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COMPARISON BETWEEN TWO METHODS OF PREDICTION OF ELECTRIC POWER GENERATION FROM WIND POWER

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ABSTRACT

More growth of wind power generation that will be established in Egypt in the coming years has highlighted the importance of wind power prediction. However, wind power is very difficult for modelling and forecasting. Despite the performed research works in the area, more efficient wind power forecast methods are still demanded. In this paper, two methods of prediction of electric power generation from wind power are presented. The first method is by using the artificial neural network for prediction of power generation in the next 10 minutes base on wind speed prediction input from weather authorities. The second method is by using poly fit function to perform regression on wind power by using MATLAB program in Zafarana site. For optimum generation management strategy, the capacity credit will be used by the best selected method of prediction of the wind power for Gabal El-zeit site of future wind farm.

KEYWORDS*:* **Wind power forecast, Artificial neural network (ANN), Poly fit function, Capacity Credit**

I. INTRODUCTION

Renewable energy (RE) is the energy which comes from natural resources like sunlight, wind, tides and geothermal heat are naturally replenished [1]. The present strategy targets in Egypt is to satisfy 20% of the electric energy demand from renewable energy resources by the year 2020, including about 12% from wind power , 8% from others RE sources (hydro power , solar energy , ...). In April 2007, the Supreme Council of Energy in Egypt has adopted this resolution. This plan is intended to establish about 7200 MW grid-connected wind farms by the red sea coast. Such plan gives a room enough to the private investments to play the major role in realizing this goal. The Zafarana wind farms are now working in complete interconnection with the unified electric power grid of Egypt. The total installed Capacity of generation wind power these will then be about 750 MW. The implementation of 120 MW wind power plant in Gabal EL-Zeit site is being made. So it will be needed to use better ways of prediction of wind power generation in short terms [2].

A case study using a real database of 12 months recorded from a Portuguese wind power farm was used. This wind farm consists of 13 towers with an individual maximum capacity power of 2000 kW. The database includes the values of the wind speed, wind direction, wind power, generator rpm, temperature, voltage, generated current, power factor and frequency, recorded with time intervals of 5 minutes. Thus, a huge amount of records was present in the final database. This work presents an ANN based approach that contributes to the development and implementation of adequate methodologies for Energy Resource Management in a distribution power network, with intensive use of wind based power generation. The proposed methodology is especially relevant because of the high accuracy of the forecasted wind power/speed values that are fed to the 5-minutes-ahead energy resource management module. This allows undertaking a re-schedule of energy resources which uses forecasted values very close to the actual ones leading to lower operation costs. The results demonstrated good estimated accuracy when the estimation used the historical database concerning wind power or wind speed [3].

2. **Artificial neural networks** [4]

ANN is highly interconnected simple processing units designed in a way to model how the human brain performs a particular task. Each one of those units, also called artificial neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent. Multilayer perceptions are the best known and most widely used kind of ANN. The artificial neurons are organized in a way that defines the network architecture. In feed forward networks, artificial neurons are often arranged in layers: an input layer, one or more hidden layers and an output layer. In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of artificial neurons in each layer and different types of transfer functions are used. The configuration chosen consists of a hidden layer that uses a hyperbolic tangent sigmoid transfer function, given by:

$$f(s) = \frac{e^{s}-e^{-s}}{e^{s}+e^{-s}} \qquad (1)$$

Also one unit output layer with a pure linear transfer function, given by:

$$f'(s') = s' \qquad (2)$$

Where s is the weighted input of the hidden layer, f (s) is the hyperbolic tangent sigmoid transfer function of the hidden layer, s' is the weighted input of the output layer, and f'(s') is the pure linear transfer function of the output layer.

This configuration has been proven to be a universal mapper, Provided that there is a relation between the hidden layer and artificial neurons. On one hand, if there are too few artificial neurons, the network will not be flexible enough to model the data well and, on the other hand, if there are too many artificial neurons, the network may over-fit the data. The number of artificial neurons in the hidden layer was chosen by trial and error. The best results were produced with six hidden artificial neurons. The number of model input parameters is four. Forecasting with ANN involves two steps: training and learning. Training of feed forward networks is normally performed in a supervised manner. One assumes that a training set is available, given by the historical data and containing both inputs and the corresponding desired outputs, which is presented to the network. The adequate selection of inputs for ANN training is highly influential to the success of training. In the learning process an ANN constructs an input output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. The error minimization process is repeated until an acceptable criterion for convergence is reached. The most common learning algorithm is the back propagation algorithm. However, the standard back propagation learning algorithm tends to converge slowly. An algorithm that trains an ANN 10e100 times faster than the Standard back propagation algorithm is the Levenberg-Marquardt algorithm. While back propagation is a steepest descent algorithm, The Levenberg-Marquardt algorithm is a variation of Newton's method. Hence, a three-layered feedforward ANN trained by the Levenberg-Marquardt algorithm is considered in this paper. Newton's update for minimizing a function V(x) with respect to the vector x is given by:

$$\Delta(x) = -[\nabla^2 V(x)]^{-1} \nabla V(x) \qquad (3)$$

where $\nabla^2 V(x)$ is the Hessian matrix and $\nabla V(x)$ is the gradient vector. Neglecting the second-order derivatives of the error vector, the Hessian matrix is given by:

$$\nabla^2 V(x) = 2J^T(x)\, J(x) \qquad (4)$$

where J(x) is the Jacobian matrix.
The Gauss - Newton update is given by:
$\Delta(x) = - [JT (x) J(x)]-1 JT (x) e(x)$ (5)
where e(x) is the error vector. The advantage of Gauss-Newton over the standard Newton's method is that it does not require calculation of second-order derivatives. Nevertheless, the matrix JT (x) J(x) may be not invertible. This is overcome with the Levenberg-Marquardt algorithm, which consists in finding the update given by:
$\Delta(x) = - [JT (x) J(x) + \mu I]-1 JT (x) e(x)$ (6)

where parameter μ is conveniently modified during the algorithm iterations. When μ is very small or null the Levenberg-Marquardt algorithm becomes Gauss-Newton, which should provide faster convergence.

3. POLYNOMIAL FITTING: THE APPROACH [5]

This approach is known as regression analysis, curve-fitting, least-squares, or sometimes trend-lines. Say we take some data: it's a vector of $(x_i; y_i)$ pairs, where x is the independent variable, y the dependent. If, for instance, we have reason to expect that the law governing the process that produced this data is a polynomial equation of order n, then we need to find the coefficients c_i such that then for every $(x_i; y_i)$ pair (ideally)

$$y_i = c_0 + c_1x_i + c_2x^2_i + \ldots\ldots + c_{n-1}x_i^{n-1} + c_nx^n_i \quad (7)$$

This is an equation in n + 1 unknowns. It has constant coefficients ci. It arises from one (x; y) data point and our hypothesis about the order of the polynomial governing the process. Our job now is to find values for those coefficients c_i. We know that if we have n + 1 unknowns we need n + 1 equations, each arising from an (x; y), (independent, dependent) pair. We know that to solve for the n + 1 coefficients of an nth -order equation, we need n + 1 equations (e.g. two points determine a line, three a quadratic curve, etc.). But we can make an equation like the above for every (x; y) data point we have. So we need to collect enough (x; y) data points to fit the model to the data. If our model is an n-th degree polynomial, we need n + 1 data points (hence equations). Here the model is "an n-th order polynomial", the data is the (x; y) pairs from the experiment, and the fit is the coefficients ci that determine the n-th order polynomial that predicts or explains the variation of our dependent effect (y) with some other variable (x). It is reduced the problem of finding an nth order polynomial to solving a system of linear equations. Putting this into matrix form, we get:

$$y = Xc; \quad (8)$$

With y the dependent variable vector, c the coefficient vector we seek, and X is known as a Vandermonde matrix. Solving this system gets the desired values for the coefficients of our model and we're done. Using MATLAB package doesn't need to know this or use it, but MATLAB can represent polynomials and interpret them (as in the roots command that finds the roots of a polynomial). MATLAB represents a polynomial, as we do here, by the vector of its coefficients. Our treatment above is standard and what you see in the literature – in MATLAB , however, the coefficients are in descending order in powers of x.

4. FORECASTING ACCURACY EVALUATION

To evaluate the accuracy of the proposed ANN and Poly fit approach in forecasting wind power, different criterions are used. This accuracy is computed in function of the actual wind power that occurred. These criterion allow comparing alternative techniques. The mean absolute percentage error (MAPE) criterion, the sum squared error (SSE) criterion, correlation coefficients (CC) and the standard deviation of error (SDE) criterion, are defined as follows. The MAPE criterion is defined as follows:

$$\text{MAPE} = \frac{100}{N}\sum_{h-10}^{N}\frac{|\hat{P}_h - P_h|}{\bar{P}} \quad (9)$$

$$\bar{P} = \frac{1}{N}\sum_{h-10}^{N} P_h \quad (10)$$

where $\hat{P}_h$ and P_h are respectively the forecasted and actual wind power at 10 minutes h, $\bar{P}$ is the average wind power and N is the number of forecasted 10 minutes. The SSE criterion is given by:

$$\text{SSE} = \sum_{h-10}^{N}(\hat{P}_h - P_h)^2 \quad (11)$$

The SDE criterion is given by:

$$\text{SDE} = \sqrt{\frac{1}{N}\sum_{h-10}^{N}(e_h - \bar{e})^2} \quad (12)$$

$$e_h = \hat{P}_h - P_h \quad (13)$$

$$\bar{e} = \frac{1}{N}\sum_{h-10}^{N} e_h \quad (14)$$

where eh is the forecast error at 10 minutes (h) and e is the average error of the forecasting period [5]. Where k is the step forecast, CC should be zero and the forecast is simply the mean. It is thus reasonable to define CC as the correlation coefficient between P_h and P_{h-k} [6]:

$$\text{CC} = \frac{\frac{1}{N}\sum_{h-10}^{N-k}\tilde{P}_h\tilde{P}_{h+k0}}{\frac{1}{N}\sum_{h-10}^{N-k}\tilde{P}_h^2} \quad (15)$$

Where,

$$\tilde{P}_h = P_h - \bar{P} \quad (16)$$

5. NUMERICAL RESULTS

The proposed is to apply wind power forecasting in Egypt. It is planned to reach the level of the wind power generation in Egypt to 7000 MW. So it is needed to have forecasting methods in Egypt related to the equipment of wind farms there. The numerical results presented take into account one unit of Gamesa 52 – 850 KW in the wind farms in Zafarana site (fig. 1). Historical wind power data, available at the Zafarana site are the main inputs to train the ANN, and for poly fit function for the seventh order to get the eight constant for cut in 4 m/s, cut out 25 m/s, rated wind speed 11 m/s for one unite and 850 KW. The value of the wind power for 7899 sample for wind speed (As an input) and wind power (As an output) , every sample for 10 minutes are considered. It should be noted that the input layer is comprised by twenty artificial neurons. The following days are selected from January, 1, 2015, until February, 24 2015.

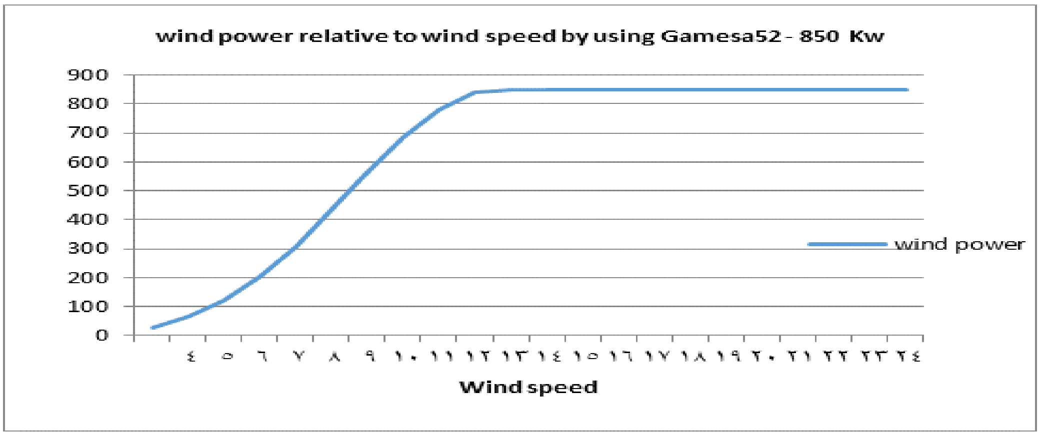

Fig. 1: Wind power relative to wind speed for manufacturing of Gamasa52 - 850 KW

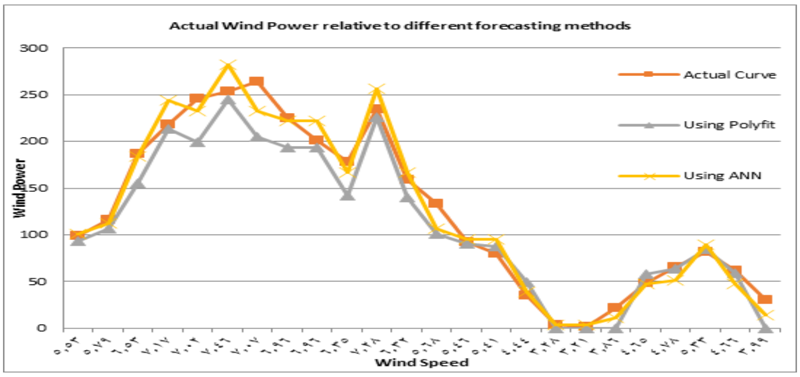

Fig. 2: Actual Wind power relative to different forecasting methods

In fig(2) it shows Actual wind power in Zafarana site relative to the two different methods used in this paper, it is found that the proposed ANN approach provides lower average MAPE, $\sqrt{SSE}$ and SDE than poly fit function while for CC, ANN is higher than poly fit (Table 1). So it can be safe to mounted there as the base wind generator use ANN for prediction of generation in Gabal El-zeit site.Gamesa80 – 2 MW will be in this site.

The capacity credit for wind in Gabal El-zeit site is based on the wind generator's capacity factor (cf) during the hours from 5 p.m. to 10 p.m (peak load time), from June 1 to Aug. 31. The cf is given by [7]:

$$cf = \frac{\sum_{h-10}^{N} \hat{P}_h * h}{installed\ cpacity * \sum_{h-10}^{N} h} \qquad (17)$$

Where installed capacity is 2 MW while $\hat{P}_h$ wind power forecasted for Gabal El-zeit site by ANN method and h is every 10 minutes.

Because of insufficient wind generation data, Gabal El-zeit site will apply a capacity credit of 64.6 percent for this new wind projects to be operated in the peak load period during the hours from 5 p.m. to 10 p.m. from June 1.

Table 1

Method	MAPE (%)	$\sqrt{SSE}$ (KW)	SDE (KW)	CC
ANN	6.057	1721.888	19.097	0.996
Poly fit	13.54	3271.93	31.275	0.993

6. CONCLUSIONS

The ANN method can be proposed for short-term wind power forecasting in Egypt. The MAPE has an average value of 6.057%, CC is 0.996. The results presented confirm the considerable accuracy of the proposed ANN method in forecasting wind power. For optimum generation management strategy, Capacity credit (64.6 %) confirms that Gabal El-zeit site can be reliably of 64.6% of generated wind power for the peak load period in Egypt during the hours from 5 p.m. to 10 p.m. from June 1 to Aug. 31, where this percentage is very high relative to the other wind sites.

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