Aerodynamic Power Forecasting In Order To Enhance Wind Farm Supervision "ADRAR Station in South Algeria"

B. Benlahbib*, ** F.bouchafaa. N. Bouarroudj*. B. Batoun ***

[*]Unité de Recherche Appliquée en Energies Renouvelables, URAER, Centre de Développement des Energies Renouvelables, CDER, 47133, Ghardaïa, Algeria

***Laboratoire d'Instrumentation, Faculté d'Electronique et d'Informatique USTHB, Alger (Algérie)*

E-mails :bouallam30@gmail.com,

Abstract: This paper proposes forecasting aerodynamic power of wind in order to improve different supervision algorithms of wind farm based on artificial neural network ANN. The study described in this paper develops a simple and robust algorithm that describes short-term wind power forecasting. As wind energy varies during day time depending on the wind speed hitting the generator blades, If an accurate prediction of the wind speed for the following hour can be evaluated, the total amount of active power that can be produced by each generator on a wind farm can be determined and therefore, the amount of energy that could be sold during the next hour would be known too. A set of recent wind speed measurement samples from meteorological stations at ADRAR located in the south of Algeria, are used to train and test the data set. The performance of the proposed algorithm is verified by using MATLAB software. The result obtained has given rather promising results in view of the very small mean absolute percentage error (MAPE).

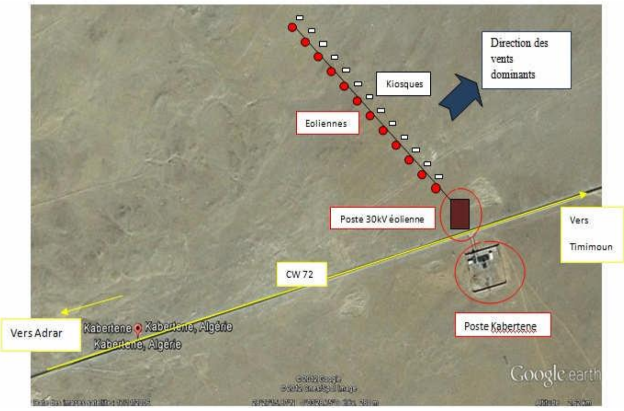
Keywords: Power forecast, Wind farm supervision, Wind speed, Artificial Neural Network (ANN). MPPT, PCC.

1. INTRODUCTION

Today, the rate of penetration of wind farms becomes increasingly significant in the electrical network. However, several problems of instability are generated at the time of the connection of these farms to the network, because so far it does not participate to the ancillary system (voltage regulation, frequency regulation, black-start, operation in islanding). Following these problems of instability of the electrical network; ones procedure of obliteration must be necessarily planned by the manager of network, which causes a forced disconnection of the wind generators based on the network instability, furthermore, the supervision of the wind farms is considered to be necessary in order to connect them to the electrical network .Improving prediction of energy output of a wind energy conversion system can help to reduce risks and enable assets to be operated in the most cost-effective manner. In other words, by applying accurate wind forecasting, the wind energy can be scheduled and wind power penetration will be increased this has significant economic impact on the system operation and can substantially reduce costs as shown by[1,2]. Therefore, applying wind power prediction methods offering the best possible accuracy over a number of time scales is required as can be found in paper[3,4] Since time series data on wind speed are chaotic, it is a very complex task to predict the wind velocity. Additionally, prediction accuracy is heavily dependent on the time interval as there is a negative correlation between accuracy and the increasing prediction time frame. A variety of methodologies have been proposed in the literature for the wind prediction, depending on the existing meteorological data and the time-scale of the application [5,6-]. Generally, wind speed prediction is divided into three categories, namely, short-term, medium-term, and long-term predictions. Short-term prediction can refer to forecasting data of no more than afew hours ahead. The medium range forecasts are for a period extending from about a few hours to three days in advance. Long-term forecasts, refer to a period greater than three days ahead.thz subject of this paper is forasting wind pawer on a chort –term for reel time supervision wind farm. A set of recent wind speed measurement samples from ADRAR station in south of Algeria , were used to train and test the data sets. It is believed that the general framework proposed in this study can be applicable in a variety of decision-making situations [7,8].

2. WIND POTENTIAL IN ADRAR, ALGERIA REGION

The city of Adrar is located south west of Algeria, about 1540 km from Algiers. The region is characterized by relatively flat topography and geomorphology by a desert. Adrar and its surroundings are characterized by a high potential of wind from the north east. Wind data from the Adrar region ranked it as the one with the best wind potential in Algeria. This site is located about 72km north of the city of Adrar near an electrical substation SONELGAZ its geographical coordinates are 27° 12'30 "N



and 0° 10'30" W (Fig.1).

Fig. 1. Aerial view of the site

Wind potential is characterized by the mean wind speed. In what follows, it is given the average wind speeds from data Algerian Meteorological office (AMO) and those calculated from the measured values stations as CREDEG (Centre for Research and Development Electricity and Gas) has installed in some regions of Algeria. It gives the average wind speeds of AMO with which a wind map has been drawn over the period 1999 to 2004. Southern regions: Adrar, In Salah, Timimoun Bordj Badji Mokhtar, Tindouf emerge as the best windy regions of Algeria. Among these is Adrar with the best wind potential in Algeria. But other criteria than the wind taken into consideration for the choice of implantation site of a wind farm such as altitude, the presence of obstacles, the situation with respect to the wind direction and the electricity distribution network . A site that meets all these requirements is located at the region Kabertene wilaya of Adrar. The results of extrapolation with Atlas 50m wind speed at 50m ground estab is done by[9],(Fig. 2), and the feasibility study[10] which estimates the average speed of the Adrar region between 8.38m/s and 9.38m/s at a height between 50m and 80m, we deduce that the extrapolation method which approximates most of its values is the power method modified and adjusted by Mikhail.

3. FORECASTING THE AERODYNAMIC POWER

The study described in this paper develops a simple and robust algorithm that describes short-term wind power forecasting. As wind energy varies during day time depending on the wind speed hitting the generator blades, the possibility of predicting wind energy production in the following hour becomes crucial for wind farm owners in order to work efficiently on the electricity market. These predictions will help producers take decisions for the sale of energy and thus to increase production and profits. If an accurate If an accurate prediction of the wind speed for the following hour can be evaluated, the total amount of active power that can be produced by each generator on a wind farm can be determined and therefore, the amount of energy that could be sold during the next hour would be known too.

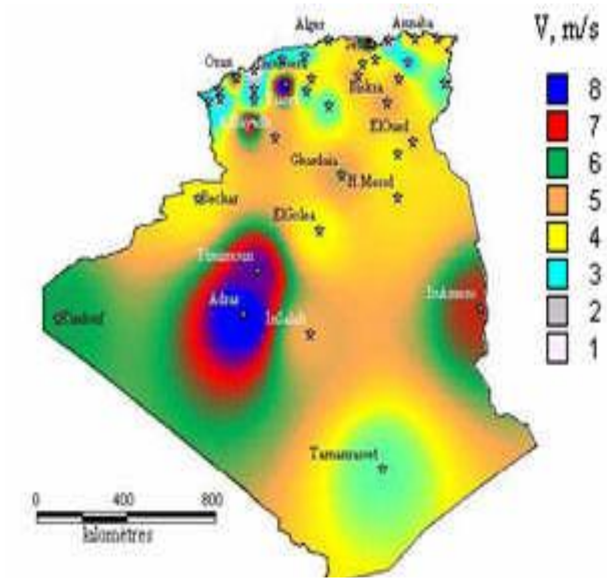


Fig. 2. Atlas of seasonal average speed (10m ground)

In order to analyses the amount of energy that is going to be produced by a generator (produced active power), the wind speed prediction and some aerodynamical test results of the generator are needed. So, it is important to consider the mechanical power (Paer), developed by a wind turbine, which depends directly on the blade radius, the power coefficient and the wind speed hitting the blades of the generator.

$$P_{aer} = C_p P_v = C_p * \frac{\rho \Pi R^2 V^3}{2} \qquad (1)$$

Where V is the wind speed ($m.s^{-1}$), ρ is the air density (kg/m^3), R is the rotor radius (m), and C_p is the power co-efficiency of the wind turbine.

In this part, we suggest giving the estimation of wind power in advance, a new method based on the ANN is proposed. With the historical data of wind speed are used. The main study in this paragraph is as follows: the prediction model of wind speed is constructed by ANN, which gives the predicted data of wind power. Considering the fact that wind power relates to wind speed.

3.1 Wind Speed Prediction Model

In this study, artificial neural networks (ANN) were applied to predict the hours monthly wind speed of any target station, using the hours monthly wind speeds of Adrar region (in Algerian) station which is indicated as reference data. Hourly wind speed data, collected by the Algerian Meteorological office (AMO) at measuring data located in the region of Adrar were used. The wind data, containing hourly wind speeds, directions and related information, covered the period between 1995 and 2004. These data were divided into two sections. Data for the period 1995-2003 have been used to train a neural network, where the data for the year 2004 were used for validation; the hours monthly wind speeds of reference station were used and also corresponding months were specified in the input layer of the network. On the other hand, the hours monthly wind speed of the target station was utilized in the output layer of the network. Artificial neural network (ANN) testing algorithm was applied in the present simulation.

3.2. Artificial Neural Network (ANN)

Kalogirou [7] stated that during the past years there has been a substantial increase in the interest of the ANN. Researchers have been applying the ANN method successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, in the prediction of mineral exploration sites, in electrical and thermal load predictions and in adaptive and robotic control and many other subjects. This method learned from given examples by constructing an input–output mapping in order to perform predictions [11] . In other words, to train and test a neural network, input data and corresponding output values are necessary (Çam et al.,2005). ANNs can be trained to overcome the limitations of the conventional approaches to solve complex problems that are difficult to model analytically [8]. Fundamental processing element of a neural network is a neuron. The network usually consists of input layers, hidden layers and output layer[8]. The model of a neuron is shown in (Fig. 3). A neuron j may be mathematically described with the following pair of "equations (2),(3)":

$$u_j = \sum_{i=0}^{p} w_{ji} y_i \qquad (2)$$

The artificial neuron receives a set of inputs or signals y with weight w, calculates a weighted average of them (u) using the summation function and then uses some activation function $\varphi(.)$ to produce an output y.

And

The use of threshold y has the effect of applying an affine transformation to the output u of the linear combiner in the model of (Fig. 3).as shown by [8].

$$y_i = \varphi(u_j - \theta_j) \qquad (3)$$

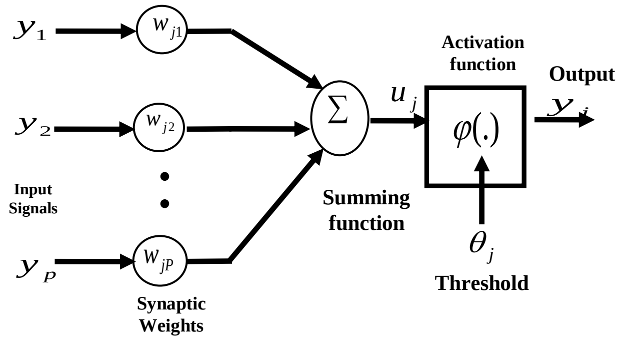


Fig. 3. Nonlinear model of a neuron .

The sigmoid logistic nonlinear function is described with the following equation:

$$\varphi(x) = \frac{1}{1+\exp^{-x}} \qquad (4)$$

3.3 ANN Architecture

ANN architecture used in this study for Adrar meteorological station which is selected as a target station is shown in (Fig. 2). This network consists of an input layer, two hidden layers and an output layer. The hours monthly wind speeds of reference data and corresponding month were used in the input layer of the network. The wind data, containing hourly wind speeds, cover the period between 1995 and 2003 considering as reference data were used in output layer. The most significant point in the selection of these reference data is that there is a good relation with high correlation coefficient between the target and reference data, the number of the neurons in the hidden layers of the network and the number of patterns in the training and testing procedures are given in Table 1. Train learning algorithm was used in the present simulation. Neurons in the input layer have no transfer function. Logistic sigmoid transfer function (logsig) and linear transfer function (purelin) were used in the hidden layers and output layer of the network as an activation function, respectively. Simulations were performed to estimate the hours monthly wind speed of target station.

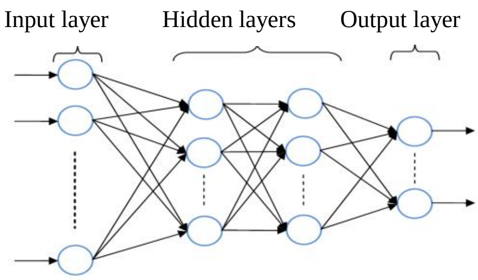


Fig.4. ANN architecture.

Table 1. Characteristic of ANN used

Target station	Number of neurons in hidden layers	Number of patterns in training	Number of patterns in testing
ADRAR	12-6	200	900

3.4 Results and discussion

In this simulation, the years [1995 ...... 2003] are used for learning or training of neural network. The year 2004 is used to validate our prediction .The figures (3 and 4) show the effectiveness of the use of neural network for the prediction of wind speeds.

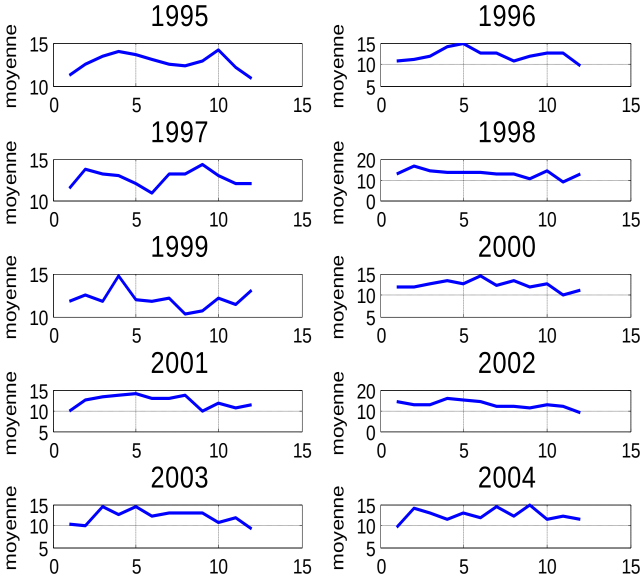


Fig. 3. The real shapes of the wind speeds.

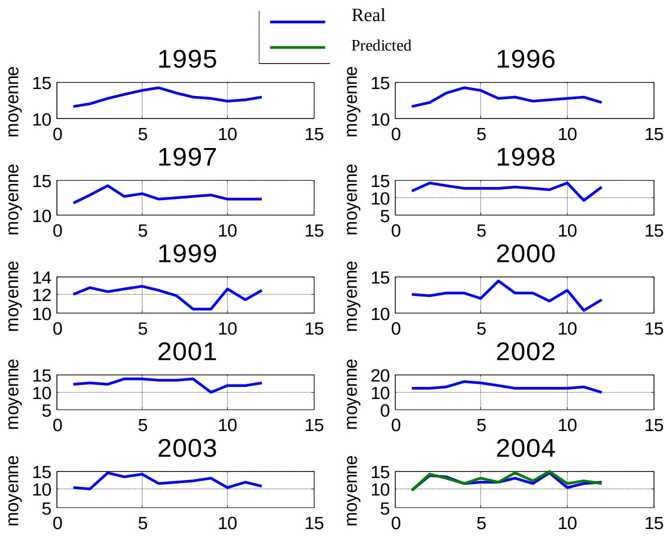


Fig. 4. Results of learning and validation prediction with a long term wind speeds.

In general, we see that the speed values of the predicted winds are very close to those given by the National Office of Meteorology [NOM] Fig. 4. (2004).

•Figure 5 show ANN repetitions during a validation.

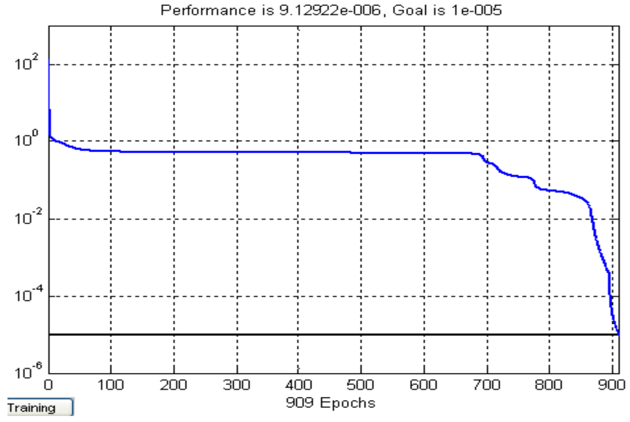


Fig. 5. The ANN iterations during validation.

In the same way that we used for the prediction of wind speed for a year or long term, it has the ability to predict for one month or a day that is to say the short term prediction using the same historical data of wind speed retrieved by the National Office of Meteorology (NOM).

The predicted short term wind speed is shown in the following figure:

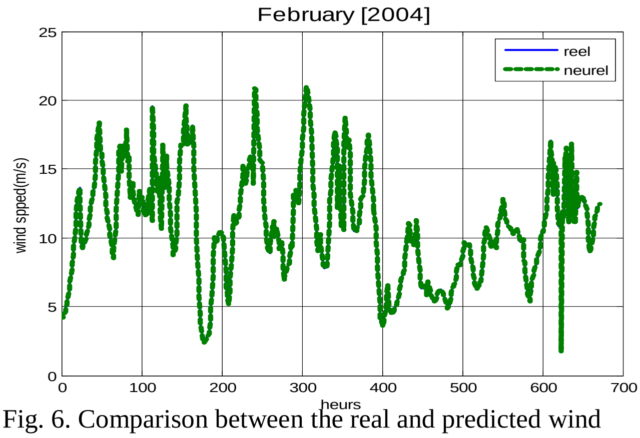


Fig. 6. Comparison between the real and predicted wind speed by ANN for Adrar meteorological station; February 2004.

In the present study, it is realized that ANN is a convenient method to apply for the prediction of the wind speed. The mean absolute percentage error (MAPE) was used to see the convergence between the target and the output values. This parameter is defined as Follows :

$$MAPE = \frac{1}{2}\sum_{i=1}^{n} abs(\frac{O_i - t_i}{O_i}) * 100 \quad (5)$$

where t is the target value, o the output value, n the total number of months,

The values determined by ANN model were compared with the actual data. The maximum mean absolute percentage error was found to be 14.13% for Adrar region meteorological station.

3.5. Wind Power Prediction

Wind power can be calculated by wind speed-power conversion formula, which is computed in equation (1). which is based on the above predicted wind speed by ANN, Different steps of prediction wind power shown in following Flow chart:

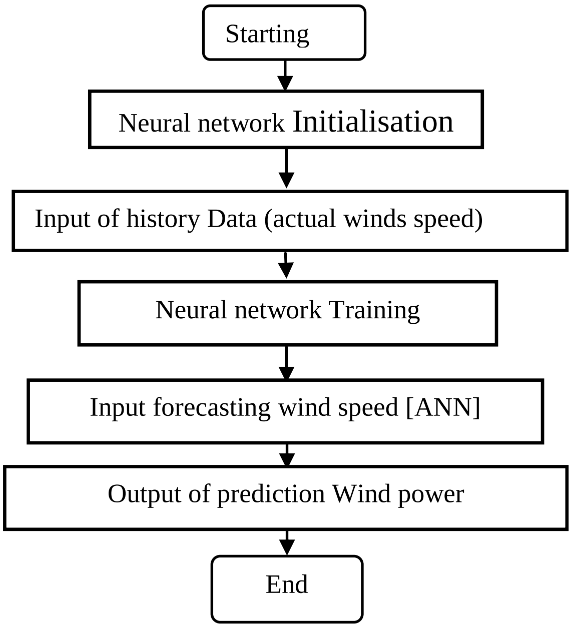


Fig 7. Flow chart of prediction wind power

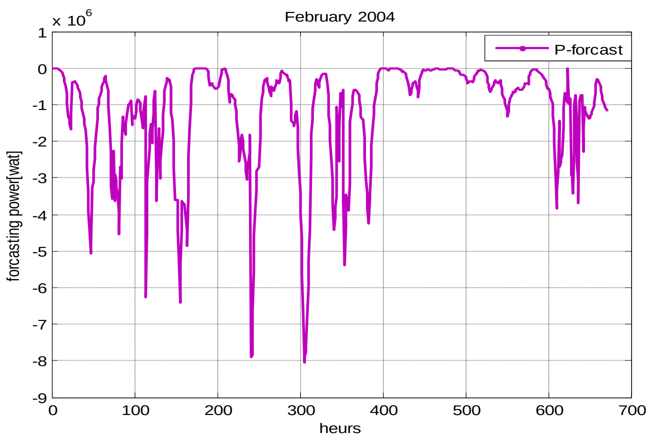


Fig.8. Wind Power Prediction

4.POWER SYSTEM CONFIGURATION

The total diagram of an inter-connected electrical network which has several electrical devices is presented on fig.1, the wind farm is connected to HTA 20KV buses through a transformer of 20KV/690V.Differents fixed and variables loads are connected to the same bus with another transformer. A central unit of wind farm supervision is installed in order to control the exchanges (P_{WF} , Q_{WF}) powers with the electrical network[10].The objective of this unit is a management of the total active and reactive powers of the wind farm according to a plan of production required by the system operator. On the hand, A central supervisory control level decides the active and reactive power references (P_{WF-ref} Q_{WF-ref}) for each wind generators local control level, based on received production orders (maximum production or power regulation ($P_{WF-\max}$, $Q_{WF-\max}$) from the system operator in other hand.

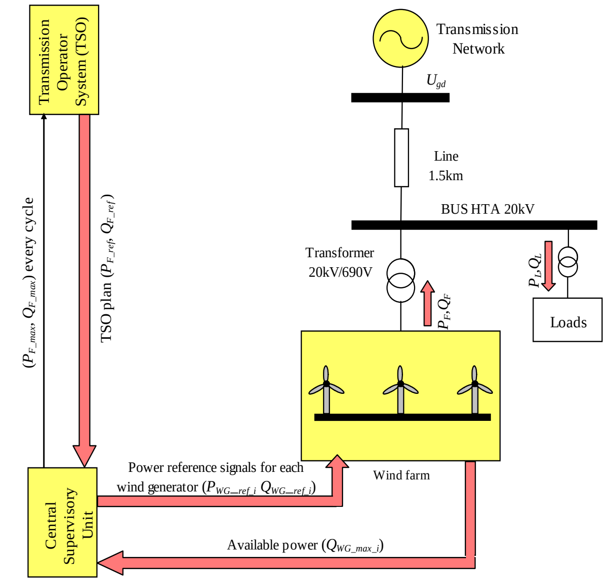


Fig.9. Power System Configuration(Ghannam,2009).

5.IMPROVED PROPORTIONAL DISTRIBUTION [PD] ALGORITHM FOR WIND FARM SUPERVISION USING THE AERODYNAMIC POWER PREDICTION

In order to enhance PD algorithms for wind farm supervision[12,13-14-15-17] by avoiding its problem presented in the different wind generators and ensuring your connection in electrical network. We propose a forecasting model of aerodynamic power based on the artificial neural network [ANN][5,16] to obtain the information on available active and reactive powers (fig.10).

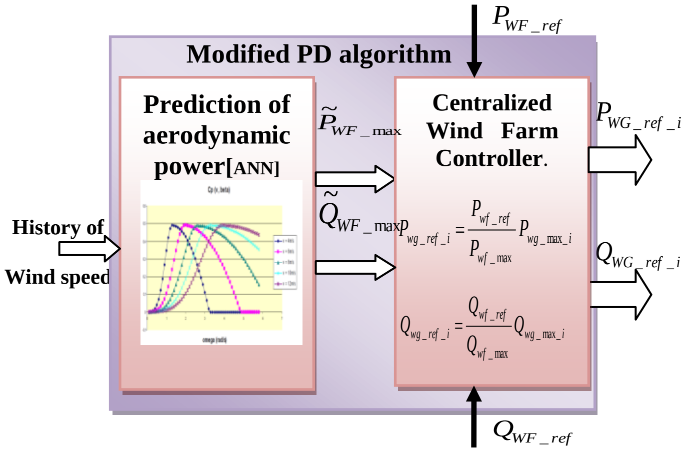


Fig.10.Modified PD algorithm for wind farm supervision

5.1. Control algorithm

As the wind farm active power generation is closely related to the wind speed, it is important to maintain the active power levels while ensuring are active power generation absorption. In consequence, it is important maintain the necessary power factor to achieve the correct electric parameters of the electric grid that the farm is connected to. Once the active and reactive power set points are defined, it is necessary to develop the control-law that will guide the system. There are different ways to design the control-law but the one presented in this paper is based on a proportional distribution of the active and reactive powers that the farm must generate, taking into account that the generated active power must be always the maximum obtained in each moment from the wind.

The designed control-law takes into account the machine operating limits and tries to follow the set point the farm. This law appears in (5)(6).

$$P_{WG\_ref\_i} = \frac{P_{WF\_ref}}{P_{WF\_max}} P_{WG\_max\_i} \qquad (5)$$

$$Q_{WG\_ref\_i} = \frac{Q_{WF\_ref}}{Q_{WF\_max}} Q_{WG\_max\_i} \qquad (6)$$

Where, $P_{WG\_ref\_i}$ $Q_{WG\_ref\_i}$, are the active and reactive powers that each (i) machine must generate; $P_{WG\_max\_i}, Q_{WG\_max\_i}$, are the maximum active and reactive power that each machine can generate in one specific moment and P_{WF_ref}, Q_{WF_ref}, are the active and reactive power set point for the farm.

The procedure followed to implement the control law is described below:

1. Measurement of the active and active power produced in the farm
2. Read of the active and reactive power needed to maintain the electric parameters of the grid, (P_{WF_ref}, Q_{WF_ref},).
3. Measurement of the active power generated by each machine and its reactive power limit ($P_{WG\_max\_i}, Q_{WG\_max\_i}$)
4. Apply (1) (2) to calculate the active and reactive power that each machine ($P_{WG\_ref\_i}$ $Q_{WG\_ref\_i}$) must generate and send it to the machine as the active and reactive power sets points to follow.
5. Measurement of the active and reactive power generated by the overall farm.
6. Comparison between the sets points (P_{WF_ref}, Q_{WF_ref},) and the obtained active, reactive power and return to 2

5.2. Combined Prediction Wind Power with PD Algorithm for Wind Farm Supervision.

If we know ahead the available aerodynamic power for each wind generators of the wind farm, we have the possibility of cured the major problem of PD Algorithm for Wind Farm Supervision, i.e. estimation aerodynamic power on the level of the wind generators. By considering into account the maximum active and reactive powers to calculate this algorithm.

Thus the controller of each wind generators received a consign in active and reactive powers has to leave the system of centralized supervision the wind farm and the limits in active and reactive powers according to its diagram (P, Q)[12]. If the reference is inferior to extreme in active power also for reactive power the wind generator must be produced this instruction. On the contrary case the wind generator is sufficient to produce its maximum in active or reactive powers.

The following flow chart in (fig.11) illustrates the context of this modification:

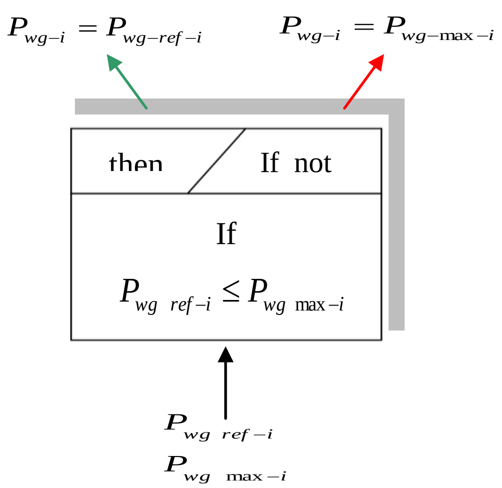
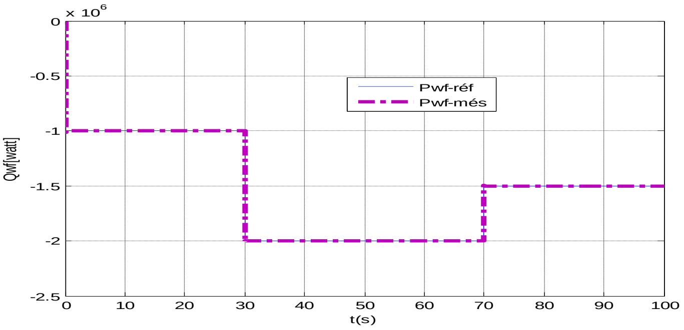


Fig.11. Flow chart of the management of the active power on the level a local wind generator controller

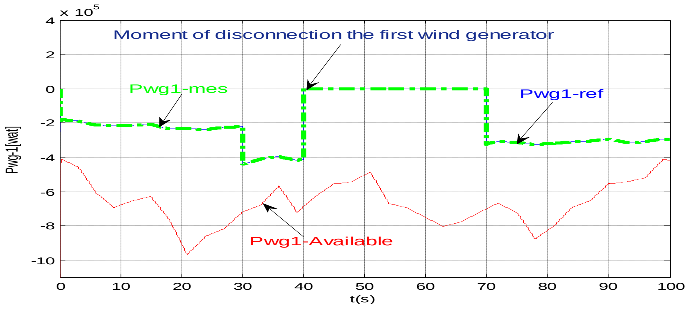
5.3. Simulation Results and Discussion

The validation of this type of supervision was made on the model of a wind farm of three wind generators situated in different wind profiles.

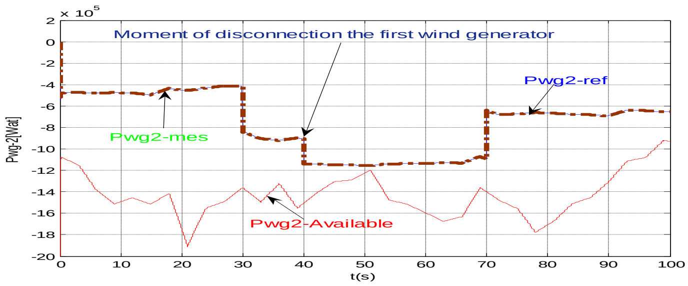
In order to observe the behaviour of this regulation we applied to our system different level of active and reactive powers, take into account the disconnection of each wind generators during the defects (saturation, short-circuits,). Figures (Fig.12, Fig.13) Show the dynamics of this control.



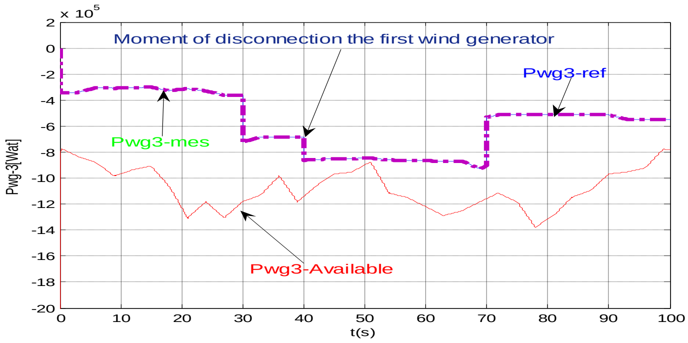
(a) active Power of the wind farm



(b) active power the first wind generator



(c) active power the second wind generator

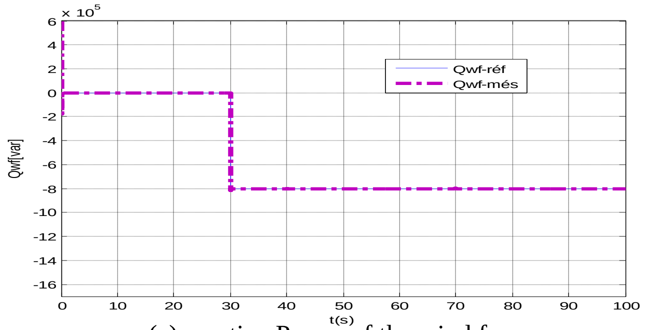


(d) active power the third wind generator

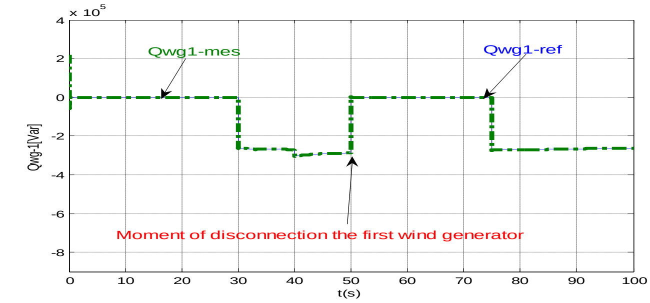
Fig.12.Simulation Results the centralized supervision of the active power [PD]: disconnection the first wind generator.

Supposing that the wind generators of the wind farm are worked in "MPPT"(maximum power point tracking).

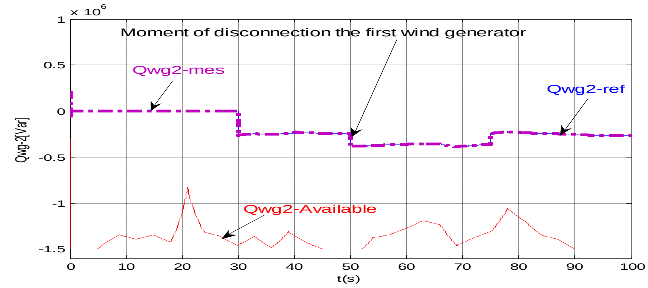
In order to demonstrate the performance of the wind farm Controller, it is considered that at the moments of (40 s .Fig.12) for the active power and (50 s .Fig.13) for the reactive power the first wind generator is disconnected from the farm, being thus unable to contribute with both active and reactive power, I.e.



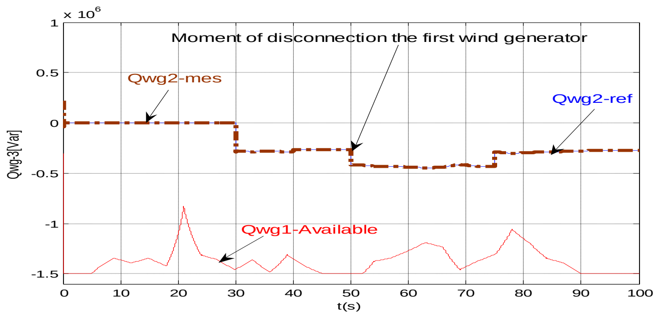
(a) reactive Power of the wind farm



(b) reactive power the first wind generator



(c) reactive power the second wind generator



(d) reactive power the third wind generator

Fig.13.Simulation Results the centralized supervision of the active power [PD]: disconnection the first wind generator.

- **Fig.12(a), Fig.13(a)** illustrates both the available active power, actual active and reactive powers at the wind farm level,

namely in the PCC (point common coupling) of the wind farm level, namely in the PCC of the wind farm. The disconnection of the first wind generator is illustrated as a step to another level of the available power. Noticed that the wind farm controller manage to keep the required 2 MW actual active power and 0.8 Mvar actual reactive power, in both cases before and after the disconnection of the first wind generator.

- **Fig.12 (b, c, d), Fig. 13 (b ,c ,d)** illustrates the Simulation results at the wind generators control level. At the moment of disconnection of the first wind generator, its active and reactive power reference signals becomes zero. The dispatch function block figure.9, recomputed then the references for the remaining two wind generators in order to maintain the 2 MW active power and the 0.8 MVar reactive power in the PCC. Noticing that the wind farm keeps the required 2 MW active power very smoothly (see Fig. 12.a), although the active power varies at the individual wind generators (see Fig.13 (b, c, d)). Noticing that the production of the active power and the absorption of reactive power from the two remaining wind generators increase to compensate the disconnected a first wind generator.

The simulation results show a good performance of the control system.

6. CONCLUSION

In this paper we have shown an application of artificial neural networks in a problem of short-term wind speed forecast. In order to enhance wind farm supervision by predicted aerodynamic power can be produced by each wind generators. A set of recent wind speed measurement samples from meteorological stations in Algeria, namely ADRAR located in south of Algeria, were used as training and testing data sets. The simulation results illustrate good performance of this approach.

REFERENCES

1. Yiannis S. Boutalis (Neural Network Approaches For Feedback Linearization) Control Engineering And Applied Informatics, CEAI, Vol.6, No.1, pp.15-26. 2014.
2. Vigu. C , Gota. D. I , Capatana. D (Improving the wind speed estimation algorithms using results obtained in the field) Control Engineering And Applied Informatics, CEAI, Vol.12, No.3, pp. 13-17. 2010.
3. Negnevitsky. M, Johnson .P, and Santoso .S (Short term wind power forecasting using hybrid intelligent systems) in Proc. IEEE Power Eng. Soc. Gen. Meet., Tampa, FL, USA, , pp.1–4. 2007.
4. Jabbari Ghadi. M, Hakimi Gilani. S, Afrakhte. H, and Baghramian. A (Short-Term and Very Short-Term Wind Power Forecasting Using a Hybrid ICA-NN Method) International Journal of Computing and Digital Systems, Int. J. Com. Dig. Sys. 3, No. 1, 61-68. 2014.
5. Hanieh .B. A,Saad .M, and Vellapa. G(Long-Term Wind Speed Forecasting and GeneralPattern Recognition Using Neural Networks) IEEE transactions on sustainable energy, vol. 5, no. 2, pp, 1949-3029. 2014.
6. Barbounis .T. G and Theocharis .J. B (Locally recurrent neural networks for long-term wind speed and power prediction) Neurocomputing, vol. 69, no. 4–6, pp. 466–496. 2006.
7. Kalogirou.SA (Artificial neural networks in renewable energy systems applications) a review. Renew Sustain Energy Rev;5:373. 2001.
8. Sozen.A,Arcaklıoglu.E,Ozalp.M,çaglar.N(Forecasting based on neural network approach of solar potential in Turkey). Renew Energy;30:1075–90. 2005.
9. Çam.E,Arcaklıog.E.lu, çavusoglu.A, Akbryık B (classification mechanism for determining average wind speed and power in several regions of Turkey using artificial neural networks) Renew Energy; 2005.
10. Haykin(Neural networks, a comprehensive foundation) New Jersey: Prentice-Hall. 1994.
11. Mohandes.M,HalawaniT,Rehman.S,Hussain.A(Support vector machines for wind speed prediction) Renew Energy; 29:939–47. 2004.
12. Ghennam .T (Supervision d'une ferme éolienne pour son intégration dans la gestion d'un réseau électrique, Apports des convertisseurs multi niveaux au réglage des éoliennes à base de machine asynchrone à double alimentation) Thèse de doctorat, Ecole Militaire Poly technique, (EMP) Alger, Ecole Centrale de Lille, 2011.
13. Beugniez .A, Ghennam. T, François. B, Berkouk .E. M. et Robyns.B.(Centralized supervision of reactive power generation for a wind farm) 12th European conference on power electronics and applications (EPE 2007), ,Aalborg, Denmark 02-05. 2007.
14. Benlahbib**.**B,bouchafaa.F.,Noureddine.B, Bachir.B (Centralized Algorithm For Wind Farm Supervision) Conférence Nationale sur les Energies Renouvelables et leur Applications, Adrar, Algérie. 2014.
15. Ghannam. T,François.B, Berkouk.E.M(Local supervisory algorithm for reactive power dispatching of a wind farm) 13th European Conference on power Electronics and Applications (EPE 2009),Barchalona ,Spain, 2009.
16. Chen. Y.W, Lee .Y.L, Kung.C.C (Application of Particle Swarm Optimization Based on Neural Network for Artillery Range Prediction) Journal Of Control Engineering And Applied Informatics,CEAI, Vol.16, No.4 pp. 73-80. 2014.
17. B.Benlahbib, F.bouchafaa, B.Noureddine, B.Bachir, B. bendjedia (PSO-PI Algorithm For Wind Farm Supervision) Journal of Electric Engineering ISSN1582-4595(2014).