- Represents method of hybrid prediction, combining ANN and Wavelet Transform.
- Verify and compare proposed method effectiveness.

Forecasting Analysis of PV Production Output

To forecast the PV power generation is a typical task due to environmental conditions like changing solar irradiance and weather parameter. In previous studies, various methods have been used. To overcome this problem, a method is used to analyses the data in the frequency domain is described here. The research above calculates changes in power generating output values with regard to numerous frequencies. As a result, different frequencies correspond to different lengths of time during which changes are estimated. When weather conditions are less predictable, such as cloud, fog, and so on, the output PV power is more difficult for system operators to manage. When solar irradiation reaches a high level of penetration, there is a lot of unpredictability and uncertainty. The quality and quantity of solar irradiation varies depending on geographical factors. It is extremely difficult to forecast the output of a given PV power system when the sun's position in space is dependent on the solar system's position at any given time.

In this paper, data is obtained from 2017 to 2019 at 01:00 pm from PV array which is located at a 28.367°N latitude and 79.4304°E longitude. The proposed technique aims to forecast the PV power generation output using WT and ANN. Specification of technical parameters are presented in Table 1.

Solar forecasting corresponds to environment of partial observation which represents problem of data analysis, which includes prediction and pattern completion. The power production of solar panel is

Table 1 — PV Power Plant Description

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

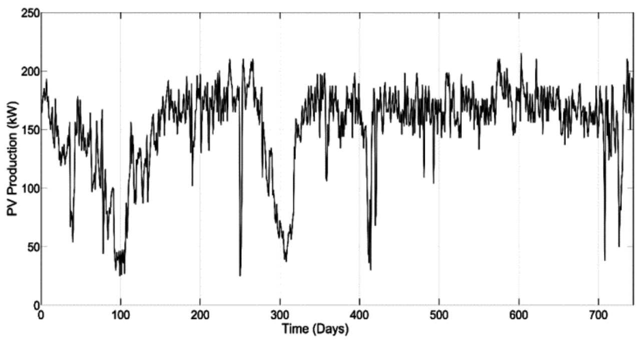

Fig. 1 — Power production curve of PV generation @ 1:00PM for two years

observed, and power production output data of two years for the forecasting analysis firstly a typical power production curve is measured by using the power output which represented as Fig. 1.

The prediction of power in PV plant keeps sufficient utilization regarding grid connection. Since PV power has characteristics of periodicity and non-stationary, traditional method of power prediction which are based upon time series or linear model have limited application. Therefore, proposed technique developed containing benefits of WD and ANN is utilized. As ANN has capability for addressing relationship of nonlinear type, theoretical values of PV power output considered like input in this hybrid model which is based upon ANN and WD.

Hybrid Forecasting Model

The model represents PV generation data for forecasting purpose. For achieving it, decomposition technique is proposed using wavelet transform, extract relevant features vectors (components) and then trained all the components, get the forecasting error. For reducing the error, artificial neural network is used. PV production is unstable and unpredictable so it may correct the stability of system. Therefore, forecasting is an alternative to attain good integration regarding PV plant output.

Wavelet Transform

The method of wavelet transform represented as tool of mathematics, similar to Fourier transform, which analyses signals in time series. The wavelet transform facilitates local replica of signal in frequency and time, which make it suitable in signal analysis having various time and frequency resolution, like output power for power plant of PV.

WT may be defined using two different categories viz- CWT (Continuous WT) and DWT (Discrete WT),

$$CWT\ (a, b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*_{a,\,b}(t)\,dt \quad \ldots (1)$$

$$\Psi a, b(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad \ldots (2)$$

CWT may be defined using Eq. 1, which represent x(t) as signal for analyzing, Ψa , b (t) represents scaled 'mother wavelet' using factor and shifted using b as 'translated parameter', finally * represents 'complex conjugate' for chosen set wavelets. Wavelets set may be defined using Eq. 2, in which set is generated using mother wavelet "ψ" and translation special values and signal scale, using factor for energy normalization "$\frac{1}{\sqrt{a}}$.". CWT converts nonstationary signals in wavelets series using different combination of translations and scales. Further wavelet coefficients obtained may be highly redundant and CWT not contained analytical solution in majority of functions, and numerical calculation of its solution is required. For resolving these issues, DWT may be introduced. DWT is defined using Eqs 3 & 4.

$$\psi j, k(t) = \frac{1}{\sqrt{aj\ 0}}\psi\left(\frac{t-kb0aj0}{aj0}\right) \quad \ldots (3)$$

where, j & k represents integers and a0 & b0 represents discretized scales and translation values.

$$DWT_x(m,n) = (2^{(-m/2)}) \sum_{t=0}^{T-1} x(t)\ \psi\left(\frac{t-n.2^m}{2^m}\right) \quad \ldots (4)$$

where, 'T' represents signal length x (t). Translation and Scaling parameter been integer variable function, m and n, representing $a = 2^m$ and $b = n2^m$ and t represents index in 'discrete' time.

Wavelet Decomposition

The unstable property and non-stationary nature of starting power signal of PV represents positive sign for using WT to determine frequency and temporal pattern for improving the difference in error in forecast. DWT is used in analyzing PV production signals in various bands of frequency, having several resolutions using decomposition of starting signal in detailed and coefficient value with approximation. For achieving it, DWT uses functions of two type viz scaling function attached in low pass filters and wavelet function attached in high pass filters.

Proposed Forecasting Technique of PV Power

WT signal decomposition procedure is represented by Fig. 2 and Fig. 3, represents the down sampling and up sampling process, low pass filter rejects component of higher frequency in signal and provides approximate coefficient whereas high pass filter results in signal's detailed coefficient. In this study, five level decomposition have been used. Using decomposition analysis, PV signal is splits into high pass frequency components and low- pass frequency components.

Technique of wavelet transform breaks signal in the layer of various scale having several resolution levels. This break in several scale is done due to technique of wavelet transform depends upon function with square integrable and representation of group theory.

WT-ANN Model

Data time series of PV power includes several disturbances, spike and several non-stationaries. WT may be deemed as tool of feature management for isolating above spikes. So, forecast the PV power of solar with use of WT may be utilize for improving the error in forecasting of PV power. Main concept behind this analysis in proposed model of hybrid nature as shown in Fig. 4, consist of use of artificial neural network trained with coefficient obtained from wavelet decomposition process of the PV production output signal. This hybrid network been trained for performing multistep forecasting regarding individual detailed and approximate coefficient for DWT extracted signal for PV production. It may be useful information in case of prediction based upon ANN which enables further developments in this field.

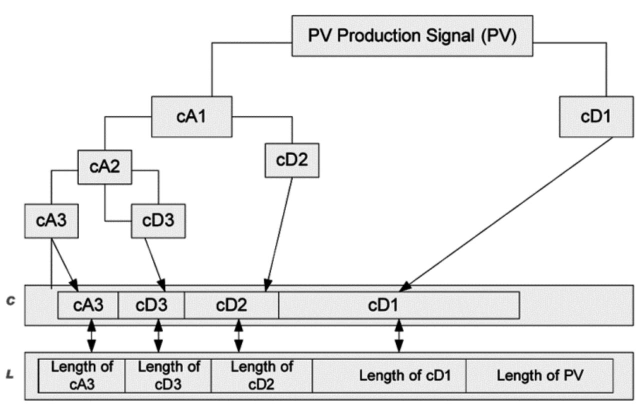

Fig. 2 — Procedure of Decomposition of DWT signal

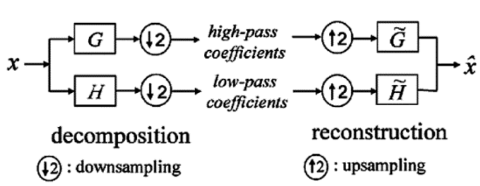

Fig. 3 — DWT signal decomposition and reconstruction process

Simulation Results

In the context of overall grid balance and planning, this propensity utility of power versus PV power is quite difficult to overcome. Solar energy integration in an efficient manner with the grid will be highly fruitful if a reliable algorithm is developed that can reduce inaccuracy in forecasting future generation of PV electricity. PV power forecasting has the potential to play a critical role in addressing the aforementioned challenge. So, using a combination of PV output data and PV system, anticipate PV system output using WT (wavelet transform) and AI (artificial intelligence) approaches. The WD breaks signal P_{pv} in its layer which are smooth and detailed. Output power signal related to power plant of PV consists sharp edge and caused jumps due to solar radiation fluctuation, having nonlinear periodicity and characteristics. Let $P_{pv}(n)$ represents signal in discrete time, in power plant of PV output power $P_{pv}(n)$ required for breaking in layer with details and a smooth layer. Using WD technique, spiltssignal on scale represented A1(n) and D1(n), also A1(n) represents input signal with smooth feature, D1(n) represents input signal x(n) detail version, represented in coefficients of wavelet transform, it can extend it until, get actual information. The approximation coefficients (A5, A4, A3, A2, A1) and detailed coefficients 'D5, D4, D3, D2, D1' from wavelet break obtained in PV production output as shown in Fig. 5. Further, for establishing the forecasting model, remove disturbances to be removed which contain frequencies.

To obtain the better frequency representation of PV generation signal, CWT (continuous wavelet transforms) is used and take the scalogram of the given signal. The scalogram represents values in absolute form

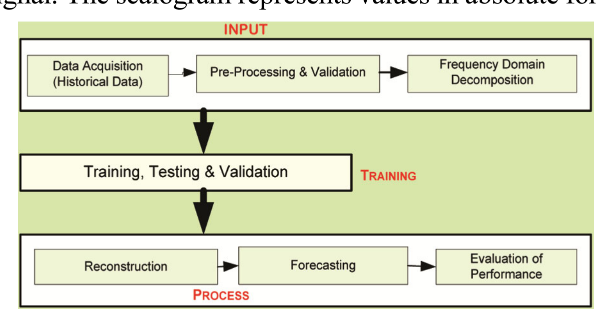

Fig. 4 — Hybrid system combined with ANN

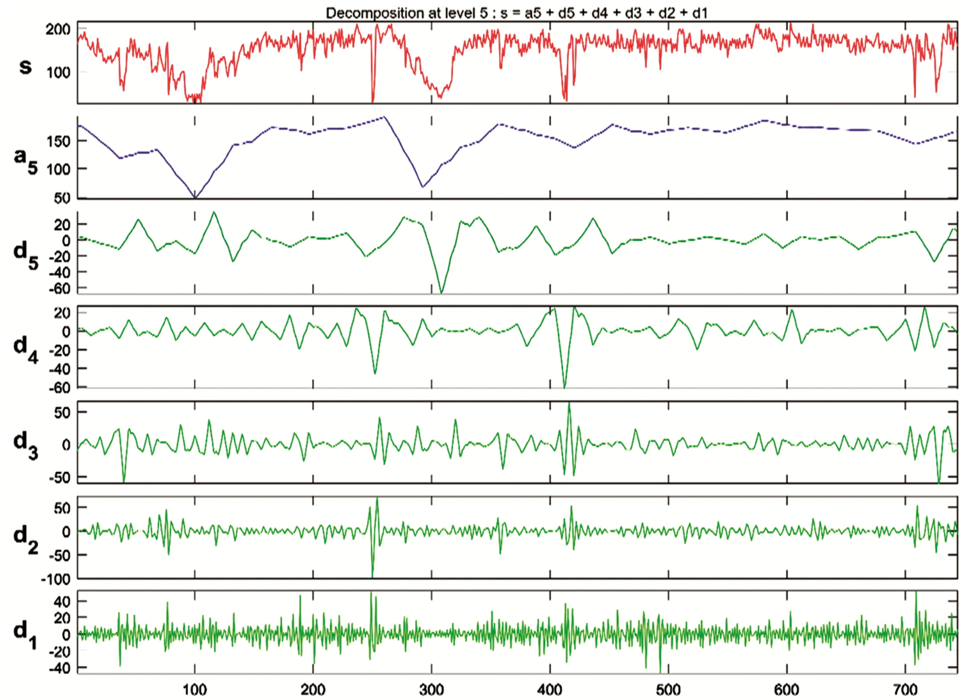

Fig. 5 — Decomposition of PV production (Fig. 1) at level 5 where x-axis represents time in days and y-axis represent decomposition of signal ‘s’ at 5th levels

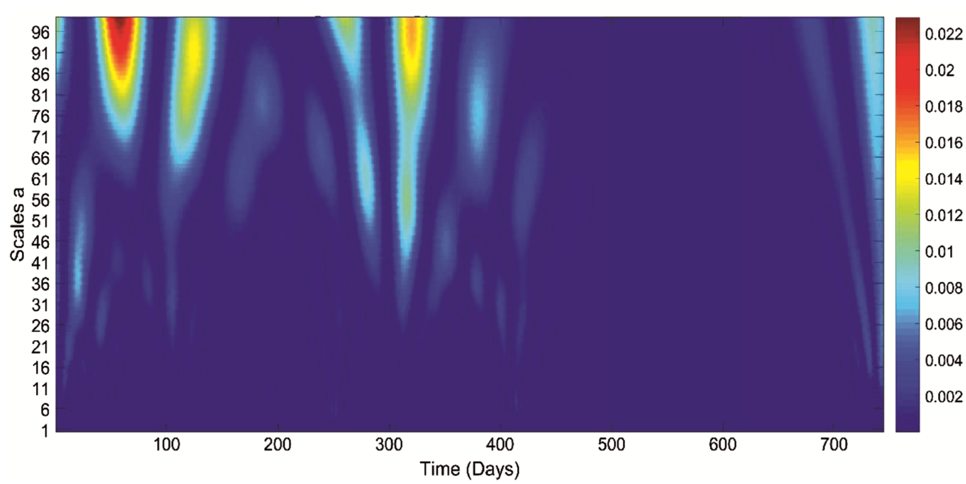

Fig. 6 — Scalogram of percentage of energy of each wavelet coefficient using continuous wavelet transform

for transform of continuous wavelet related to signal which is plotted in time & frequency function Fig. 6. The scalogram is used when we want improved localization time in case of high frequency of short duration event & improved frequency localization in events of longer duration with low frequency. Contour plot (Fig. 7) shows the wavelet spread in time and frequency preserving the energy in the analysis stage.

To improve the decomposition process (analysis and reconstruction), an orthogonal wavelet synthesis filter for the b-spline (Bior) is used, with three vanishing moments in the synthesis wavelet and five vanishing moments in the analysis wavelet as shown in Fig. 8. Hence, use of DWT has decomposed PV power production into approximation and detailed coefficient at level one as shown in Fig. 9 (a) and Fig. 9 (b) respectively. Then approximation coefficient

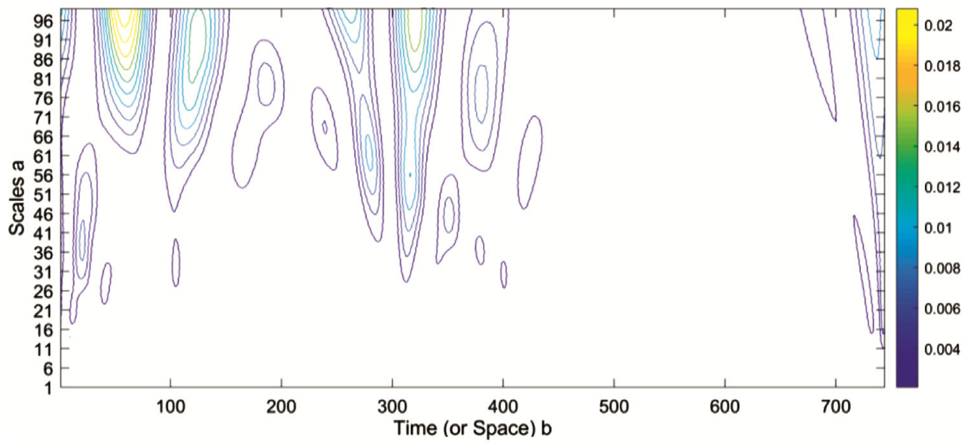

Fig. 7 — Contour of percentage energy for each wavelet coefficient

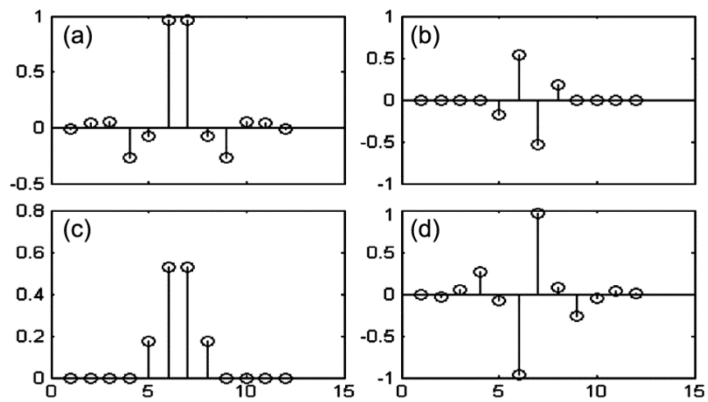

Fig. 8 — The analysis and synthesis components of continuous wavelet component of signal (Ppv)

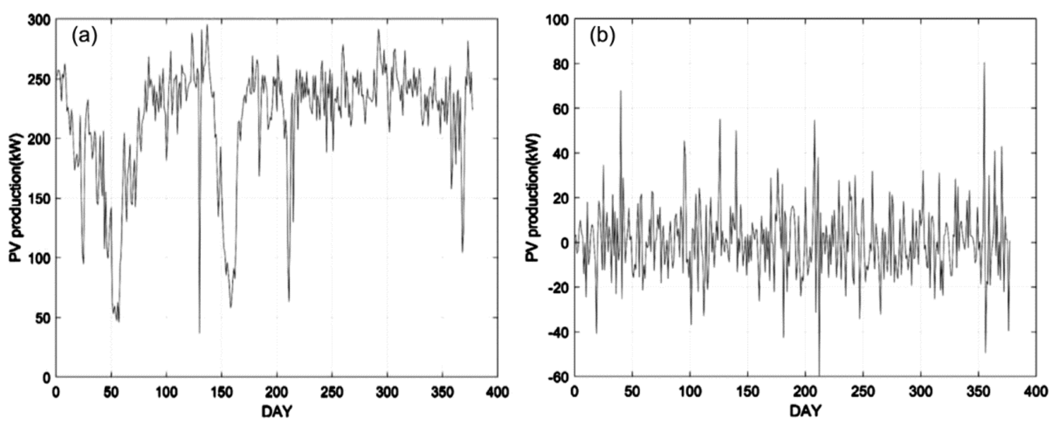

Fig. 9 (a) — Coefficient of original PV power signal at level 1: (a) Approximation, (b) Detail

and detailed coefficient will be reconstructed as shown in Fig. 10 (a) and Fig. 10 (b) respectively. By using these coefficients, the graphs are obtained as shown in Fig. 11 and Fig. 12.

In the case of signal decomposition, the observation was that introducing numerous coefficients, such as approx. 1 and 2, or further signal decomposition leads in sufficient increased complexity and training time, without increasing forecast outcomes. Many time series techniques are employed in a variety of forecasting applications, with varied model input and forecasting horizons. In

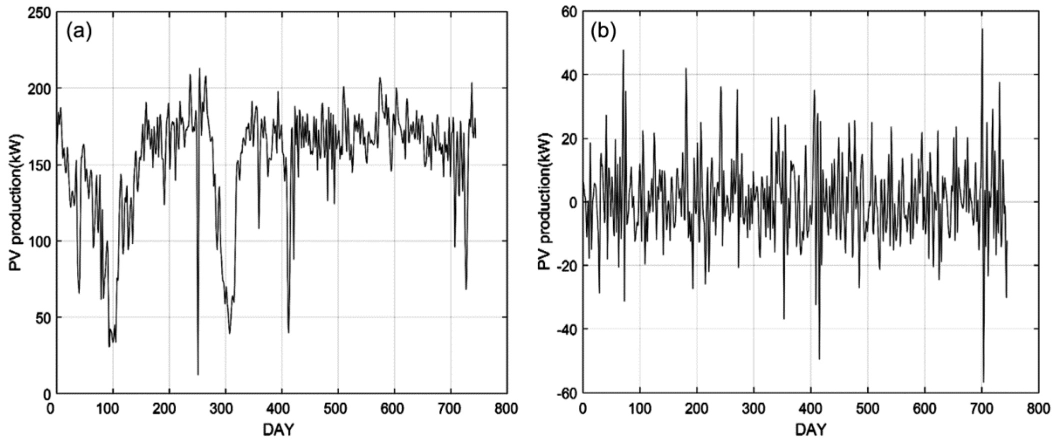

Fig. 10 — Reconstruction plots: (a) of Fig. 9(a), (b) of Fig. 9(b)

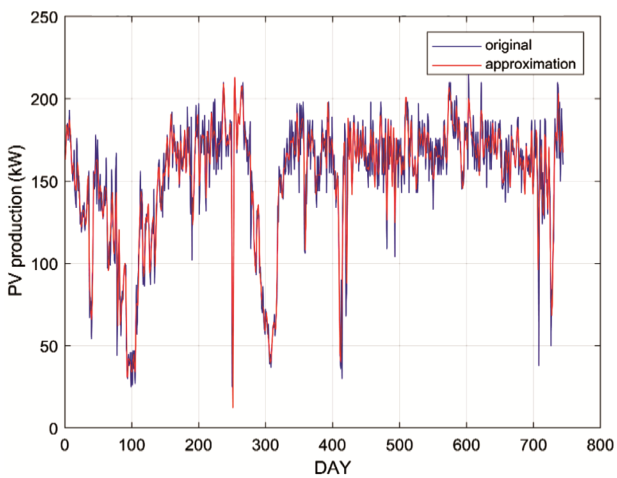

Fig. 11 — Comparison between approximation coefficient at level 1 and original PV signal

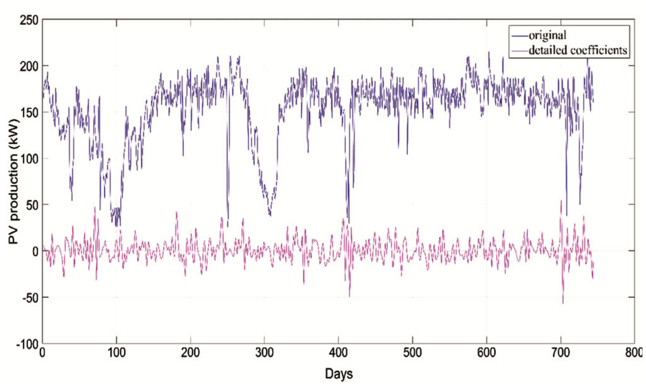

Fig. 12 — Comparison between original PV power signal and detailed coefficient D1

the application of forecasting, artificial intelligence (AI) based techniques are employed as a strong tool. The NN (neural network) gained prominence and is used as a powerful tool for computation in numerous AI techniques around 1980.

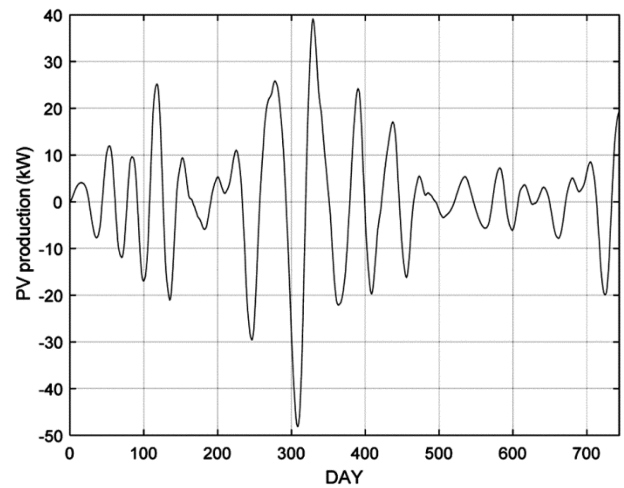

Fig. 13 — Reconstruction output of D5 coefficients

Before applying ANN, technique and performing forecasting analysis, decomposition level has to be decided. The main concept behind the operation is preprocessing of PV output data with the removing disturbances which is done by DWT. The decomposition number level depends firstly given signal under analysis. In this paper, modelutilized in other application, like forecasting of load, test is required for finding levels of optimal decomposition, in approximate and detailed level of decomposition. Thus, it is decomposed at the level 5. But it is observed that more disturbances occur at level 3 that's why B-spline by orthogonal wavelet is adopted through which the signal is analyze at 5 level and synthesized at 3 level by BiorNr.Nd. Due to this, PV production signal at the l evel 5 has been decomposed and then decomposition coefficient D5 can be obtained and reconstruct back this as shown in Fig. 13. According to the structure of the forecasting model. To train each coefficient

(A3, D5, D4, D3, D2, D1) and to recognize the non-liner behaviour of each component from DWT decomposition detailed coefficients 'D5, D4, D3, D2, D1' obtained from wavelet breaking our PV production output. After this process large changes occurs at level 2 as shown in Fig. 5.

Hence, Bi-orthogonal filter is used to decide decomposition level. WD with 5 layers is used in PV plant output power and further include detailed layer and approximation layer comparison. As per results, PV signal optimal level represented as level-3 of decomposition. It represents use of coefficients in this application of forecasting as A3, D1, D2, D3, D4, D5. After extracting the features vectors, trained all the coefficients by artificial neural network. In this final stage, the output of ANN reconstructed using Inverse Discrete Wavelet Transform (IDWT) as shown in Fig. 14 (a). After comparing these values with original PV signal error as shown in Fig. 14 (b). All these reconstructed obtained values are forecasted by ANN model as shown in Fig. 15, and achieved the forecasting graph as in Fig. 16 (a).

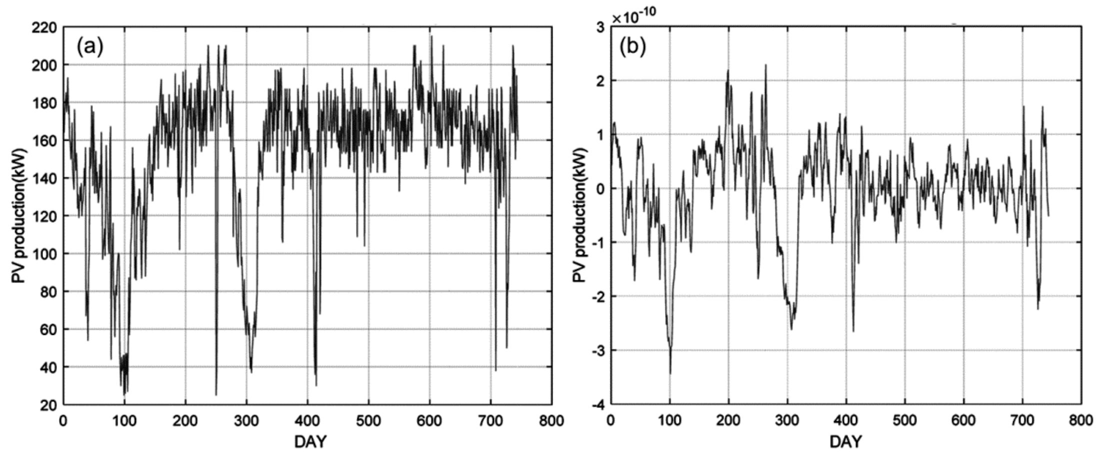

Fig. 14 (a) — Full Reconstruction output of trained coefficient Signal using IDWT, (b) — Error in Full Reconstructed output of P and original PV power signal

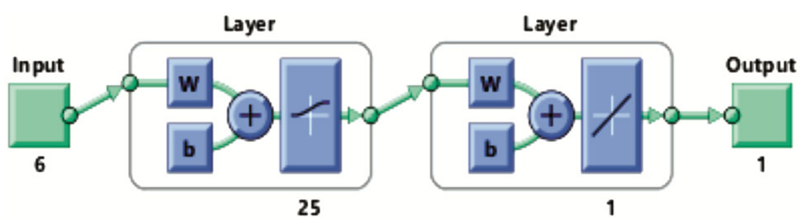

Fig. 15 — Forecasting Hybrid Model WT+ANN

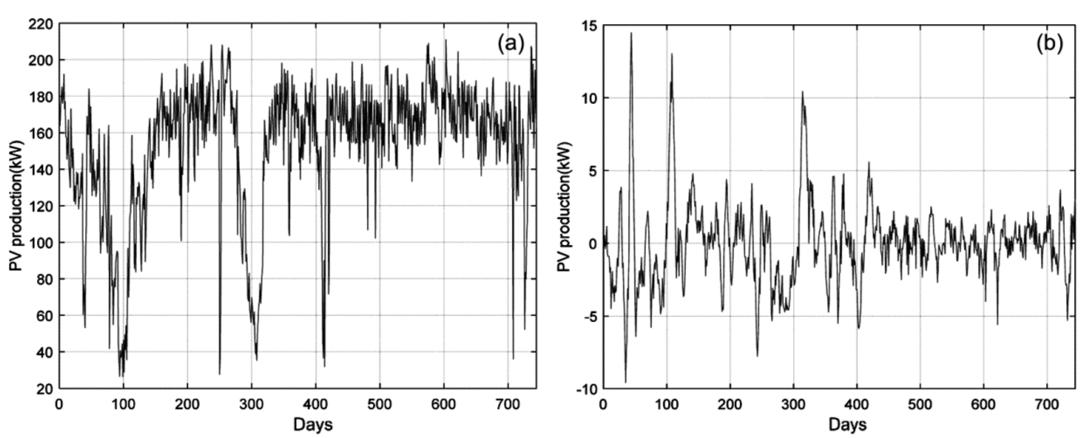

Fig. 16 — (a) Forecast output after training of reconstruct coefficients values, (b) Error in original signal PV and Forecast Output

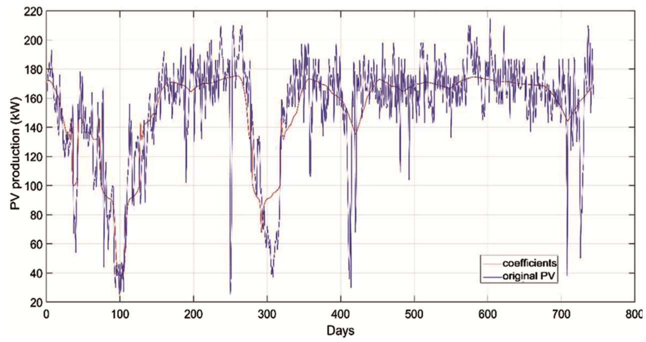

Fig. 17 — Comparison of original signal and reconstruct coefficients of PV power signal

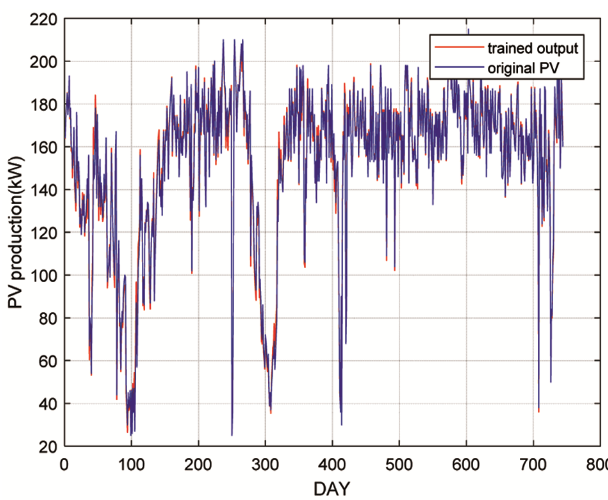

Fig. 18 — Comparison of original signal PV and forecast output

By observing the above graphs, it is predicted that graph is almost followed by the original one. For finding the error, subtract the predicted output from original PV signal. Fig. 16 (b) represents the error between predicted and original PV generation. Fig. 17 shown the comparison between reconstructed output and PV Power Generation and Fig. 18, shows comparison between forecasted output and original PV Production signal, which depicts the forecasting is well done and the accuracy is very high as compared to previous studies.

While predicting PV power, three statistical terms has been utilized for representing PV power output characteristics. The terms represented as RMSE, MAE and MAPE as shown in Table 2 and Table 3.

The PV generation data is been process for smoothness. On addendum, it is observed that missing point of input data regarding PV output data results in increment in error of forecasting. So, trained all coefficients using ANN using the process of trial and error as shown in Fig. 19. Performance is based on the hidden neurons and hidden layers. From observations it was found that 25 hidden neurons gave better results. During the process of training ANN, mainly on 1st iteration, neurons weighted link are picked randomly and further optimized for minimizing in error, the process represents several minima at local level.

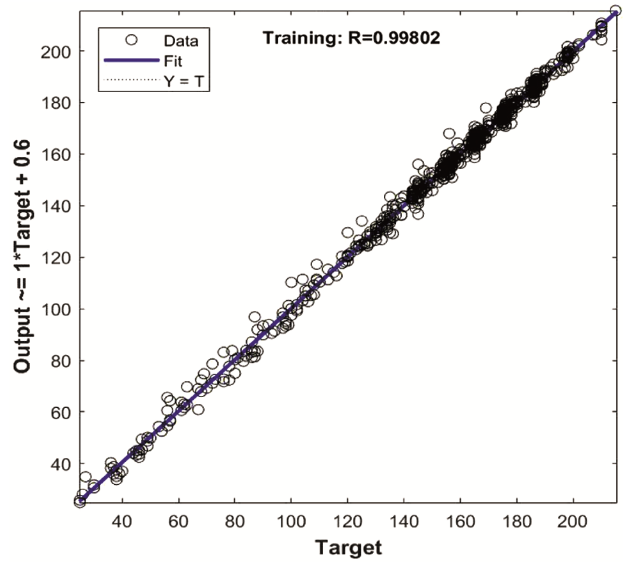

Fig. 19 — Scattered R Squared Plot for PV Power generation forecasting

Table 2 — Error in Reconstructed output signal and original PV generation Signal

Layer		Error
	RMSE (%)	8.64017e-13
	MAE (%)	6.3050e-13
	MAPE (%)	6.4969e-13
	Absolute Error	3.4417e-10

Table 3 — Forecasting Performance of Proposed hybrid model WT + ANN

Layer	Error		R	Average training time
	RMSE (%)	0.02433		
	MAE (%)	0.01725	0.99802	00:00:11
	MAPE (%)	0.01476		

With reference to the period 2011–2020, a comprehensive summary of the most relevant research dealing with the applications of ML-based methods in the field of PV power forecasting is reported in this Table 4.

According to Table 4, the proposed method gives better accuracy as compared to the previous methods.

Table 4 — Machine learning (ML)-based methods for the forecast of PV power, 2011–2020

Methods	Parameters used	MAE	MAPE	RMSE	R
ANN[19]	Historical powers andmeteorological forecast	—	MAPE: 8.29% sunny day MAPE: 54.44% rainy day	—	—
ANN[20]	Historical powers andWeather forecast	—	MAPE: 0.85%	—	—
ANN[21]	Weather data and historical Measurements	MAE < 15%	—	—	—
ANN[22]	Solar radiation	MAE=1.137		RMSE=1.523	
Deep LSTM network[23]	Historical powers			RMSE = 82.15	
Hybrid WT + LSTM-DNN[24]	Historical Power generation Data	—	MAPE (%) 4.09425	RMSE=0.08225	R=0.955
WD+ANN[25]	PV power output	Clear=4.978% Cloudy=10.259% Overcat=10.220% Rainy=13.062%	Clear=13.858% Cloudy=21.550% Overcat=35.226% Rainy=30.926%	Clear=9.313 % Cloudy=18.472 % Overcast=18.511% Rainy=22.948 %	
WT+ ANN (Proposed Method)	Historical Power generation Data	MAE (%) 0.01725	MAPE (%) 0.01476	RMSE (%) 0.02433	R=0.99802

Conclusions

In this paper, data of PV production is collected at particular time, 744 samples of PV production data have been calculated. The main aim of this paper is to forecast in frequency domain, which is done with hybrid model. Wavelet Transform enables the extraction of frequency and temporal patterns. PV power output forecasting is based upon WD and ANN. Biorthogonal filter is used to choose decomposition level which is not preferably adopted in previous studies. It supports to multiresolution analysis. Smoothed signal and detailed signal related to PV output are found with application of ANN, forecasting models upon several signal layers are obtained. At last, by obtaining of forecasting results for several signal layers, PV power array forecasting results are established. By comparing with previous forecasting method, it represents that proposed forecasting method represents better precision for forecasting, as well as required convergence time for algorithm is less. These finding shows that model based upon proposed method outperform to the models of conventional mathematics in reference to forecast accuracy and adaptability in the conditions of metrological uncertainty.

References

1 Utility-scale solar in 2018 Still growing thanks to Australia and other later entrants, *W*iki-Solar (2019).

2 Snapshot (2020)-IEA-PVPS. [iea-pvps.org (2020)].

3 Transition in Energy, Transport – 10 Predictions for (2019) – 2. Solar additions rise despite China, BNEF (Bloomberg new energy finance) 2019, .

4 Nia A R, Awasthi A & Bhuiyan N, Industry 4.0 and demand forecasting of the energy supply chain: A literature review, *Comput Ind Eng*, **154** (2021) 107128.

5 Silva J L D S, Mesquita D B de, Moreira H S, Cavalcante M M, Melo K B de, Reis M V G dos, Freitas H A de & Villalva M G, Industry 4.0 approach aligned with the challenges of grid-connected photovoltaic systems, *IEEE PES ISGT Latin America* (Gramado, Brazil) 11th Nov, 2019.

6 Mihai F, Aleca O E, Steanciu A, Gheoghe M & Stan M, Digitalization-the engine of sustainability in the energy industry, *Energies*, **15** (2022) 2164.

7 Norihiro Kawasaki, Takashi Oozeki, Kenji Otani & Kosuke Kurokawa, An evaluation method of the fluctuation characteristics of photovoltaic systems by using frequency analysis, *Sol Energy Mater Sol Cells*, **90(18–19)** (2006) 3356–3363S, doi: 10.1016/j.solmat.2006.02.034.

8 Mehdi Ebad & Grady W M, A cloud shadow model for analysis of solar photovoltaic power variability in high-penetration PV distribution networks, *IEEE Pow Energy Soci Gen Meet (PESGM)* (Boston USA) 14th Nov, 2016.

9 Jiang J A, Wan J J, Zheng X Y, Chen C P, Lee C H, Su L K & Huang W C, A novelweather information-based optimization algorithm for thermal sensor placement in smart grid*, IEEE Trans*, **9(2)** (2016) 911–922.

10 Capizzi G, Napoli C & Bonanno F, Innovative second-generation wavelets construction with recurrent neural networks for solar radiation forecasting, *IEEE Trans Neu Net Learn Sys*, ***23*(11)** (2012) 1805–1815.

11 Anuwar F H & Omar A M, Future solar irradiance prediction using least square support vector machine, *Int J Adv Sci, Engg and Info Tech*, **6 (4)** (2016) 520–523.

12 Preda S, Oprea S V, Adela B & Anda B (Velicanu), PV forecasting using support vector machine learning in a big data analytics context, *Symmetry*, **10(12)** (2018) 748.

13 Bae K Y, Jang H S & Sung D K, Hourly solar irradiance prediction based on support vector machine and its error analysis, *IEEE Trans Pow Sys, **32***(**2)** (2016) 935–945.

14 Ding M, Wang L & Bi R, Anann-based approach for forecasting the power output of photovoltaic system, *Proc Envil Sci*, **11** (2011) 1308–1315.

15 Konjic T, Jahic A & Pihler J, Artificial neural network approach to photovoltaic system power output forecasting, *18th Intell Sys Appl Pow Sys ISAP* (Porto, Portugal) September, 2015.

16 Mandal P, Madhira S T S & Haque A U, Forecastingpower output of solar photovoltaic system using wavelet transform and artificial intelligence techniques, *Proc Compu Sci*, **12** Dec (2012) 332–337.
17 Poolla C & Ishihara A K, Localized solar power prediction based on weather data from local history and global forecast, *45th IEEE Photovoltaic Specialists* (Waikaloa HI) 10th –15th June, 2018.
18 Lave M, Kleissl J & Stein J S, A wavelet-based variability model (WVM) for solar PV power plants, *IEEE Trans Sustene*, **4(2)** (2013) 501–509.
19 Chen C, Duan S, Cai T & Liu B, Online 24-h solar power forecasting based on weather type classification using artificial neural network, *Solar Ene*, **85(11)** (2011) 2856–2870.
20 Jimenez L A F, Jimenez A M, Falces A, Villena M M, Garrido E G, Santillan P M L, Alba E Z & Santamaria P J Z, Short-term power forecasting system for photovoltaic plants, *Renew Energy*, **44** (2012) 311–317.
21 Leva S, Dolara A, Grimaccia F, Mussetta M & Ogliari E, Analysis and validation of 24 hours ahead neural network forecasting of photovoltaic output power, *Math Comput Simul*, **131** (2017) 88–100.
22 Jogunuri S & Josh F T, Artificial intelligence methods for solar forecasting for optimum sizing of pv systems: a review, *Res J Chem Envi*, **24(SII)** June (2020) 174–180.
23 Ospin J, Newaz A & Faruque M O, Forecasting of PV plant output using hybrid wavelet-based LSTM-DNN structure model, IET *Renew Pow Gen*, **13(7)** (2019) 1087–1095, doi:10.1049/iet-rpg.2018.5779.
24 Nasser M A & Mahmoud K, Accurate photovoltaic power forecasting models using deep LSTM-RNN, *Springer Neu Compu Appl*, **31** (2017) 2727–2740.
25 Zhu H, Li Xu, Sun Q, Nie L Yao J & Zhao G et al., A power prediction method for photovoltaic power plant based on wavelet decomposition and artificial neural networks, *Energies*, **9(1)** (2016) 1–15, doi.org/10.3390/en9010011.