Improvement Algorithm for Wind Farm Supervision Based On Proportional Distribution

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ABSTRACT

Nowadays, the research related to the wind farms is oriented to the development of improved supervision algorithm to manage the active and reactive powers as well as to provide an ancillary system. This paper proposes an enhancement PD (proportional distribution controller) algorithm for wind farm supervision. This algorithm combines a conventional PD algorithm with the prediction of the wind power generator, by using Artificial Neural Network (ANN). In fact the prediction power permits to determine the maximum active and reactive powers, which represents the PD regulator limits. Hence, the estimation of aerodynamic power, which represents major problems of the conventional PD algorithm, can be easily avoided. The performance of the proposed algorithm is verified through simulation results considering a wind farm of three generators (1.5 MW).

KEY-WORDS : wind farm supervision, PD (proportional distribution controller), ANN artificial neural network, forecasting wind power.

1. INTRODUCTION

For several years, the environmental protection has caused much attention, and consequently, several technologies are developed. It's the case of the wind power. Nowadays, this source of energy is still used for water pump but it's mainly used for electricity production and this without any harmful impact to the environment. The high costs of exploitation of the nuclear, thermal power stations and the fossil fuels also, made possibility of wind power being more competitive.

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 without disregarding the quality of electric power produced.

The recent research tasks in the field of wind Farms are directed to design supervision algorithms for wind farm with the aim of distributing the references of active and reactive powers on different wind generators. In this context, several algorithms were proposed [2][13][16][25] and can be classified mainly in three categories:

The first algorithms are based on Proportional integral regulators PI, this class of algorithms regulates the problem of the supervision by using a simple PI regulator [8]. Two algorithms can be distinguished; the first uses this regulator to regulate the power-factor [15][21], while the second one regulates the active and reactive power directly [1] [16] [27], but the risk of the wind generators saturation is presented as the major problem of these algorithms, because the information on the maximum available active and reactive powers of each wind generators are not taken into consideration [8]. The second Algorithms are based on optimization of the objective function, which is used for the optimal active and reactive powers references distribution on the wind generators [13][23][25]. This function must formulate objectives, it is optimized by a mathematical equation which takes account of several parameters [8], it needs optimization methods like: genetic algorithm [18], neurons networks [10],[17], particles swarm optimization [4][11], and methods which combines the latter with fuzzy logic [13][24]. The last supervision Algorithms which are based on proportional distribution, were developed to distribute the power references in proportional way. From a safety point of view, these algorithms ensure that each wind generator works always far from its limits defined by the (P,Q) diagram[1][2][8]. They determine the references of the active and reactive powers of each wind generators P_{WG_ref} , Q_{WG_ref} from the global active and reactive power references required by the network system operator P_{WF_ref} . Q_{WF_ref} [8] [19] [20] [6]. Nevertheless, the implementation of this strategy is a little bit complex since it needs information on the available aerodynamic power of all the wind generators [20].

This paper proposes a model of forecasting the aerodynamic power based on artificial neural network [ANN]. Considering the wind speed, it direction and other factors. Taking into account the linear approximate relationship between a wind speed and the aerodynamic power generated, in order to improve PD algorithms for wind farm supervision by avoiding the problem of estimation the aerodynamic power presented in different wind generators mentioned previously and ensure the electrical network connection.

2. PROBLEM DESCRIPTION

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 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.

In order to analyse the amount of energy that is going to be produced by a generator (produced active power), the wind speed prediction and some aero-dynamical test results of the generator are needed. So, it is important to consider the mechanical power (P_{aer}), 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.

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

Where V is the wind speed ($m.s^{-1}$), $^\circ$ 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.

3. FORECASTING THE AERODYNAMIC POWER

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 [9] 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 [12]. In other words, to train and test a neural network, input data and corresponding output values are necessary [26]. ANNs can be trained to overcome the limitations of the conventional approaches to solve complex problems that are difficult to model analytically [22]. Fundamental processing element of a neural network is a neuron. The network usually consists of input layers, hidden layers and output layer [22]. The model of a neuron is shown in Fig. 8. A neuron j may be mathematically described with the following pair of equations [3][7]:

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

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 j to produce an output y.

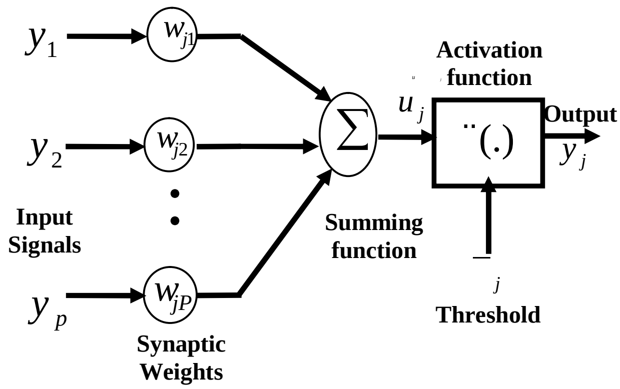


Figure. 1. Nonlinear model of a neuron [3].

And

$$y_i = {}^{\cdot\cdot}\left(u_j - {}^{-}{}_j\right) \qquad (3)$$

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. 8. [22][7].
The sigmoid logistic nonlinear function is described with the following equation:

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

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. 9. 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.

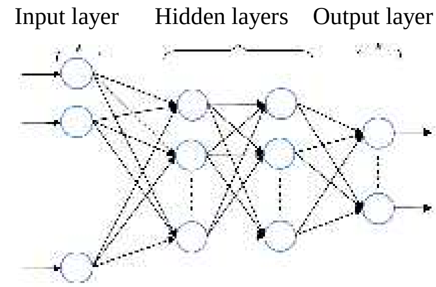


Fig.2. ANN architecture.

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

IV.1.4 Results and discussion

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 [22]:

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

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

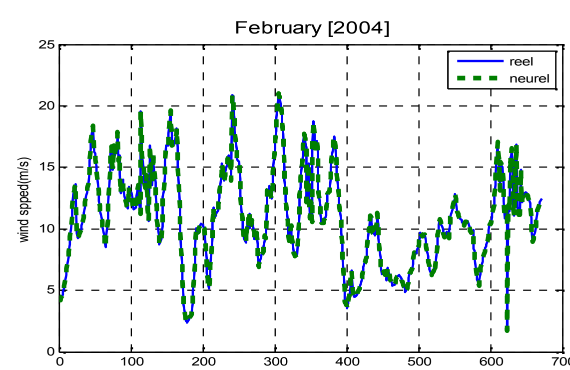


Figure. 3. Comparison between prediction of ANN and actual results for Adrar meteorological station February 2004.

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 meteorological station.

3.4. Wind Power Prediction [Fen 11]

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, i.e. fig.. 12.
Different steps of prediction wind power shown in following Flow chart:

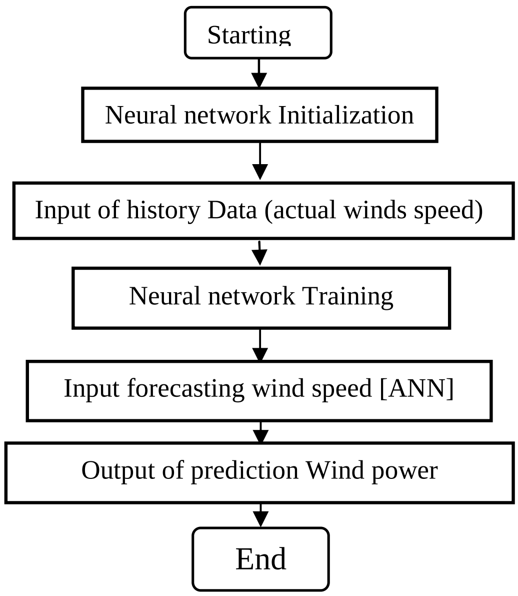


Figure.4. Flow chart of prediction wind power

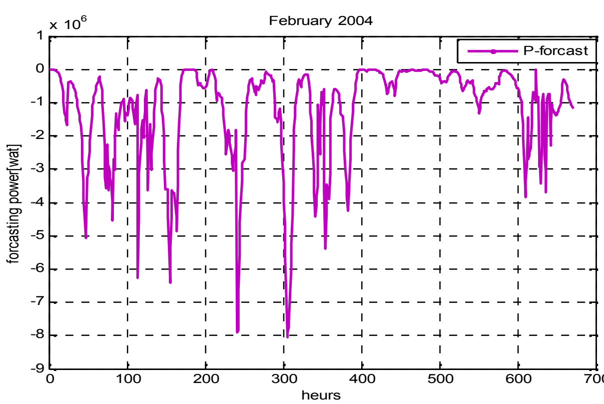


Figure.5. Wind Power Prediction

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 [8].

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.

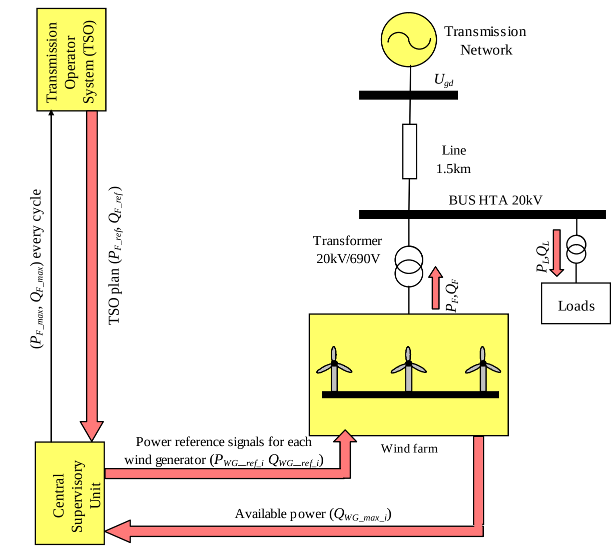


Figure.6 Power System Configuration [28]

5. IMPROVED **PD** ALGORITHM FOR WIND FARM SUPERVISION USING THE AERODYNAMIC POWER PREDICTION

In order to enhance PD algorithms for wind farm supervision 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] to obtain the information on available active and reactive powers fig.7.

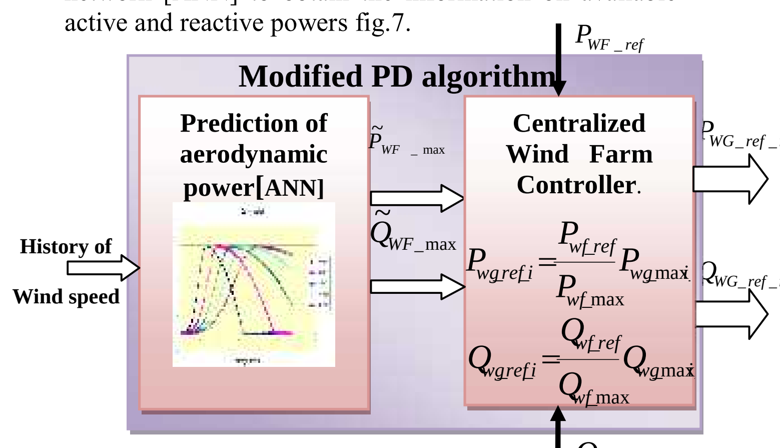


Figure.7. Modified PD algorithm for wind farm supervision

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 defined for the farm. This law appears in (6)(7).

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

$$Q_{WG\_ref\_i} = \frac{Q_{WF\_ref}}{Q_{WF\_max}} Q_{WG\_max\_i} \qquad (7)$$

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). 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 figure.8 illustrates the context of this modification:

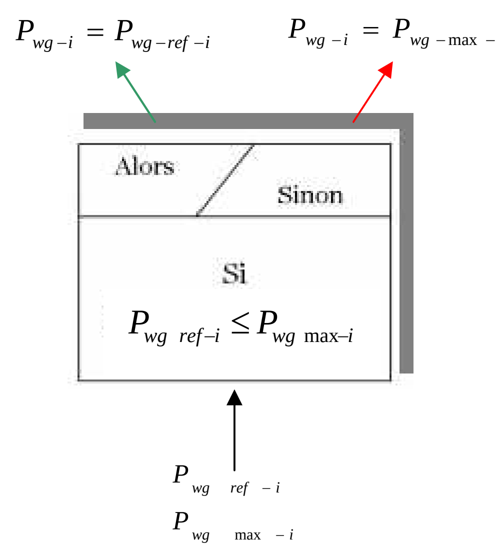


Figure.8: Flow chart of the management of the active power on the level a local wind generator controller

5.3. Simulation Results and Discussion

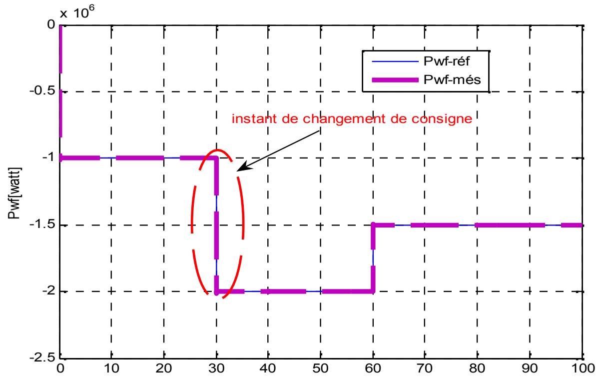
The validation of this type of supervision was made on the model of a wind farm of three wind generators situated in different wind profiles.

In order to observe the behavior of this regulation we applied to our system different level of active and reactive powers. Supposing that the wind generators of the wind farm are worked in "MPPT".

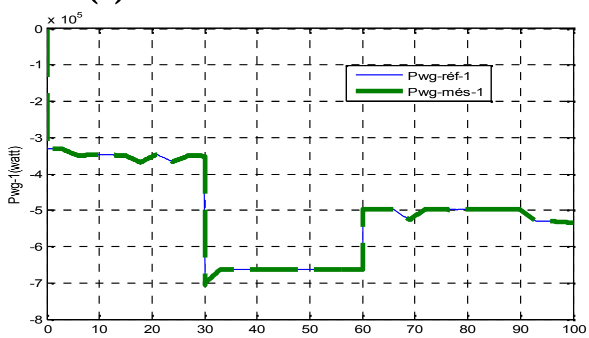
We have two scenarios of simulation:

- The first one used an proportional distribution of the active and reactive powers references not considering disconnection the wind generators [Fig.9, Fig.10].

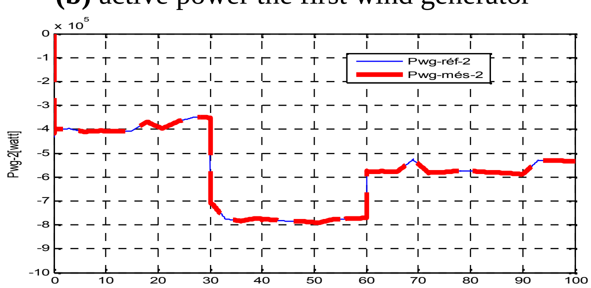
The simulation results show a good performance of the control system. The specified references both for the active and reactive power are achieved properly [Fig.9, Fig.10].



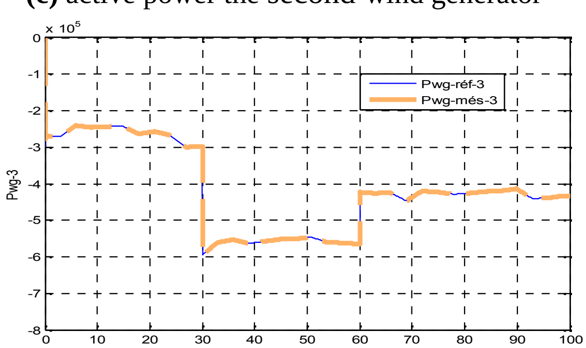
(a) active Power of the wind farm



(b) active power the first wind generator

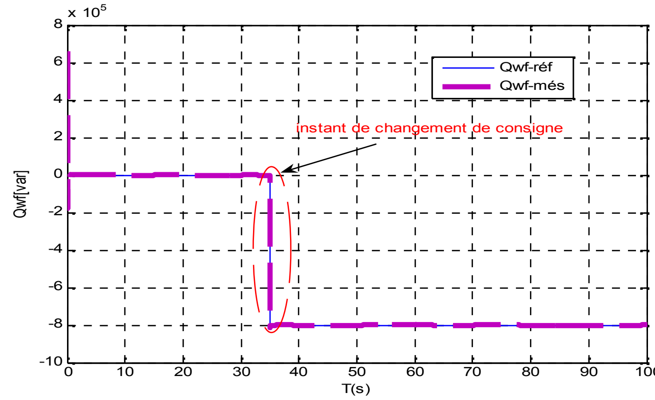


(c) active power the second wind generator

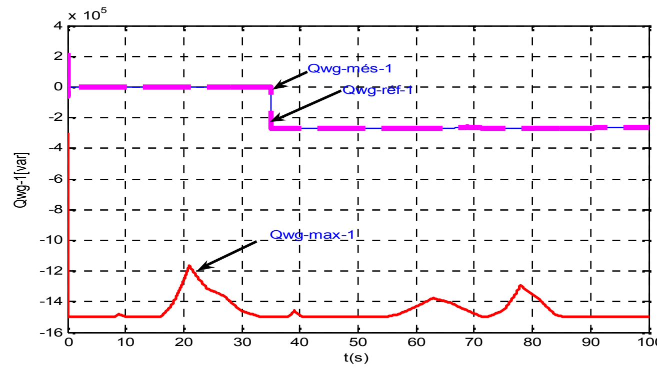


(d) active power the third wind generator

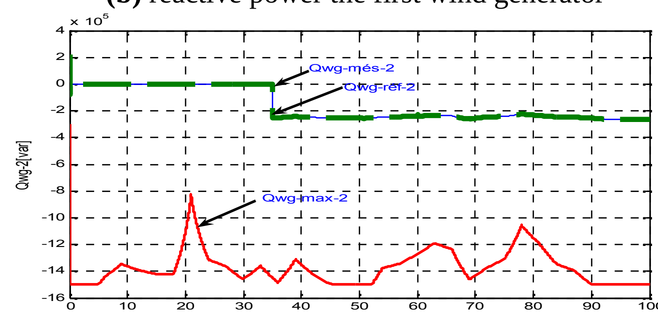
Figure .9. Simulation Results the centralized supervision of the active power [PD]:.Normal case.



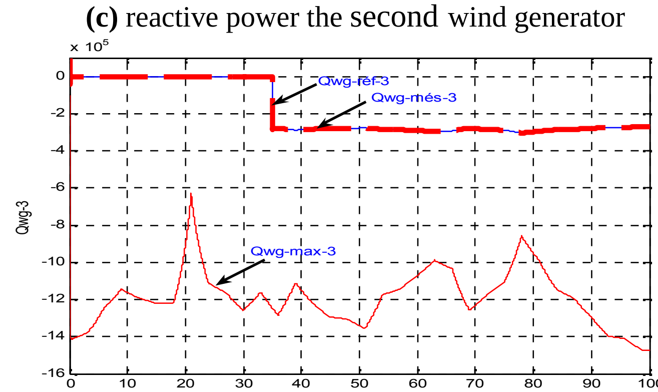
(a) reactive Power of the wind farm



(b) reactive power the first wind generator



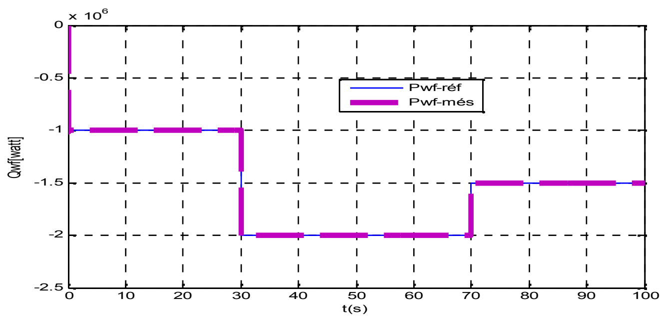
(c) reactive power the second wind generator



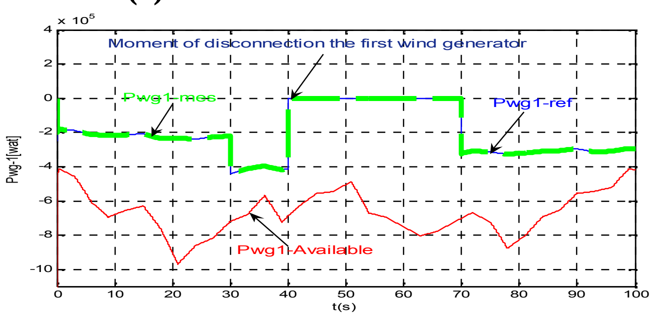
(d) reactive power the third wind generator

Fig.10. Simulation Results the centralized supervision of the reactive power [PD].Normal case.

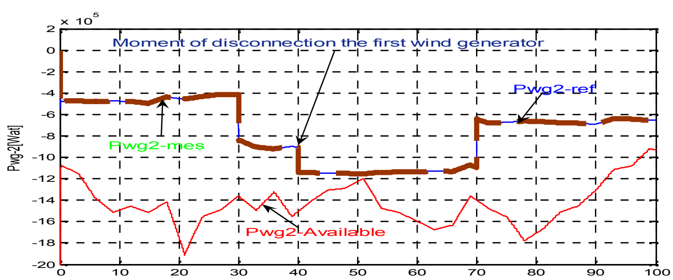
➢ In the second scenario with the distribution of different references in Active and reactive powers we take into account the disconnection of each wind generators during the defects (saturation, short-circuits,). Figures [Fig.11, Fig.12] Show the dynamics of this control.



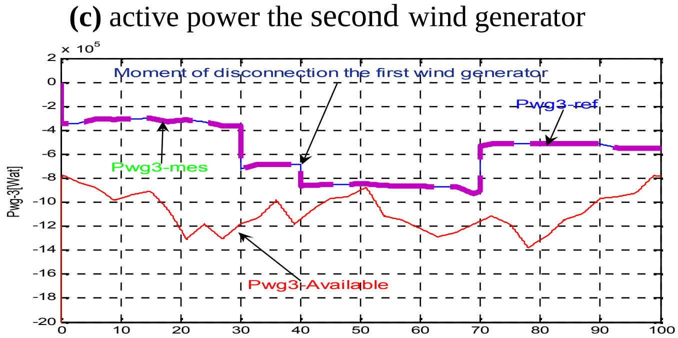
(a) active Power of the wind farm



(b) active power the first wind generator



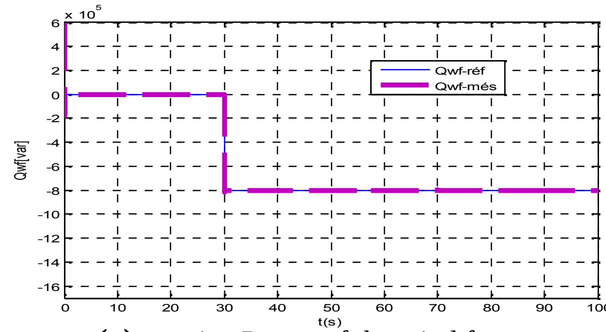
(c) active power the second wind generator



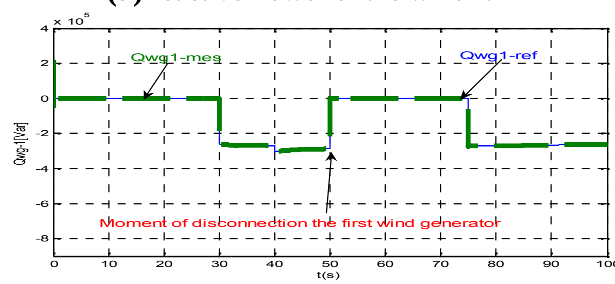
(d) active power the third wind generator

Figure .11.Simulation Results the centralized supervision of the active power [PD]: disconnection the first wind generator.

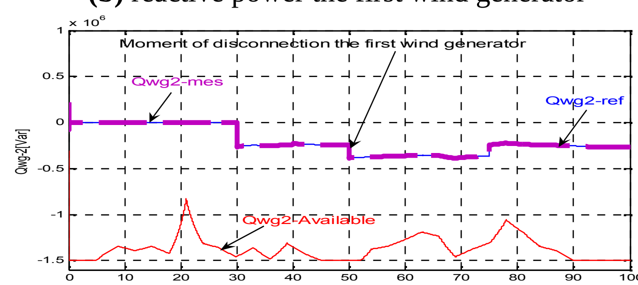
In order to demonstrate the performance of the wind farm Controller, it is considered that at the moments of [40 s .Fig.11] for the active power and [50 s .Fig.12] for the reactive power the first wind generator is disconnected from the farm, being thus unable to contribute with both active and reactive power, I.e.



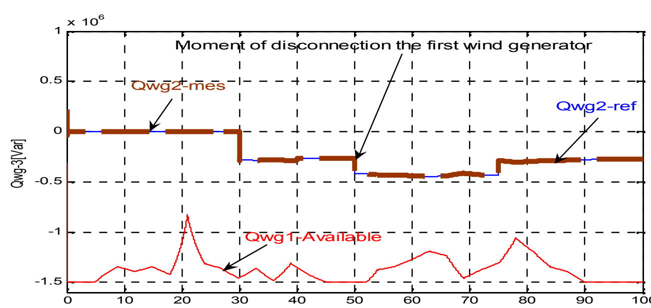
(a) reactive Power of the wind farm



(b) reactive power the first wind generator



(c) reactive power the second wind generator



(d) reactive power the third wind generator

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

- **Fig.11(a),Fig.12(a)**illustrates both the available active power, actual active and reactive powers at 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.11 (b, c, d), Fig. 12 (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 fig.7 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. 11.a), although the active power varies at the individual wind generators (see Fig.12 (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.

6. CONCLUSION

In this paper, improvement of Pd algorithm for wind farm supervision has been presented. The attention is mainly drawn on prediction of the available wind power at the level of each wind generator of wind farm based on [ANN] artificial neural network. In order to avoid the major problem of PD supervision algorithm which is the estimation aerodynamic power of different wind generator. Central supervisory algorithms are implemented and tested by simulation, under Matlab-Simulink software, on a wind farm of three wind generators. The simulation results illustrate good performance of this modification.

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