Photovoltaic Power Forecasting based on Elman Neural Network Software Engineering Method

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Abstract— **Solar energy has the property of alternating, fluctuation and periodicity, and it has severe impact on large scale photovoltaic (PV) grid-connected generation. This turn power utilities contrary to use PV power since the forecasting and overall assessment of the grid becomes very difficult. To develop a reliable algorithm that can minimize the errors associated with forecasting the nearby future PV power generation is particularly helpful for efficiently integration into the grid. PV power prediction can play a significant role in undertaking these challenges. This paper presents 3 days ahead power output forecasting of a PV system using a Theoretical Solar radiation and Elman Neural Network (ENN) software engineering technique by including the relations of PV power with solar radiation, temperature, humidity, and wind speed data. In the proposed method, the ENN is applied to have a significant effect on random PV power time-series data, and tackle the nonlinear fluctuations in a better approach.**

Keywords- Photovoltaic Power, Forecasting, Elman Neural Network, Radiation.

I. INTRODUCTION

Importance of the solar and wind energy is consistently growing high in these days to reduce CO2 emissions in China[1]. Renewable/green energies are used to substitute fossil fuels to reduce carbon emission. Among the renewable energies having been widely used, the photovoltaic (PV) system is one of the fast emerging green power generation alternatives. The part of power production by photovoltaic (PV) systems to the grid is constantly increasing[2]. One of the most critical problems is that PV power is greatly effected by weather condition. Therefore, the power produced by PV is delivered infrequently and drains the national power system stability and reliability. Developments in technology and enormous scale manufacturing have directed to the drop in PV power cost, however, like other Renewable Energy Sources(RES), PV sources pose a number of integration challenges such as the impact on operating costs of the grid, regulation and load-following requirements and other issues examined in various research papers .Knowing in advance an expected yield from PV sources will aid in tackling these challenges, which includes proper planning of available generation sources and providing insight into impact of PV power on the power network. An effective use of the alternating PV power production will get advantage from forecast information on the expected power production. This forecast information is essential for the management of the electricity grids and for solar energy exchange.

Precise forecasting of PV power output can minimize the impact of PV output ambiguity on the grid, improve the system stability, and maintain power quality. To cope with power planning, operation (e.g. reactive power compensation, voltage control), automation and power demand side management, the power generation prediction in grid-connected photovoltaic system is critically important. Research has been done in this field but the forecasting of solar power is still on theoretical stage[3-5]. In order to overcome all these problems it is essential to have a reliable forecasting method that is economical and easy to use. Artificial intelligence (AI), such as neural network (NN) has gained more significance in the field of forecasting because of its capability to cope with complex problems. NN are also applied in several areas such as control, pattern recognition, classification, vision and speech, etc. NN are trained to overcome the restrictions of various conventional methods to solve complex problems. Biological neuron obtains input from other sources, combines and executes nonlinear operation for producing better results[6,7]. To fit the neural network comprises training the model over known input and output values, the algorithm alters the hidden and output node weights until the output approaches the actual data within a given threshold. Training is performed using a back-propagation algorithm, which is similar to the steepest descent algorithms used in nonlinear regression, except that the derivatives for each weight are adjusted independently[8,9]. For this reason, the time consumed in training can be large.

This paper explains non-linear features of the output power of photovoltaic power stations by analyzing the output characteristics of photovoltaic power stations with temperature, humidity, wind speed and other weather factors on the basis of theoretical calculation of solar radiation. This paper adopts historical data to train Elman neural network software engineering technique and combines theoretical weather prediction information to forecast the output power of photovoltaic power station[10,11]. The results show that the photovoltaic power prediction method based on the calculation of theoretical solar radiation and ENN has good forecasting precision.

II. PHOTOVOLTAIC OUTPUT POWER CHARACTERISTICS

This paper analyzes output characteristics of photovoltaic power station. The data are taken from photovoltaic Power

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Station of the State Key Laboratory of Electrical Power System with Renewable Energy Sources in North China Electric Power University (NCEPU), Beijing, with installed capacity of 3 kW and sampling interval of 15 minutes. The output characteristics of photo voltaic power station are consistent with power load characteristics in one day. The rational utilization of photovoltaic power generation will play a significant role in peak power reduction. However, it is known from Fig.1 that since the output of photovoltaic power station is directly influenced by solar radiation received by the ground and meanwhile air temperature, humidity and other meteorological factors impose indirect influences on the output of photovoltaic station, the output of photovoltaic power station has obvious random fluctuations and intermittency.

This paper presents correlation coefficient to find correlation among photovoltaic power and meteorological parameters . Correlation coefficient is a significant indicator showing linear correlation of different parameters. Pearson correlation coefficient is used to find relationship degree and tendency of two parameters. The formula is :

$$r=\frac{\operatorname{cov}(X,Y)}{\sqrt{\operatorname{cov}(X,x)}\sqrt{\operatorname{cov}(Y,Y)}} \tag{1}$$

Where, correlation coefficient *r>0* show that two parameters have correlation and both parameters are directly related to each other, when *r<0* means the two parameters are inversely related. when *r* tends to be 1, the two have close relationship, *r=0* means the two are not correlated to each other. One month data of PV power and other meteorological parameters has been examined to get the relationship between PV power and meteorological parameters under different weather conditions by using Pearson correlation coefficient as shown in table 1. Pearson coefficient is commonly used to find linear connection between two parameters. Pearson coefficient of radiation and PV power has higher value as shown in table1 which means larger radiation value will produce large power.

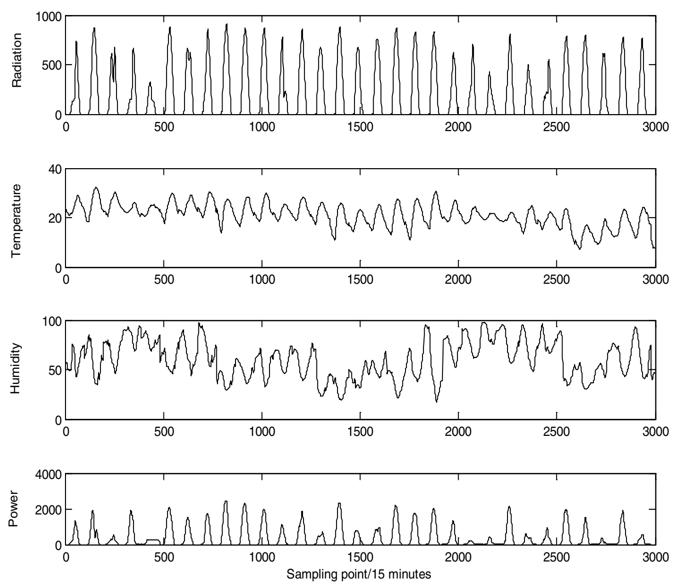


Figure1 Photovoltaic Power Characteristics and Meteorological Factors

Table 1 Pearson coefficient between PV and meteorological factors under different weather conditions

Weather Type	Radiation	Temperature	Humidity	Wind speed
Clear	0.916376	0.398646	-0.36733	0.223341
Cloudy	0.914026	0.367856	-0.35487	0.253726
Rainy	0.886601	0.302601	-0.33235	0.171378

III. ELMAN NEURAL NETWORK

A. *Overview*

The Elman network commonly is a two-layer network proposed by Elman in 1990 with feedback from the first layer output to the first layer input[12,13]. It lies somewhere between a classic feed-forward network and a pure recurrent network. The feed-forward loop consists of input layer, hidden layer and output layer in which the weights connecting two neighboring layers are variable. In contrast to the feed-forward loop, the back-forward loop has context layer which is sensitive to the history of input data so the connections between context layer and hidden layer are fixed. This feedback connection allows the Elman network to both find and create time varying data. The Elman network has Tansig neurons in its hidden (recurrent) layer, and Purelin neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can forecast any data (with a finite number of breaks) with accuracy. The structure of Elman network is shown in fig2.

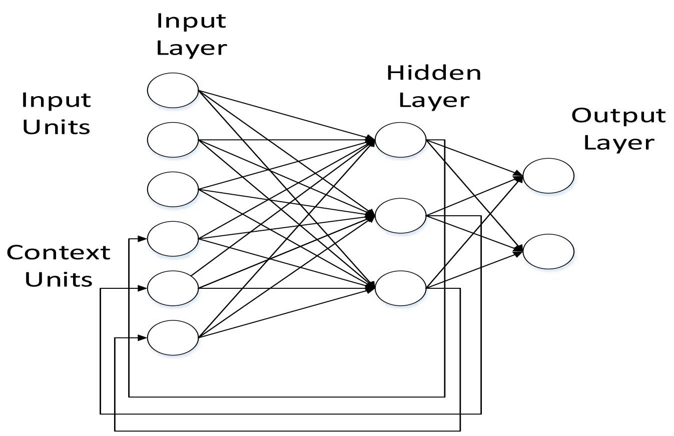


Figure 2 Structure of Elman Neural Network

B. *Algorithm*

This paper explains forecasting of photovoltaic power by using Elman Neural Network Matlab Software technique. The historical input data which is temperature, humidity, winds-peed, theoretical radiation and real power is first normalized and then applied to the input layer of Elman network. The solar radiation decides the overall trend of photovoltaic power station. The input data is divided into training data and test data. The training data(28/8/2014 to 5/9/2014) includes temperature, wind-speed, humidity, theoretical radiation and real power and test data(6,7,8 Sept 2014) include temperature, wind-speed, humidity, theoretical radiation. ENN is trained for the training data as shown in fig3. Well trained ENN is then used to predict output power of the test data of photovoltaic power station for the next 3 days in the future. The sampling time is 15min with 96 samples taken in one day. Gradient descent method is used to train the function. Based on Back-Propagation(BP) network structure, PV power for future 72 hours is calculated. Real PV power and other meteorological factors are used in training data to train ENN as shown in fig 3. The output power of the photovoltaic power station for the test data in future is predicted with well trained ENN with combination of corresponding weather parameters and historical data as shown in fig 4.

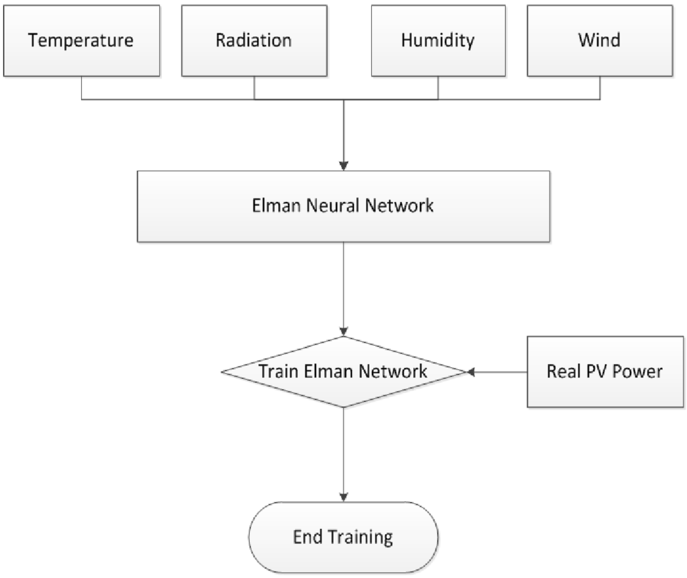


Figure 3 Elman neural network algorithm

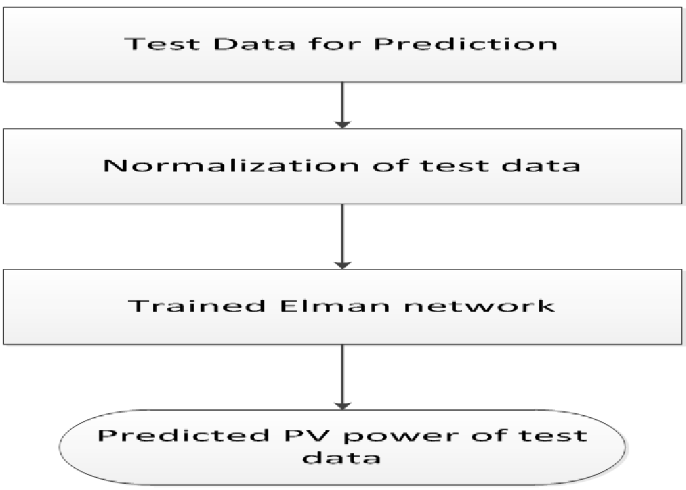
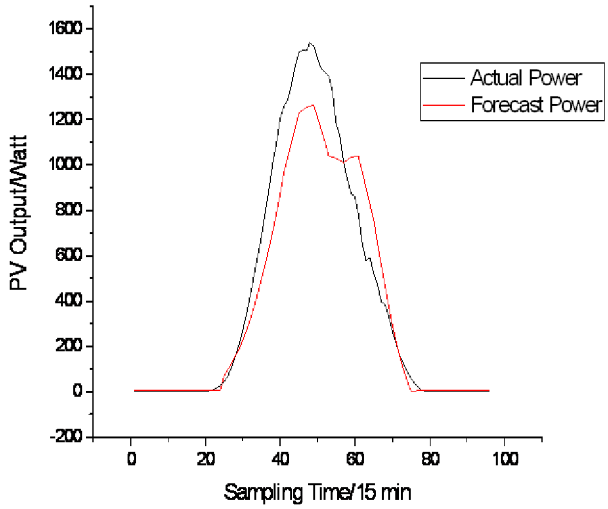


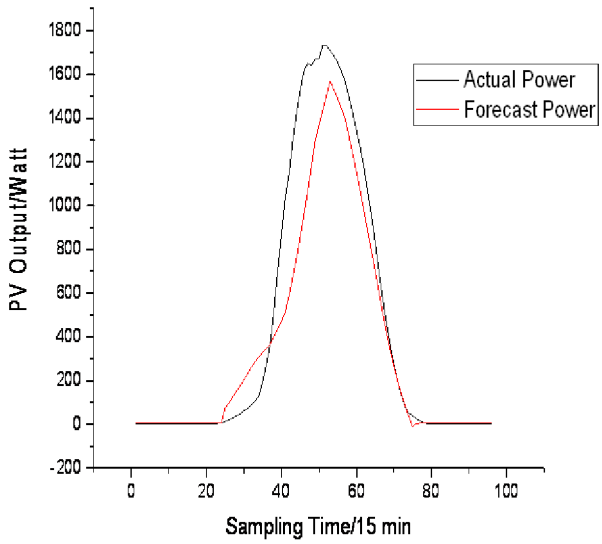
Figure 4 Predicted PV power with trained ENN

IV. EXAMPLE RESULTS

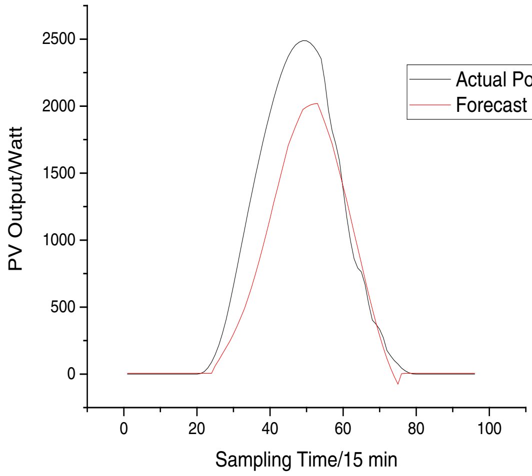
This paper applies Matlab to implement forecasting process of Elman neural networks. The training data and test data needed in the prediction model are obtained from measured data in the database of the photovoltaic power station. In the training process the real PV power and meteorological parameters are used to train ENN with training data, and then for example verification PV power for three days test data 2014/09/06 to 2014/09/08 is predicted with the well trained network in combination of weather forecast values in future. Fig.5 gives measured and predicted values of output power of the photovoltaic power station for three days. The prediction results are evaluated through Root Mean Square Error(RMSE) and Mean Absolute Error(MAE).



(a)



(b)



(c)

Figure 5 Actual Power and forecast power of 3 days (a: 6 Sept2014, b: 7 Sept 2014, c: 8 Sept 2014)

By comparing Actual power with the forecast power it is confirmed that the Elman neural network forecasting of Photovoltaic power has better prediction results. To verify the performance of the proposed approach, two criteria, Root Mean Square Error(RMSE) and Mean Absolute Error(MAE) are used as follows in equations (2) and (3) .

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_{Mi} - P_{Pi})^2}{n}} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{n}|P_{Mi} - P_{Pi}|}{n} \tag{3}$$

Where, P_{Mi} is observed power at i time; P_{Pi} is forecasting power at i time, n is the number of samples, for one day n is 96.The RMSE and MAE for three days (6,7,8 September 2014) are calculated as given in the table2

Table 2 Prediction error indicators

Date	RMSE	MAE
20140906	0.150642 kW	0.095086 kW
20140907	0.205697kW	0.1145 kW
20140908	0.327832 kW	0.195253 kW

V. CONCLUSION

In this paper three days 6,7,8 Sept 2014 ahead PV power forecast with sampling time 15 minutes is predicted by using Elman neural network with normalized input data of Temperature, Humidity, Wind-speed and Radiation. The normalized data is served as input of the proposed network, the network is trained and the data de-normalized to predict the future power of the photovoltaic station. Two criteria, the MRE and RMSE, were used to verify the forecasting errors of the proposed approach on three days testing data. Numerical results show that the proposed method attains better prediction accuracy. The example proves the practicability and accuracy of this method and can offer reference basis for planning power grid generation plan.

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