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NARX Based Short Term Wind Power Forecasting Model

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Abstract

Nowadays, with the growing needs of the consumers there is a huge demand for the electric power but the fuel reserves are also depleting at the same pace. So, this has created the need to depend up on the renewable energy resources to meet the required power demand. Since the power generated through renewable resources is eco friendly in nature and distributed, this is an added advantage. Of all the renewable energy resources solar and wind plays the most crucial part in the power generation because of their wide spread availability. But the wind energy is volatile and intermittent by nature, due to this interconnecting the power generated to grid becomes a hectic task. So in this paper a wind power forecasting model with the help of artificial neural networks (ANN) is developed so that the wind power can be forecasted well in progress, which helps in maintaining and operating grid interconnection and also scheduling of units. The developed model is based on the non-linear auto regressive with exogenous input (narx) tool which trains the ANN for the time series. The input parameters taken into consideration are wind speed, temperature, pressure, air density and the output parameter is generated power. The required data is collected from the Energy Department of KLUniversity, Andhra Pradesh which consists of 720 hours data from that 672 hours data is used for training and 48 hours data is used for prediction. Mean square error and root mean square error are calculated from the predicted and known results.

Keywords: *ANN, narx, netc, hybrid method, wind power forecasting*

1. Introduction

In the present day scenario the need for electrical power is growing in an exponential manner. The fuel reserves for the electrical power generation through conventional methods are depleting at a very faster rate and are causing severe harmful effect on the environment. According to the Global Wind Energy Outlook 2014 by Global Wind Energy Council (GWEC) power sector is the sole emitter of about 40% of the carbon dioxide and 25% of all the green house gases.

The better solution that addresses most of the problems that arises because of the fossil fuels is the usage of renewable energy. Among all the renewable energies wind energy is the most promising and cheaper to operate. GWEC in its recent publication stated that the wind energy could reach 2000GW by 2030. But the major hindrance for the expansion and integration of the wind power to the grid is the high volatile and intermittent nature of the wind power. Because of these natures of wind power it is very difficult to integrate to the grid and schedule the power. To overcome the stated problems wind power forecasting is the very helpful. Wind power forecasting model helps the power system operators in power scheduling, dispatch and maintaining the reserve capacities.

Mostly employed methods for wind power forecasting are Persistence is employed by making an assumption that the wind speed and wind power at a certain time in future will be same as it is when the forecast is made [1]. Let the wind power and wind speed at t are P(t) and v(t), then the wind power and wind speed at $t + \Delta t$ can be formulated as [2]. This method is more accurate than other forecasting methods in case of ultra-short-term forecasting. The accuracy of this method will decrease rapidly with the increase of time-scale of forecasting. [3]. Physical method uses the laws on which the atmospheric behavior depends upon, for estimating the wind flow around the wind turbines and the wind power corresponding to the wind flow obtained by the estimation, can be known by the turbine characteristics [4]. Statistical method uses a model which gives a relation between meteorological parameters and the power

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generated. This model is developed by studying the historical data. From this model wind power can be predicted [4]. Hybrid method is the combination of physical and statistical methods.

The predication carried out in this paper is by using the hybrid method. Statistical data is collected from the Energy Department of KL University, Andhra Pradesh which consists of 720 hours data from that 672 hours data is used for training and 48 hours data is used for prediction and also the physical laws are taken into account for the calculation of power generation. The developed model is based on the non-linear auto regressive with exogenous input (narx) tool which trains the ANN for the time series. The input parameters taken into consideration are wind speed, temperature, pressure, air density and the output parameter is generated power. Mean square error and root mean square error are calculated from the predicted and known results.

2. Research Method

2.1. Calculations from the Data

The wind power generated by the turbines depends upon the factors like wind speed, ambient temperature, wind pressure, air density. Among all the factors wind speed and air density dominates the power generated.

Wind power generated is known by:

$$P = \frac{1}{2}\rho A V^3 \tag{1}$$

Where P: Wind power generated
ρ: Air density at the given temperature
A: Area swept by the turbine blades
V: Wind speed

Wind power generated is highly affected by the air density and the wind speed, as the area swept by the turbines blades remain constant for a taken turbine [5].

The data is collected from Energy Department of K L University, vaddeswaram area for a time span of one month which comprises of wind speed, ambient temperature, and air pressure. The air density in the considered area is not known. For the density calculations vapour pressure is required according to the formula [5].

$$\rho = D * \left(\frac{273.15}{T}\right) * \left(\frac{B-0.378e}{760}\right) \tag{2}$$

Where ρ: Air density at the given temperature
D: Air density at absolute temperature
T: Given temperature
B: Barometric (atmospheric) pressure
e: Vapour pressure of the air at the given temperature

All the data required for the density calculation is present except the vapour pressure. In a closed system the pressure exerted by a vapour in thermodynamic equilibrium at a given temperature is the vapour pressure. Vapour pressure is calculated using the Clausis-clapeuron relation i.e.

$$\ln\left(\frac{P1}{P2}\right) = \left(\frac{\Delta Hvap}{R}\right)\left(\frac{1}{T1} - \frac{1}{T2}\right) \tag{3}$$

Where P_1, P_2: The vapour pressures at temperatures T1, T2 respectively
ΔH_{vap}: Enthalpy of vapourization of liquid
R: Real gas constant (8.314J)
T_1: Temperature at which the vapour pressure is known
T_2: Temperature at which the vapour pressure to be calculated

Take T1 and P1 at STP conditions and P2 is the vapour pressure to be calculated at which the temperature is T2. By this formula vapour P2 i.e, 'e' in the density calculation is obtained. Air density is then calculated by the stated formula. The data required for the calculation of power genration is obtained and the power that can be generated by using all these parameters is calculated by ignoring the operational losees of turbine.

2.2. Artificial Neural Network (ANN)

Artificial neural networks are the neural networks derived from the inspiration of biological neural networks (animal central nervous system). These artificial neural networks are used to take logical decisions based on the inputs. ANN can deal with non-linear and complex problems in terms of classification or forecasting by extracting the dependence between variables through the training process. So the ANN based method is an appropriate method to apply to the problem of forecasting wind power because it is directly proportional to wind speed which is highly intermittent in nature. Among the available methods using artificial neural networks the NARX, a dynamic recurrent method, is used to solve the time series problem.

2.2.1. ANN Training

One of the key elements of neural networks is their ability to learn. A neural network is a complex adaptive system, which means it can change its internal structure based on the inputs and targets. These ANNs need to be trained for doing a particular task. There are three types of training paradigms to train the artificial neural network and are as follows:

a) Supervised training: It is the process of providing the network with a series of sample inputs and comparing the output with the expected response. The training continues until the network is able to provide the expected response. The proposed work is supervised training with back propagation technique.

b) Unsupervised training: In this method of training, the input vector and the target output is not known. The network may modify in such a way that the most similar input vector is assigned to the same output unit.

c) Reinforcement training: It is the process of training the network in the presence of a teacher but in the absence of target vector. The teacher gives only the answer whether it is correct (1) or wrong (0).

2.2.2. Non Linear Auto Regressive with Exogenous Input (NARX)

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling.

The defining equation for the NARX model is:

$$y(t) = f\big(y(t-1)\big), y(t-2), \; \ldots., y(t-ny), u(t-1), u(t-2), \ldots., u(t-nu)) \qquad (4)$$

a) Series parallel architecture

Used when the output of the NARX network is considered to be an estimate of the output of some nonlinear dynamic system. The output is fed back to the input of the feed forward neural network as part of the standard NARX architecture. Because the true output is available during the training of the network, you could create a series-parallel architecture, in which the true output is used instead of feeding back the estimated output. This has two advantages which are the first is that the input to the feed forward network is more accurate. The second is that the resulting network has a purely feed forward architecture, and static back propagation can be used for training.

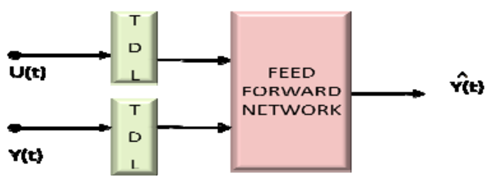

Figure 1. Series Parallel Architecture

b) Parallel architecture

Later this architecture is converted into parallel architecture for the prediction. The prediction of the next value depends on the inputs and previous outputs to the network. The dependence on the previous output can be adjusted by using delays, input delays and feedback delays.

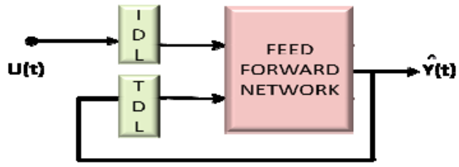

Figure 2. Parllel Architecture

3. Results and Error Analysis

3.1. Performance of the ANN

The collected data is given as inputs which are temperatures, pressure, air density, speed and calculated power generation is given as output to the NARX tool box for training. After training, the neural network is ready for the prediction. The last 2 days data is given to the neural network and the predicted output is obtained. The predicted output is compared to the calculated power and the performance is monitored by calculating the errors by various means of error calculations.

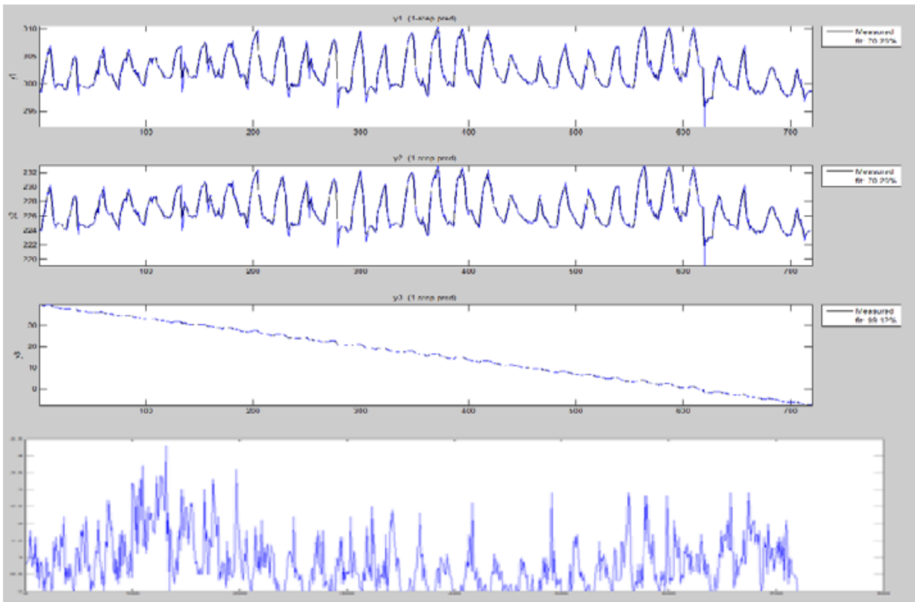

Figure 3. Plot between temperatures, pressure, air density, speed vs time (hours)

a) Mean Error (ME): It is the basic type of error calculation. It is the average of the errors.

$$ME = \frac{1}{N}\sum_{i=1}^{N} Ti - Pi \quad (5)$$

b) Mean Square Error (MSE): It is one of the basic types of error calculation. It is the average of the squares of the errors.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Ti - Pi)^2 \quad (6)$$

c) Root Mean Square Error (RMSE): RMSE is the standard deviation of the differences between predicted values and actual values. It is the square root of the average of squares of the errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Ti - Pi)^2} \quad (7)$$

Where N: No. of samples
T: Actual Output
P: Predicted Output

Prediction is carried out by varying the delays of the input and also the number of neurons in the hidden layer. The errors at different delays and different number of neurons in the hidden layer are

Table 1. The Performance of the predicted ANN model

ANN	DELAY	ME	MSE	RMSE
4-3-1	2	0.17734	4.942264	1.771711
4-3-1	4	0.54563	23.30557	4.339749
4-3-1	6	0.323178	8.445927	2.561335
4-3-1	8	0.0919	4.925418	1.362869
4-5-1	2	0.29408	11.84562	2.808699
4-5-1	4	0.03643	4.728486	1.436289
4-5-1	6	0.03457	4.2436	1.7854
4-5-1	8	0.16524	5.371358	1.867995

3.2. Performance Plots of the ANN

The trained neural network is employed for the prediction of the power generated for the last 48 days by giving the input parameters by varying the input time delays and also changing the number of neurons in the hidden layer. In case of 3 neurons in the hidden layer the minimum error is attained when the time delay given is 8 and in case of 5 neurons in the hidden layer the minimum error are attained when the delay given is 6 are shown below.

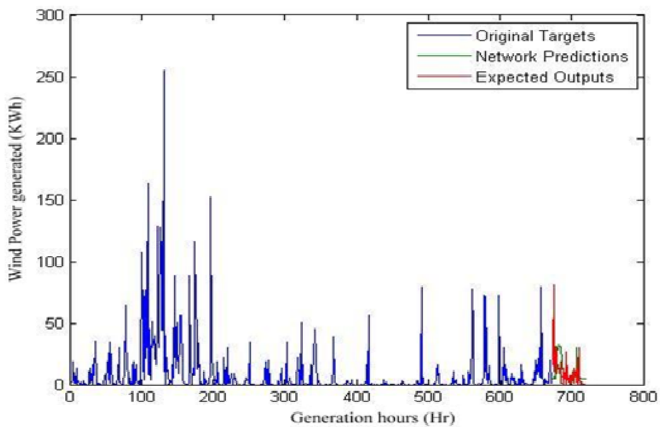

Figure 4. The ANN predicted output plot when 3 hidden layer neurons and time delay of 8

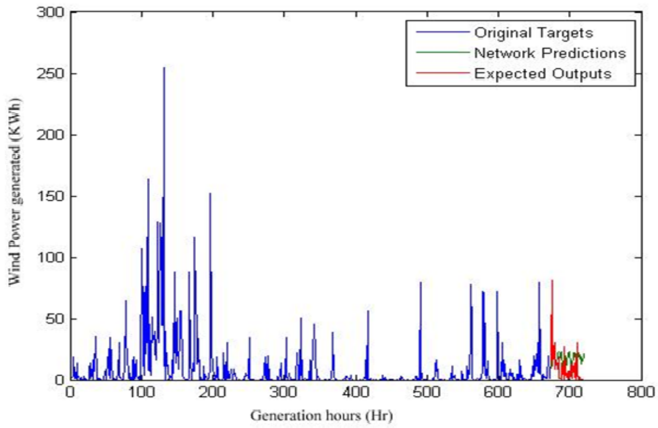

Figure 5. The ANN predicted output plot when 5 hidden layer neurons with time delay of 6

4. Conclusion

To address this problem a wind power forecasting model with the help of artificial neural networks (ANN) is developed so that the wind power can be forecasted well in advance, which helps in maintaining grid interconnection and also scheduling of units. The developed model is based on the non-linear auto regressive with exogenous input (narx) tool which trains the ANN for the time series. Wind power generations depends on the parameters like wind speed, temperature, pressure, air density. So these parameters are given as input to the ANN model developed and after training of the model wind power is predicted. Prediction is carried out by varying the number of neurons in the hidden layer and also the delay given to the network. From the results, it came to know that if the delay is increased the error is going to be reduced and also if the number of hidden layer neurons increases the computational power of the model increases which also reduces the errors in the predicted output.

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