PSO Tuned ANFIS Model for Short Term Photovoltaic Power Forecasting

Harendra Kumar Yadav, Yash Pal, Madan Mohan Tripathi

Abstract*: Solar power is a green and abundant renewable energy source. Photovoltaic (PV) power forecasting is very essential for the integration of PV power generation to a competitive electricity grid. The production of photovoltaic energy depends to a great extent on solar radiation, which is inherently irregular, so the forecast of photovoltaic energy is necessary for the operation, stability, and reliability of the grid. This article presents a new hybrid approach that combines particle swarm optimization (PSO) and Adaptive neuro-fuzzy inference system (ANFIS) for predicting photovoltaic power. PSO is used to optimize ANFIS parameters. The proposed PSO-ANFIS approach is evaluated on the grid-connected PV power plant data situated in Ghaziabad India. The proposed approach performance is compared with some reported approach and performs better. The computational complexity of the proposed method also appreciable as compared with the other reported methods.

Index Terms*: Solar irradiation, PV power forecasting, PSO and ANFIS.

I. INTRODUCTION

From the last three decades, PV power generation is growing exponentially worldwide. PV power is a renewable, abundant, green and echoes friendly to the environment. But the integration of PV power to the electricity grid is a very challenging task because of its intermittent nature and its dependency on the solar irradiation and environmental condition [1]. Therefore, an accurate forecast of photovoltaic power for transmission planning, network stability, system security, unit commitment, maintenance, and regulation will be required [2].

In the literature it is found that the following three approaches are mainly used for the forecasting:

- Physical approach
- Statistical approach
- Hybrid approach

In the physical approach of forecasting metrological and satellite data are used for modeling and testing. But this approach of modeling is very complex and gives an inaccurate result for short term forecasting, generally used for long term forecasting. Statistical approaches of modeling are mainly used for short term forecasting because of some prior parameters assumptions. In the statistical approach, historical metrological data are used for modeling as well as testing purpose. In literature there are many statistical methods are available such as ARMA, ARIMA etc.

The hybrid approach combines the advantages of two or more methods for modeling and testing. In recent years, many hybrid methods have been developed for engineering applications in the field of prediction, such as artificial neural networks with the fuzzy system (ANN-FS) [3], adaptive neuro-fuzzy inference system (ANFIS), wavelet-ANFIS-PSO [4], ARMA-ANN and ARMA-SVR [5]. Table 1 summarizes the method to forecast the PV power presented in recent years. Several forecasting methods have been presented in recent years to predict photovoltaic power [13]-[14].

The rest of this paper is organized as follows. Section II describes the operation of PSO. The adaptive neuro-fuzzy inference system (ANFIS) is explained in section III. Section IV provides a detailed explanation of the PSO-ANFIS hybrid approach. Evaluation parameters and discussion of results are outlined in Section V. Finally, the conclusion is given in section VI.

II. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is an evolutionary optimization algorithm developed by Kennedy and Eberhart in 1995 [15]. PSO is a social behavior based evolutionary algorithm instead of evolution. Other evolutionary optimization algorithms are evolution based. PSO algorithm utilizes the personal experience, overall experience and present movement of swarms to decide their next position in search space [4], [14]. If S is the size of the swarm and j represents each particle of the search space. Particles of the population are initialized on a random basis by selecting their current position X_i and velocity V_i at the current time, and fitness function F_i is calculated accordingly. Each particle continuously tracks to find the best solution in search space and this individual particle best solution is known as particle personal best possible solution denoted by $P_{best\ jd}$. In the next step, each particle searches a global best feasible solution among their individual best solutions and it is known as a global best feasible solution and denoted by $G_{best,jd}$. In every iteration, the velocity, position, $P_{best\ jd}$ and $G_{best,jd}$ of particles are changes toward the global optimum solution. PSO algorithm consists of following important working steps:

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Harendra Kumar Yadav, School of Renewable Energy and Efficiency, NIT, Kurukshetra, Haryana, India.
Yash Pal, Electrical Engineering Department, NIT, Kurukshetra, Haryana, India.
Madan Mohan Tripathi, Electrical Engineering Department, DTU, New Delhi, India.

Table 1. A literature review of PV power forecasting

Reference	Method	Data Pre-processing	Contribution
[6]	BPNN	No	BPNN is used for 24-hour ahead PV power forecasting. BPNN is not applicable for short term and ultra sort term forecasting because of its local approximation of network and slow training process.
[7]	BPNN and RBFNN	WT	The wavelet transformation is used for preprocessing the data. The BPNN and RBFNN technique is used to predict photovoltaic power. Here weights and other parameters are selected randomly.
[8]-[9]	SVM	Weather-based classification of data.	In this paper, data is classified into different seasons according to weather. After classification SVM is used for the modeling and forecasting purpose.
[10]-[11]	RNN	NA	Recurrent neural network (RNN) is a deep learning method and used for the accurate PV power forecasting. But RNN requires more computational memory during the testing process.
[12]	ESN	Different classifications are used as data pre-processing.	ESN uses a dynamical reservoir at the place of the traditional hidden layer of RNN and known as a forced recurrent neural network. ESN only requires training for the output node weights and inputs as well as reservoir weights are randomly selected.

Step-1: In step-1 particle of the population is initialized by randomly selecting their position and velocity within a specified range of possible solution. The fitness functions of each particle are evaluated and allocate memory to each individual to store their personal best solution. A global best solution $G_{best,jd}$ is decided from above personal best solution $P_{best\ jd}$.

Step-2: In the next iterations velocity of each particle is updated according to the Eq.(1).

$$v_{jd}(t+1) = \omega \times v_{jd}(t) + c_1 r_1 (P_{best_{jdi}} - x_{jd}(t)) + c_2 r_2 (G_{best_{jd}} - x_{jd}(t)) \quad (1)$$

Where ω is inertia factor, c_1 and c_2 are positive acceleration coefficients and r_1 and r_2 are two different random numbers uniformly distributed between [0 1]. In this paper, the inertia weights decrease iteration by iteration and modified by Eq.2 [14].

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{ite_{\max}} \times ite_{current} \quad (2)$$

Where

ω_{max} -Maximum value of inertia weight

ω_{min} -Minimum value of inertia weight

ite_{max} -Maximum number of iteration

$ite_{current}$ -Shows current iteration

Step-3: Fig.1 shows the position update of the particles. In the step-3 position of each particle is updated according to the Eq.(3).

$$x_{jd}(t+1) = x_{jd}(t) + v_{jd}(t+1) \quad (3)$$

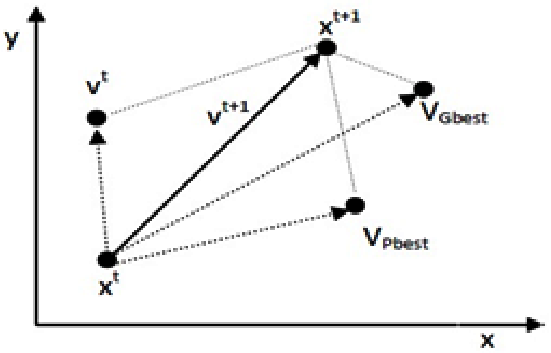

Fig.1. PSO search mechanism for updating the position of the particle

Step-4: In the step-4 best individual position of every particle ($P_{best\ jd}$) and global best position ($G_{best,jd}$) are updated using the following Eq.4 and Eq.5 respectively.

$$P_{best,jd}(t+1) = X_{jd}(t+1)$$

$$if \quad f(X_{jd}(t+1)) < f(P_{best,jd}(t)) \quad (4)$$

$$G_{best,jd}(t+1) = X_{jd}(t+1)$$
$$if \quad f(X_{jd}(t+1)) < f(G_{best,jd}(t)) \tag{5}$$

Where f(x) is the objective function of the problem and required, to be minimized.

Step-5: Algorithm repeats step-2 to step-4 until the required objective function is not achieved. PSO algorithm terminates if the defined objective function or fitness is achieved or meet the following condition:

- The fitness function is achieved
- A maximum number of iteration/epoch.

III. ANFIS

The adaptive-network-based fuzzy inference system (ANFIS) is a data-driven neural network [16]. It is used for function approximation purpose in engineering applications. ANFIS work as a great tool for nonlinear forecasting because of its great learning availability. Fig. 2 shows the generalized ANFIS structure, as shown in the ANFIS network, consisting of five layers and each layer contains several nodes explained by the node function. All individual layers of the above ANFIS structure are described below:

Layer-1: In the first layer, each node t is adaptable to a node function as in Eq. (6):

$$o_t^1 = \mu A_t(x) \tag{6}$$

Where x and A_t are input to node t and linguistic value associated with the corresponding node. Generalized bell function $\mu A_t(x)$ is calculated by the Eq.(7):

$$\mu A_t(x) = \frac{1}{1+\left|\frac{x-r_t}{a_t}\right|^{2bt}} \tag{7}$$

where [a_t, b_t, r_t] are premise parameter set.

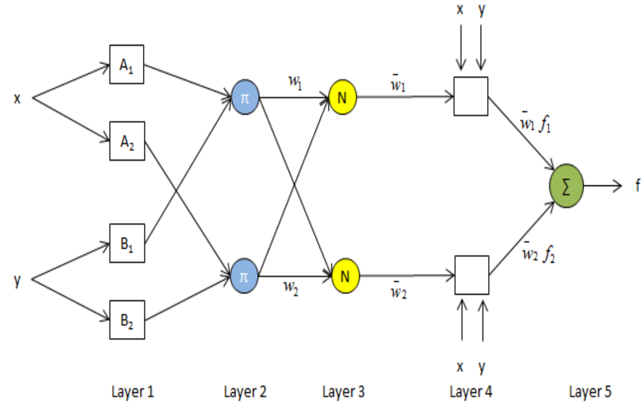

Fig.2. ANFIS structure

Layer-2: Each node is fixed and used to calculate the firing strength w_t of a rule. The output of every node is equal to the product of all incoming signals at that node and calculated by the following Eq.(8)

$$O_t^2 = w_t = \mu A_t(x) \times \mu B_t(y), \quad t = 1,\ 2 \tag{8}$$

Layer-3: Each node of this layer is also fixed and calculates the relationship between the activation power of the respected node rule and the sum of the strength of all the activation rules. The results of the t^{th} layer are called normalized firing strengths are given by Eq. (9).

$$O_t^3 = \overline{w_t} = \frac{w_t}{w_1 + w_2}, \qquad t = 1,2 \tag{9}$$

Layer-4: Each node of this layer is adaptable with a function as shown in Eq.(10).

$$O_t^4 = \bar{w}_t \times f_t = \overline{w_t} \times (a_t x + b_t y + c_t) \quad t = 1,2 \tag{10}$$

$\bar{w}_t$ is calculated in layer-3 and [a_t b_t c_t] is consequent parameter set.

Layer-5: The 5^{th} layer is a single layer node and calculates the final outputs by summing all the incoming signals as shown in Eq.(11).

$$O^5 = \sum_t \bar{w}_t f_t = \frac{\sum_t w_t f_t}{\sum w_t} \tag{11}$$

IV. PROPOSED PSO-ANFIS METHOD

The proposed hybrid method was a combination of PSO optimization algorithm and ANFIS. Here PSO was used to optimize the ANFIS parameters. Fig.3 shows the flow chart and detail working of the proposed hybrid method.

A. Data

In this paper one month data of 15-minute interval of Ghaziabad, India based 100 kW PV power plant was used for training and testing purpose. After collecting the data moving average was applied to remove the missing data.

B. Data normalization

As we know that nature of PV power output is nonlinear in nature. ANFIS is a nonlinear model that maps input variables to the large search space and it is difficult to map the data having huge nonlinearity. This problem is minimized by normalizing the historical input data so that search space is reduced. In this paper, the input data is normalized between 0.1 to 1 by the following Eq.(12).

$$a_{scaled} = c_{\min} + (c_{\max} - c_{\min}) \times \frac{a - a_{\min}}{a_{\max} - a_{\min}} \tag{12}$$

Where c_{max} and c_{min} are constant term 1 and 0.1 respectively, a_{max} and a_{min} is the maximum and minimum value of the data set. a_{scaled} is the normalized value of the data set.

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C. Data classification

Normalized data set of March 2018 was classified into four-week data sets. In the next step develop method was used to forecast the PV power output of 9/03/2018, 16/03/2018, 23/03/2018 and 30/03/2018 of 100 kW PV power plant situated at Ghaziabad India by using their previous 6 days data sets respectively.

D. ANFIS training

Normalized data of every week from the previous stage was used to train ANFIS. ANFIS parameters were adjusted according to the training data set. The training process stop when the desired objective function was achieved or the termination condition is achieved. Training and testing data set were prepared by using the following Eq.13.

$$y(h) = f(y(h-1), y(h-2), y(h-3), ... y(h-24)) \tag{13}$$

Where f(.) indicate the training function. After preparing data set, type of membership function and neuro-fuzzy inference system was optimized by the PSO. PSO is used to optimize the parameters associated with the fuzzy inference system membership functions.

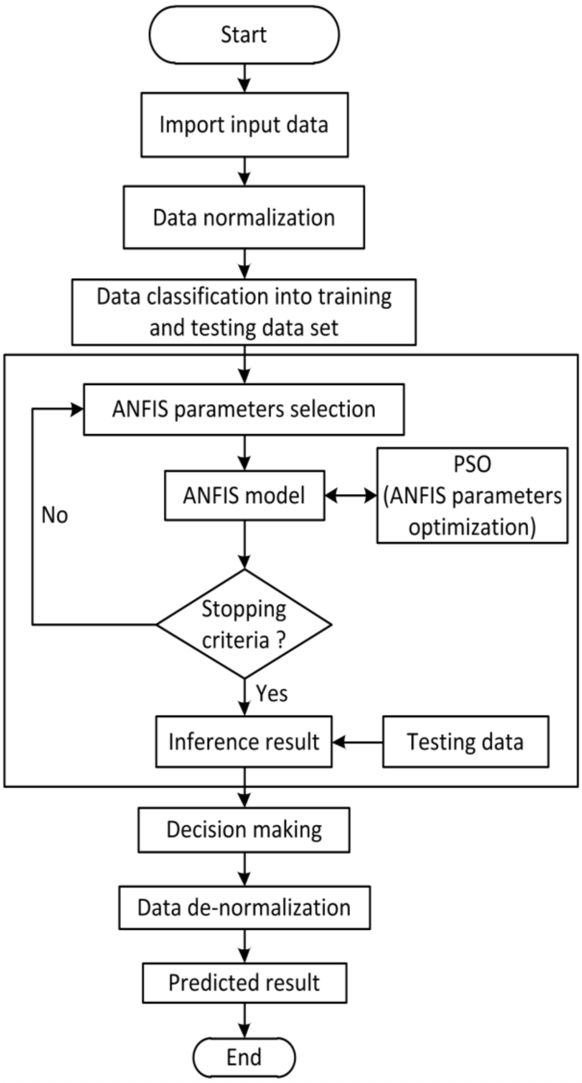

Fig.3 Flow chart of the proposed model

E. ANFIS output:

In the last stage-trained ANFIS model parameters were updated by the optimized parameters of PSO. After updating the optimized ANFIS parameters, updated ANFIS method was used to extract the future PV power output by using the testing data set.

V. RESULT AND DISCUSSION

One month (March) 15 minute interval time series data of 100 kW PV power plant were obtained. The PV power data was normalized between 0.1 to 0.9 intervals. Normalized data was distributed for 70% training and 30% testing. Input data was generated by 24-hour historical data points. Six inputs were used to model and test the developed model.

Root mean square, mean absolute percentage and symmetric mean absolute percentage error were used to calculate the performance of the developed approach as explained in Eq.14 to Eq.17 [1].

Root mean square error:

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(PV\ Power_{mi} - PV\ Power_{ci})^2} \tag{14}$$

Mean absolute percentage error:

$$MAPE = \frac{100}{T}\sum_{i=1}^{T}\frac{(PV\ Power_{mi} - PV\ Power_{ci})}{\overline{PV\ Power_m}} \tag{15}$$

$$\overline{PV\ Power_m} = \frac{1}{T}\sum_{i=1}^{T} PV\ Power_{mi} \tag{16}$$

Symmetric mean absolute percentage error:

$$sMAPE = \frac{2}{T}\sum_{i=1}^{T}\left|\frac{(PV\ Power_{mi} - PV\ Power_{ci})}{(PV\ Power_{mi} + PV\ Power_{ci})}\right| \tag{17}$$

Where PV $Power_{mi}$ and PV $Power_{ci}$ are respectively the i^{th} measured values and the calculated values and T corresponds to the number of measurements made. $\overline{PV\ Power_m}$ corresponds to the average photovoltaic energy during the T interval. The average solar photovoltaic energy is used in Eq. 16 to avoid the negative consequences of solar photovoltaic energy close to zero [4].

The proposed approach was compared with some of the existing benchmark methods: BPNN and ANFIS. The developed approach was used to forecast PV power output of 9/03/2018, 16/03/2018, 23/03/2018 and 30/03/2018 of 100 kW PV power plant situated at Ghaziabad India. RSME of the proposed method and some benchmark methods were shown in Table 2.

Table 3 shows the mean absolute percentage error of the developed method and comparison with the pre-existing methods BPNN and ANFIS. MAPE of the developed method outperforms better for

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W-3 and W-4. The result of the week 1 and week 2 was also comparable with the developed method.

Table 2. RSME of the proposed and some benchmark approaches

Week	RMSE		
	BPNN	ANFIS	PSO-ANFIS
W-1	0.0522	**0.0496**	0.0729
W-2	0.1024	0.0844	**0.0821**
W-3	0.0200	0.0185	**0.0174**
W-4	0.0374	0.0335	**0.0285**

Table 3. % MAPE of the proposed and some benchmark approaches

Week	% MAPE		
	BPNN	ANFIS	PSO-ANFIS
W-1	9.7310	**10.2891**	11.2893
W-2	12.13204	**10.7300**	10.7388
W-3	3.7600	4.2765	**3.5196**
W-4	11.5852	8.28240	**8.11917**

Table 4 shows symmetric mean absolute percentage error of the developed method and from the table, it is clear that the proposed method outperforms in all four weeks. sMAPE of week 3 was best as compared with the other three weeks.

Table 4. sMAPE of the proposed and some benchmark approaches

Week	sMAPE		
	BPNN	ANFIS	PSO-ANFIS
W-1	8.2803	9.8404	**7.6756**
W-2	10.5408	10.2483	**8.6805**
W-3	3.8978	6.3387	**3.3094**
W-4	16.8101	9.3187	**7.8313**

From Fig.4 it was clear that the proposed method outperforms for 3rd and 4th week. The forecasted result of the proposed method is much closer to the actual PV power generation as shown in Fig.4 (c) and (d). The forecasted result of week-1 and week-2 have had a significant difference between the forecasted and actual PV power output as shown in Fig.4 (a) and (b). As per weather report of the same region from where data is collected, it was concluded that the forecasting accuracy is directly affected by the weather parameter change and rate of change of weather condition. Weather changes rapidly in the first and second week so the forecasting error of the developed method as well as benchmark methods was poor as compared with two other week-3 and week-4.

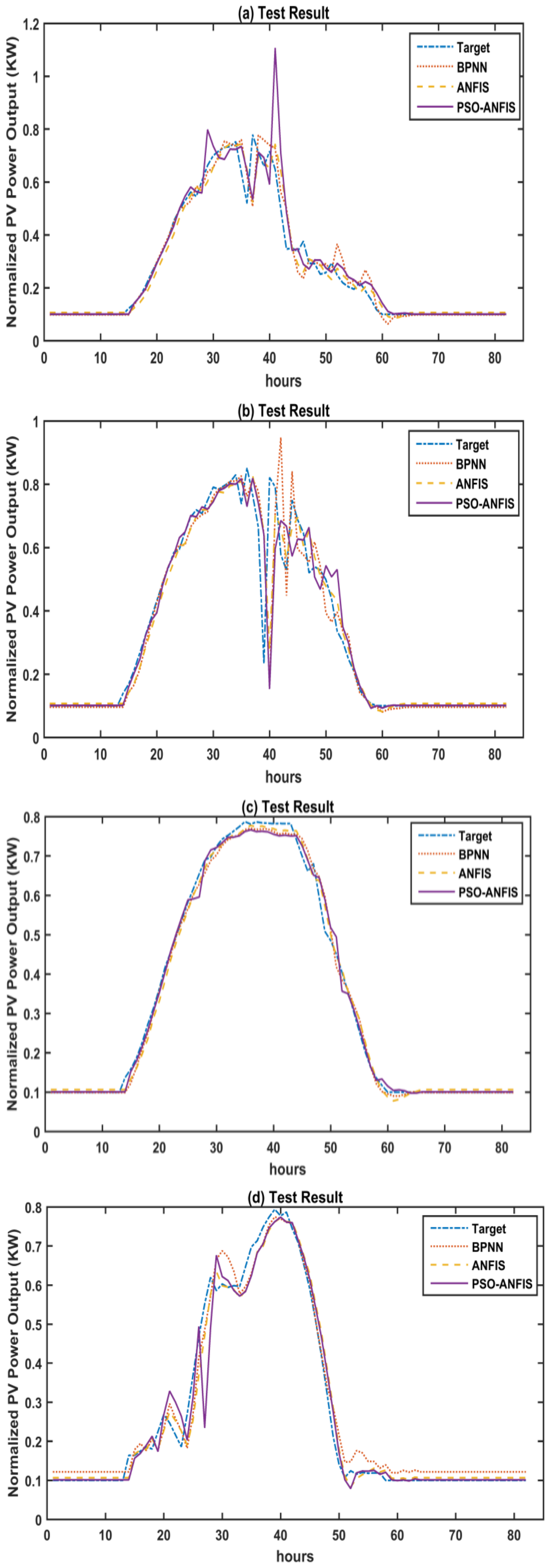

Fig.4 Result of the proposed method for 24-hour ahead PV power forecasting of March 2018 (a) week-1 (b) week-2 (c) week-3 (d) week-4

VI. CONCLUSION

This paper outlines a new hybrid approach to photovoltaic energy prediction. The proposed approach used the PSO algorithm to optimize ANFIS parameters. After optimization, the ANFIS parameters were updated and tested, taking into account the production of photovoltaic power of the plant situated in Ghaziabad (India). The predicted results of the proposed method were compared with some existing methods BPNN and ANFIS. As a result, it is clear that the predicted result of the proposed method is significant in four seasons. The average % MAPE of the predicted result is 8.42 % of the proposed method. Four-week sMAPE is much better than previous reference methods, with mean sMAPE being 6.88. Therefore, the proposed method shows the promising result of photovoltaic energy with acceptable computing time.

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AUTHORS PROFILE

Harendra Kumar Yadav received his B. Tech. from IMSEC, Ghaziabad, India, and M. Tech. from NIT, Kurukshetra, India, in 2009 and 2011, respectively. He is working as a research scholar with a school of renewable energy and efficiency of NIT Kurukshetra, India. His research interest’s areas are Electricity market forecasting, renewable energy and distributed generation.

Yash Pal received his Bachelor of Technology from MMMEC, Gorakhpur, India in 1994. He did his M. Tech. and Ph. D from NIT, Kurukshetra, India. He is working as Professor with the Electrical Engineering Department, NIT Kurukshetra, India. His research interests include power electronics, power system and control applications.

Madan Mohan Tripathi received B.Tech from MMMEC, Gorakhpur, India and his Ph.D. from GBTU Lucknow, India, in 1994 and 2010, respectively. He is currently an associate professor at DTU New Delhi. His research interest’s areas are sustainable energy, restructuring of the electrical system and uses of soft computing for electrical engineering applications.