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A new strategy for controlling wind turbines against sensor faults and wake effects to harvest more electrical energy

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Abstract

This paper describes a new method for harvesting maximum electrical energy in wind farms. In proposing technique, the stochastic process principles are applied for detecting fault measurements of sensors. On the other hand, the wind farm is modeled by using fuzzy concept. Thereby the turbines are controlled against continuous changes in speed, direction and eddy currents of the blowing wind. To evaluate the performance of the proposed method three practical conditions of wind blowing are simulated. In the first scenario, the normal wind is simulated with low turbulence and slow changes. The second scenario belongs to high turbulence winds with sudden shifts in their parameters, and finally in the most complex scenario, several eddy currents are considered in blowing winds too. The obtained results show that the proposed method provides greater and more uniform harvested power compared to alternative methods. Furthermore, its superiority against other techniques has increased in parallel with the scenario become more complicated.

1. Introduction

Wind energy is a free renewable energy resource which has been concerned in the last decades because of its benefits in availability, energy prices and environmental impacts [1-2]. Today the share of wind energy in global electricity production of the world is 2.1% compared to 0.2% in 2001 [3]. In order to harvest more electrical energy, wind turbines have been reached higher into the atmosphere, and wind farms have been expanded beyond more than ten kilometers in length.

Furthermore, to obtain maximum efficiency variable speed wind turbines are being used [4]. These parameters make the efficient control strategy as a vital factor for management of wind farms. There are two main factors which limit the performance of such a control strategy. The first limitation is continuous changes in wind speed and direction. These changes lead to sudden shifts in generating electrical powers.

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So forecasting of wind speed and direction is vital to produce uniform electrical power [5-6].
The second limitation is the faults of sensors which are installed on turbines [7-8]. The wind turbines must be feathered to reduce unwanted destructive vibrations, especially when wind gusts are blowing. Therefore, their sensors send feedback signals to the controller in order to load reduction. If these sensors send incorrect alarms, the loads may be increased instead of reduced. The above limiting parameters not only decrease the performance of the produced electricity, but also increase fluctuations, which leads to structural fatigue [9]. Therefore, estimating wind parameters and detecting sensor faults may help the control strategy to minimize both uncertainties in power production and fatigue load in wind farms.
Several algorithms have been developed for controlling wind farm turbines, which a group of them is based on simplifying assumptions that allow the use of a vector control techniques similar to those employed in induction machine control [10]. Unfortunately, these assumptions are not correct in real condition and therefore the performance of the controller is degraded in wind farms.
Another group of wind farm controllers uses field oriented techniques. These controllers generally work based on the locally linearized model of the wind turbine around its operating points [11]. Though these methods may achieve high-performance control during the transient period, but the non-deterministic and nonlinear nature of wind causes considerable faults in their performance for long time periods.
Some techniques have been utilized nonlinear controllers based on this assumption that the wind turbine operates under steady state conditions [12]. Unfortunately, the dynamical aspect of the wind and the turbine is not taken into consideration by these controllers.
Another group of methods uses an adaptive control concept based on recursive algorithms [13]. Although they have shown a fast response in low turbulence winds, they don't lead to a reliable long-term controlling because of the stochastic nature of wind parameters.
Another group of methods includes Kalman filter-based controllers [14]. The main limitation of these methods is the non-Gaussian and non-linear treat of high turbulence winds which is not compatible with the common theory of Kalman filters. Therefore, the performance of these methods decreases in high turbulence winds.
Artificial neural networks have been used to predict wind parameters and controlling turbines [15]. This approach provides acceptable results in low turbulence winds and in the lack of considerable faults of sensors. However, there is a considerable decrease in its performance when it is applied to control turbines in high turbulence winds.
In this paper, a novel method is introduced for optimum energy harvest from wind farms. In the proposed method, firstly the blowing wind is considered as a stochastic process. The belonging of each measurement to correct or faulty observations is determined by calculating the probability of its belonging to the above stochastic process. In the second step, the wind farm is modeled by fuzzy-logic framework and turbines are controlled based on the predicted parameters for blowing the wind which is obtained from this model. The proposed method has a considerable consistency with the stochastic nature of the wind and its nonlinear treat in a wind farm. Furthermore, it controls turbines by considering their sensor faults and wake effects. Therefore, it harvests more qualified electrical energy compared to existing methods.
In the second section of this paper, the proposed algorithm is introduced, including detecting sensor faults by using stochastic models, constructing a fuzzy model for wind farm based on turbine spatial information and finally updating this model based on wind parameters and wake effect. In the third section, three different scenarios, based on real wind blowing conditions, are described to test the proposed algorithm. In the fourth section, the performance of the proposed method is evaluated in the above scenarios. In the fifth section, the obtained results are compared with the results of existing methods by using their effective parameters. The conclusion is presented in the last section of the paper.

2. Materials and methods

As shown in Fig. 1, suppose a wind farm containing wind turbines, which their polar coordinates are as:

$$X_i=[r_i,\theta_i]^T,\quad i=1,2,...,N \tag{1}$$

where X_i represents the position of turbine i in wind farm. Each turbine is equipped with an anemometer and vane to measure velocity and direction of its received wind in time slot t:

$$\omega_{jt}=[v_{it},\phi_{it}]^T,\quad i=1,2,...,N,\quad 0\le t<T \tag{2}$$

Furthermore, the wind farm is covered using M pairs of external anemometers and vanes which are located at positions:

$$X'_j=[r'_j,\theta'_j]^T,\quad j=1,2,...M \tag{3}$$

Using the external sensor j the velocity and direction of blowing wind in each time slot are measured as:

$$\omega'_{jt'}=[v'_{jt'},\phi'_{jt'}]^T,\quad j=1,2,...,M,\quad 0\le t'\le t<T \tag{4}$$

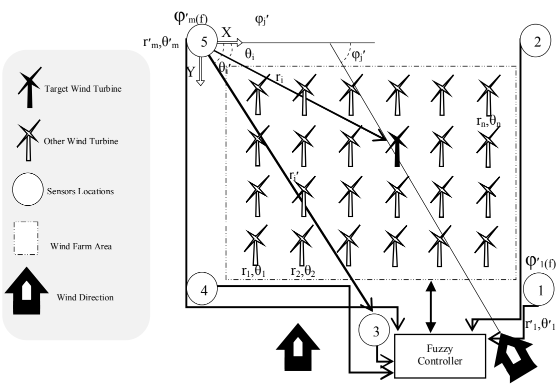


Fig. 1. Topology of turbines and sensors.

2. 1. Vane fault detection

Let $\{\phi_{it}\}$ be a time sequence of wind directions which are received by turbine i constructed from its vane measurements during time period $[0\ t]$.

$$\{\phi_{it}\}=\{\phi_{i0},\phi_{i1},...\phi_{it}\} \tag{5}$$

To determine the dependence probability of $\phi_{i(t+1)}$ to correct blowing wind or faulty measurement, its history is supposed as a stochastic process with a distribution function:

$$\beta(\phi_{i0},\phi_{i1},...\phi_{it}\mid\gamma_{it1},\gamma_{it2},...\gamma_{ito},..\gamma_{itO}) \tag{6}$$

In the above equation, γ_{ito} is the distribution parameter of $\beta(.)$ which may be estimated based on $\{\phi_{it}\}$. For brevity γ_{ito} parameters are shown as:

$$\gamma=\{\gamma_{it1},\gamma_{it2},...\gamma_{ito},..\gamma_{itO}\} \tag{7}$$

Eqs. (6) and (7) may be combined as:

$$\begin{aligned}&\beta\ (\varphi_{i0},\varphi_{i1},...,\varphi_{it}\ \mid\gamma)=\\&\beta\ (\varphi_{i0}\mid\gamma).\ \beta\ (\varphi_{i1}\mid\gamma)...\beta\ (\varphi_{it}\mid\gamma)\end{aligned} \tag{8}$$

The likelihood function $L(.)$ is defined as:

$$\begin{aligned}&L(\gamma\mid\phi_{i0},\phi_{i1},...,\phi_{it})=\\&\beta(\phi_{i0},\phi_{i1},...,\phi_{it}\mid\gamma)=\prod_{t''=0}^{t}\beta(\phi_{it''}\mid\gamma)\end{aligned} \tag{9}$$

Equation (9) may be re-written as sum of probability distribution components in logarithmic form as:

$$\ln\ (L\ (\gamma\mid\varphi_{i0},\varphi_{i1},...,\varphi_{it}))=\sum_{t'=0}^{t}\ \ln(\beta(\varphi_{it'}\mid\gamma)) \tag{10}$$

Therefore, the likelihood function may be estimated as:

$$\hat{L}=\frac{1}{t+1}\ln\ (L(\gamma\mid\varphi_{i0},\varphi_{i1},...,\varphi_{it})) \tag{11}$$

Based on maximum likelihood estimation, γ is estimated as [16-17]:

$$\hat{\gamma}=\arg\max\ (\hat{L}(\gamma\mid\varphi_{i0},\varphi_{i1},...,\varphi_{it})) \tag{12}$$

Substituting the above estimated parameters in Eq. (6) leads to determine belonging of $\phi_{i(t+1)}$ to correct or faulty measurements by defining $Z(\phi_{i(t+1)})$ as:

$$Z(\phi_{i(t+1)})=P(\phi_{i(t+1)}\,|\,\beta(\phi_{i0},\phi_{i1},...\phi_{it}\,|\,\gamma)) \qquad (13)$$

In the above equation, P is the probability of depending $\phi_{i(t+1)}$ to $\beta(.)$. Finally the decision Eq. (14) associates $\phi_{i(t+1)}$ to fault measurement set $\{\chi_t\}$ if its probability of dependence to stochastic model $\beta(.)$ is less than the threshold η.

$$\chi_t=\begin{cases} i & Z(\phi_{i(t+1)})<\eta \\ \Phi & otherwise \end{cases} \qquad (14)$$

2. 2. Wind farm fuzzy clustering

The wind energy which is received by each turbine is tightly associated with velocity and direction of wind received by it. Based on Eqs. (2) and (4), let $\Delta\phi'_{ijt}$ and $\Delta v'_{ijt}$ be velocity and direction differences between turbine i and external sensor j. Therefore, a $2M+1$ dimensional feature vector f_{it} may be constructed for turbine i as:

$$\begin{gathered} f_{it}=[r_i,\Delta\phi'_{i1t}..\Delta\phi'_{ijt}..\Delta\phi'_{iMt},\Delta v'_{i1t}..\Delta v'_{ijt}..\Delta v'_{iMt}] \\ i=1,2,...,N,\ j=1,2,...,M,\ 0\le t\le T \end{gathered} \qquad (15)$$

The feature space F_t which is the set of all f_{it} vectors is defined as:

$$F_t=\{f_{1t},f_{2t},...,f_{kt},...,f_N\,|\,f_{kt}\in R^{2M+1}\} \qquad (16)$$

Based on this fact that the wind farm is affected with several wind fronts, F_t may be partitioned into different clusters in such way that all turbines of each cluster receive the similar wind. If each cluster considered as a fuzzy set of some turbines, then a fuzzy entropy function E_t may be defined for the entire wind farm as [18]:

$$\begin{gathered} E_t=\sum_{q=1}^{Q_t}\sum_{k=1}^{N}p_{qkt}.\log p_{qkt} \\ 1<q<Q_t\ ,\ 1<k<N \end{gathered} \qquad (17)$$

This function explains the uncertainty in belonging of turbine k, with feature vector f_{kt} to clusters and may include values in the range $\left[0\ \frac{1}{N}\right]$. Furthermore, Q_t and p_{qkt} represent the number of clusters and probability of belonging turbine k to cluster q in each time slot t which constructs the belonging probability matrix as:

$$P_t=\begin{bmatrix} p_{11t} & p_{12t} & \cdots & p_{1kt} & \cdots & p_{1Nt} \\ p_{21t} & p_{22t} & \cdots & p_{2kt} & \cdots & p_{2Nt} \\ \vdots & & & & & \\ p_{q1t} & p_{q2t} & \cdots & p_{qkt} & \cdots & p_{qNt} \\ \vdots & & & & & \\ p_{Q_t1t} & p_{Q_t2t} & \cdots & p_{Q_tkt} & \cdots & p_{Q_tNt} \end{bmatrix} \qquad (18)$$

Now let the fuzzy decision function to be defined in terms of a mean of fuzzy weighted distances and fuzzy entropy function of the wind farm as:

$$\begin{gathered} G(P_t,\mu_t,F_t)=\sum_{q=1}^{Q_t}\sum_{k=1}^{N}p_{qkt}\left\|f_{kt}-\mu_{qt}\right\|^2 \\ +N.\sum_{q=1}^{Q_t}\sum_{k=1}^{N}p_{qkt}.\log p_{qkt} \end{gathered} \qquad (19)$$

where μ_t shows a vector contacting centers of clusters - e.g. μ_{qt} - in time t. Minimizing the above function leads to obtaining the probability of belonging turbines to clusters as [19]:

$$p_{qkt} = \left(\sum_{q'=1}^{Q_t} \left[\frac{e^{\|f_{kt}-\mu_{qt}\|}}{e^{\|f_{kt}-\mu_{q't}\|}} \right]^{1/Q_t} \right)^{-1} \tag{20}$$

To determine the number of clusters in each time slot, e.g. Q_t, firstly the scattering of clusters is defined as:

$$S(Q_t) = \frac{\sum_{q=1}^{Q_t} \|\sigma_{\mu_{qt}}\|}{Q_t \|\sigma_{F_t}\|} \tag{21}$$

In above equation members of $\sigma_{\mu_{qt}}$ are:

$$\sigma^l_{\mu_{qt}} = \frac{1}{N} \sum_{k=1}^{N} p_{qk} (f^l_{kt} - \mu^l_{qt})^2 \tag{22}$$

where μ^l_{qt} is member l of μ_{qt} and $1 < l < 2M + 1$. Also σ_{F_t} represents the variance of F_t and $\|\sigma_{F_t}\|$ is computed as:

$$\|\sigma_{F_t}\| = (\sigma^T_{F_t} . \sigma_{F_t})^{1/2} \tag{23}$$

The second term which may be computed in determining Q_t is distance function:

$$D(Q_t) = \frac{D_{\max t}}{D_{\min t}} \sum_{q=1}^{Q_t} \left(\sum_{q'=1}^{Q_t} \|\mu_{qt} - \mu_{q't}\| \right)^{-1} \tag{24}$$

where $D_{\max t}$ and $D_{\min,t}$ are determined as:

$$\begin{aligned} D_{\max t} &= \max(\|\mu_{qt} - \mu_{q't}\|) \\ D_{\min t} &= \min(\|\mu_{qt} - \mu_{q't}\|) \\ &\forall q, q' \in \{1,2,3,\dots Q_t\} \end{aligned} \tag{25}$$

To construct or maintain the best clusters they must be determined in such way that each cluster has maximum compactness and maximum separation with other clusters. For this purpose, the function $\Lambda(Q_t)$ estimates the number of clusters by combining two criterions which were introduced in the Eqs. (21) and (24).

$$\Lambda(Q_t) = \iota . S(Q_t) + D(Q_t) \tag{26}$$

where ι is a regulating parameter which modifies the weights of compactness and separation in determining the number of clusters. Therefore, Q_t may be obtained as:

$$\begin{aligned} &\xi_t = \left[\Lambda(Q_{\min,t}), \dots, \Lambda(Q'_t), \dots, \Lambda(Q_{\max,t}) \right] \\ &\{Q_t = Q'_t \mid \Lambda(Q'_t) = \min(\xi_t)\} \end{aligned} \tag{27}$$

Therefore, in each time slot, the wind farm is partitioned into Q_t fuzzy clusters as:

$$C_t = \{c_{1t}, c_{2t}, \dots c_{qt}, \dots c_{Q_t t}\} \tag{28}$$

where c_{qt} represents cluster q that contains N_{qt} feature vectors.

$$\begin{aligned} &c_{qt} = \{f'_{q1t}, \dots, f'_{qnt}, \dots f'_{qN_{qt}t}\} \\ &f'_{qnt} = [f_{kt} \mid p_{qkt} = \max(p_{q'kt}),\ 1 \le q' \le Q_t] \end{aligned} \tag{29}$$

2. 3. Decision and control

By combining Eqs. (14) and (28-29) each cluster of turbines, e.g. c_{qt}, is partitioned into two subsets χ_{qt} and χ'_{qt} which the first one contains the index of turbines of cluster q with faulty vane measurements and the second one represents the index of turbines without faulty measurements in the same cluster.

$$\begin{aligned} &\chi_{qt} = \{i' \mid f_{i't} \in c_{qt}, i' \in \chi_t\}, \\ &\chi'_{qt} = \{i'' \mid f_{i''t} \in c_{qt}, i'' \notin \chi_t\} \end{aligned} \tag{30}$$

To detect the yawing faults firstly the efficiency of non-vane-fault turbines in each cluster is computed as:

$$R_{qt}=\left\{R_{qi''t}=\frac{V_{i''t}}{\Omega(v_{i''t})}\,|\,f_{i''t}\in c_{qt},i''\in\chi'_{qt}\right\} \tag{31}$$

Where $V_{i''t}$ and $\Omega(v_{i''t})$ represent the obtained and the expected voltages from the non-vane-fault turbine i'' in time slot t. It is important that the expected voltage of each turbine, e.g. $\Omega(v_{i''t})$, is obtained as a function of the velocity of its received wind, e.g. $V_{i''t}$, by utilizing its standard curve. Using $V_{i''t}$ in calculating of efficiency allows it to include the wake effects of turbines. By applying the threshold α, the set χ'_{qt} is partitioned into two subsets χ''_{qt} and $\overline{\chi''_{qt}}$ which the first one contains the index of low efficient turbines encountered with yawing faults and the second one represents the index of turbines without such a fault:

$$\chi''_{qt}=\{i'''\,|\,R_{qi'''t}\le\alpha\},\qquad \overline{\chi''_{qt}}=\{i'''\,|\,R_{qi'''t}>\alpha\} \tag{32}$$

Based on Eqs. (30) and (32), the sets χ_{qt} and χ''_{qt} contain turbines with vane and yawing faults respectively, and therefore, they are controlled by using the predominant wind information of their cluster, e.g. q, instead of their installed sensors. To perform this control an allocated Neuro-fuzzy model is constructed for each c_{qt} only based on its $\overline{\chi''_{qt}}$ subset, e.g. turbines with neither vane nor yawing faults. The Takagi-Sugeno neuro-fuzzy model [20] which is shown in Fig. 2 is updated in successive time slots to regulate nacelle direction ε_{qt}. Having the time sequence of velocity and direction of the blowing wind in each cluster, the fuzzy rules of this model may be explained as [21]:

$$\begin{aligned}&If\ v_{qt''} is\ A_1\ and \phi_{qt''}\ is B_1\Rightarrow h_1=\lambda_1x+\psi_1y+\tau_1\\&If\ v_{qt''}\ is\ A_2\ and\phi_{t''}\ is B_2\Rightarrow h_2=\lambda_2x+\psi_2y+\tau_2\end{aligned} \tag{33}$$

In the above equations A_1, A_2, B_1 and B_2 show the fuzzy rules of the Takagi-Sugeno model. Based on the Neuro-fuzzy theorem ε_{qt} may be estimated as:

$$\begin{aligned}\varepsilon_{qt}=&\overline{w_1}v_{qt''}\lambda_1+\overline{w_1}\phi_{qt''}\psi_1+\overline{w_1}\tau_1+\\&\overline{w_2}v_{qt''}\lambda_2+\overline{w_2}\phi_{qt''}\psi_2+\overline{w_2}\tau_{22}\end{aligned} \tag{34}$$

In equation above the model parameters are divided in two groups: the linear premise parameters $O_1=(\lambda_1,\lambda_2,\psi_1,\psi_2,\tau_1,\tau_2)$ and consequent parameters $O_2=(\overline{w_1},\overline{w_2})$ with nonlinear nature. The premise parameters are estimated by using minimum square error algorithm while the steepest descent algorithm is utilized for estimation of consequent parameters.

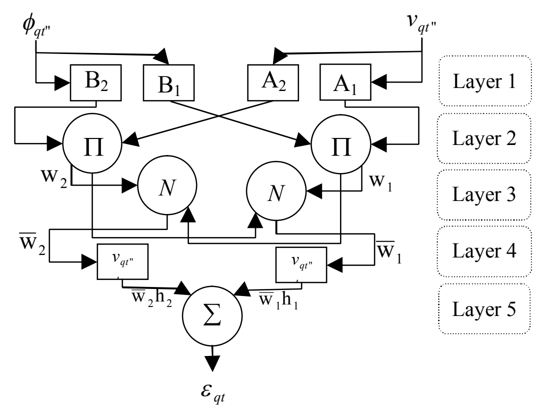


Fig. 2. Takagi-Sugeno neuro-fuzzy model for cluster q of turbines in wind farm.

3. Proposed model

The proposed algorithm was evaluated using simulation. The simulation was carried on a wind farm which contained 24 wind turbines and equipped with 5 external sensors around with equal distances. The topology of the simulated wind farm, sensors and turbines are shown in Fig. 1. The proposed method was implemented by using Matlab 2009 on a PC with a six-core CPU with 2.40GHz processor and 32 GB RAM. Furthermore, two recent algorithms were implemented to compare with the proposed method. The first alternative algorithm was "fuzzy gain-scheduled active fault-tolerant control of a wind turbine" which has been introduced in [22] and is called AFTCS for brevity in this article. The second one was "control strategy of maximum wind energy capture of direct-drive wind turbine generator based on neural-network" which has been introduced in [23] and is called MWEC for brevity in this article. Tests were carried on three different scenarios which had been generated using Wind-Pro software. In the first scenario, the low turbulence wind was simulated, while in the second one the simulated blowing winds had high turbulences. Finally, in the third scenario, high turbulence blowing winds were simulated containing several eddy currents. Specifications of the simulated turbines are shown in Table 1.

Table 1. Specifications of simulated turbines.

Specification	Value
Turbine Model	Vestas V100-1.8 MW™
Rated power	1,800 kW
Cut-in wind speed	3 m/s
Rated wind speed	12 m/s
Cut-out wind speed	20 m/s
Wind class	IEC 3A
Rotor diameter	80 m
Swept area	5,027 m²
Air density	1.225
Hub height	80 m

3. 1. First scenario

In the first scenario a long historical record of wind speed with the turbulence bellow 10% and the speed of less than 12 m/s, containing no eddy current were used to simulate the real world condition and to utilize the typical site wind characteristics. In this scenario, wind blows south more than 85% of the time, whereas south-east only 15% within ± 2.3% discrepancy in direction. All the turbines had an average gross yield within -0.2% and +0.7% of the mean gross yield.

3. 2. Second scenario

In the second scenario the blowing winds were simulated with turbulence more than 80% and speed more than 8m/s and like the previous scenario containing no eddy current. Unlike the first scenario, this time wind blows south equal than 40% of the time, whereas south-east 15%, east 23% and north 22% within ±5.8% discrepancy in direction and an average gross yield for all turbines within -0.4% and +1.1% of the mean gross yield.

3. 3. Third scenario

In the third and the most complex scenario the blowing winds were simulated with turbulence and speeds similar to the second scenario but they contain 21% eddy currents. The scenario introduced at a unidirectional wind rose with predominate wind direction perpendicular to the row direction. It means wind blows south equal than 35% of the time, whereas south-east 15%, north-west 14%, east 23% and north 13% within ±9.5% discrepancy all turbine groups had an average gross yield within -0.9% and +1.8% of the mean gross yield.

4. Results

Figure 3 show an example of the results obtained from the first scenario. Figure 3(a) shows a simulated wind during 4950 second period. Figures 3(b), 3(c) and 3(d) show the obtained power by using proposed, AFTCS and MWEC algorithms, respectively. All of above results have been obtained for three sample turbines in front, middle and end of wind farm (e.g. turbines, which have been located at column 2 of first row, column 4 of third row and column 6 of the final row of wind farm).
These figures show using the proposed method which led to a stable electrical power with mean levels equal to 1732, 1683 and 1628 Watts for the above three examined turbines, respectively. The levels of generated powers were obtained typically 1720, 1659 and 1626 Watts by using AFTCS and 1718, 1662 and 1618 Watts by using MWEC. These values have the same order with values obtained using the proposed method. In the same manner, the proposed method achieved maximum variance equals to 16, 18 and 17 Watts for sampled turbines. These parameters were obtained typically 21, 28 and 27 Watts and 24, 31 and 38 Watts by

using AFTCS and MWEC algorithms, respectively. The results which were obtained in this example show when the low turbulence wind blows, the power and uniformity of the generated electricity improve a little by using the proposed method.

Figure 4 show an example of the results obtained from the second scenario. Figure 4(a) shows the simulated wind during 4950 second period. Figures 4(b), 4(c) and 4(d) show obtained power by using proposed, AFTCS and MWEC algorithms respectively, for those three sample turbines which their performances were investigated in section 3.1. These figures show that the proposed method leads to obtain electrical energy with mean powers equals to 1331, 1083 and 979 Watts and maximum variances equal to 31, 67 and 71 Watts for the sampled turbines. The generated powers were 950, 631 and 588 Watts for AFTCS algorithm and 791, 508 and 390 Watts for MWEC algorithm. In parallel with the loss of generated powers, the alternative algorithms showed less uniformity compared with the proposed method in such way that the variances of generated power obtained by using AFTCS were 71, 228 and 329 Watts. These parameters were obtained as 103, 357 and 345 Watts by utilizing MWEC algorithm. The above parameters show that in the second scenario, AFTCS and MWEC algorithms resulted in power levels and uniformities considerably weaker than which were obtained by using the proposed method.

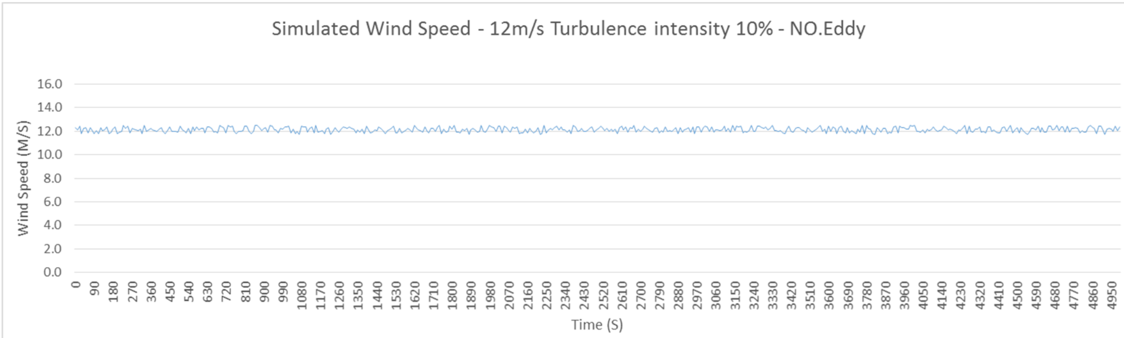
Figure 5 shows an example of the results obtained from the third scenario. Figure 5(a) shows the simulated wind during 4950 second period with eddy current equals to 40% of total time. Figures 5(b), 5(c) and 5(d) show the obtained power by using proposed, AFTCS and MWEC algorithms for those three sample turbines which their performances were reported in the previous sections. These figures show that using the proposed method led to an electrical energy with mean powers equal to 1061, 793 and 638 Watts and maximum variances equal to 60, 83 and 109 Watts for sampled turbines. However, the power levels of generated electricity by using AFTCS were 361, 185 and 160 Watts, while the power levels of generated electricity by using MWEC were 213, 80 and 62 Watts. Furthermore, the variances of the generated electricity by using AFTCS were 162, 31 and 18 Watts while the same parameters for MWEC were 150, 41 and 20 Watts. These parameters show dramatically increases in variance and a considerable decrease in levels of generated power in AFTCS and MWEC algorithms in contrast with the proposed method.

5. Discussion

Three practical wind types were simulated. In the first scenario, the wind maintained low turbulence and its parameters changed slowly while in the second scenario, the wind demonstrated high turbulence and its parameters undergone sudden shifts. Finally, in the last scenario, several eddy currents were added to high turbulence. The proposed, AFTCS and MWEC algorithms were applied to the simulated winds and the results were compared using three standard parameters: i) the mean of generated power, ii) the power uniformity which was indexed by using the variance of the generated electricity, and iii) the error in estimation of the wind speed. The obtained parameters for the entire wind farm in several examined scenarios are shown in Table 2.

These results clearly show the superiority of the proposed method compared to its alternatives in all scenarios. Based on this table, in low turbulence scenario the generated power by using proposed algorithm showed typically 22 and 44 Watts more than those obtained by two alternative algorithms. In the same manner, the variance of the generated electricity by using the proposed method had 8.66 and 21.04 Watts better than the two other algorithms.

Furthermore, the wind estimation error of the proposed method was a little better than the two other algorithms (e.g. 6.03% and 9.14%). All of these low differences show that the examined algorithms worked properly in the first scenario (e.g. normal conditions), but the proposed algorithm resulted in a little better output.



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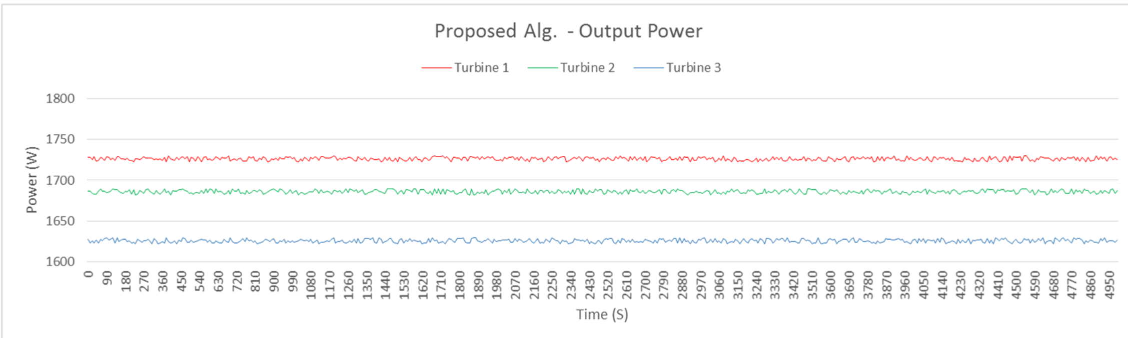

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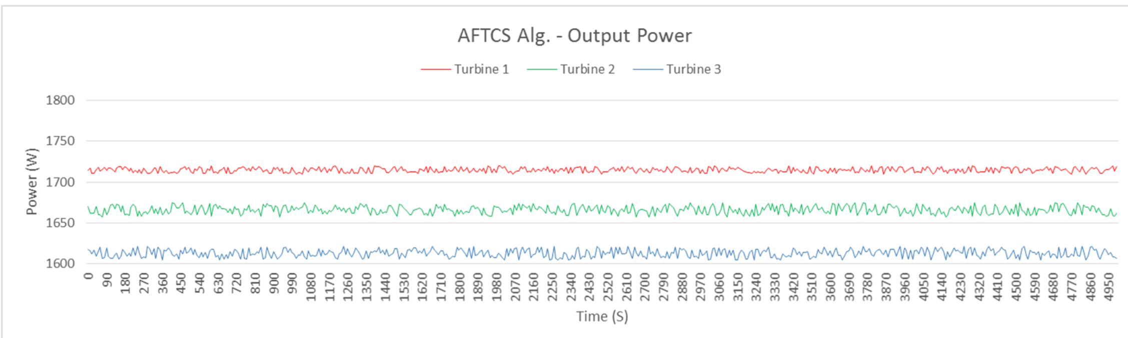

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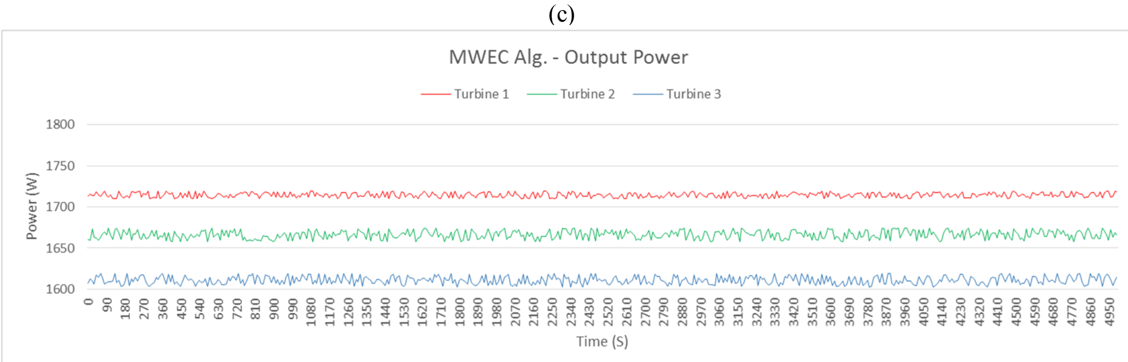


(d)

Fig. 3. An example of the results obtained from the first scenario: (a) the simulated wind and the obtained power by using (b) the proposed method, (c) AFTCS algorithm, (d) MWEC algorithm.

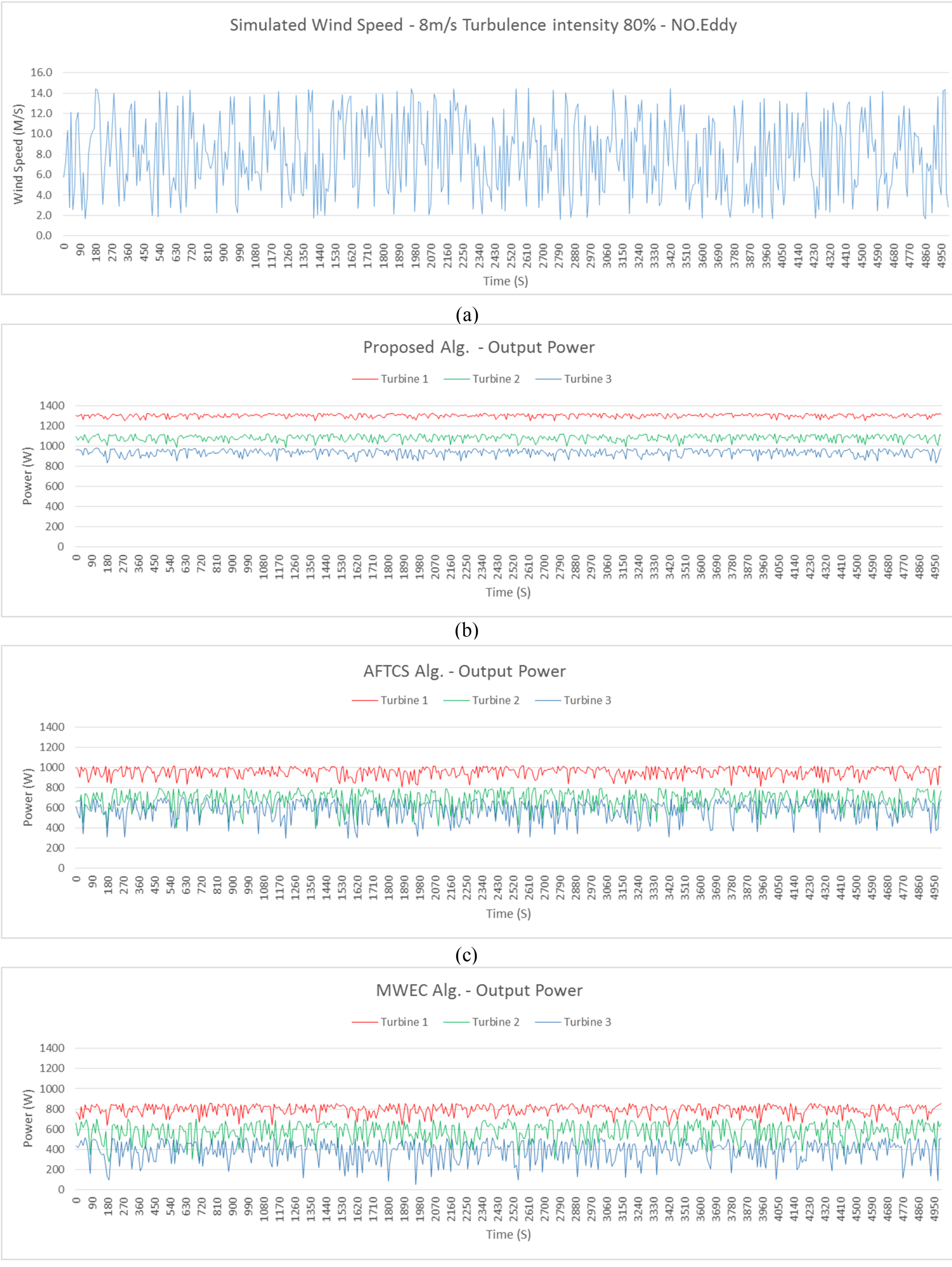
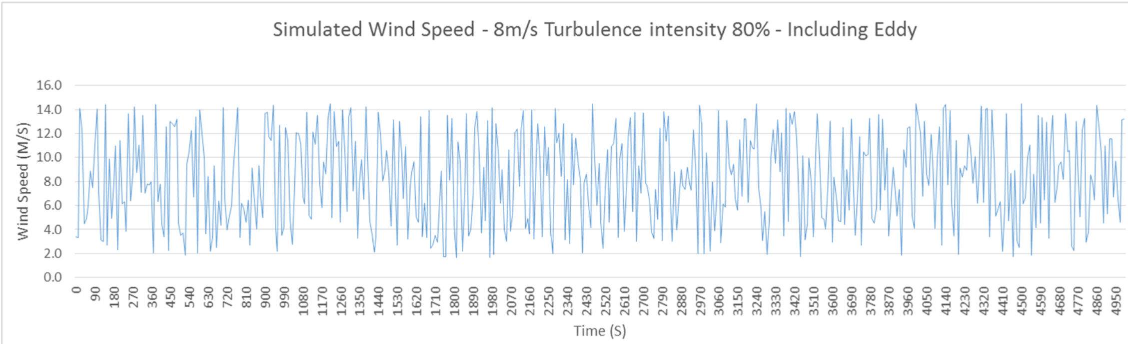


Fig. 4. An example of the results obtained from the second scenario: (a) the simulated wind and the obtained power by using (b) the proposed method, (c) AFTCS algorithm, (d) MWEC algorithm.



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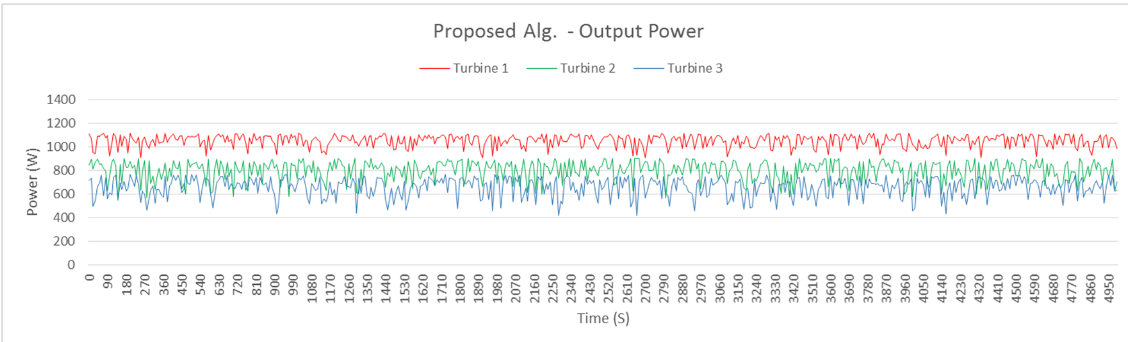
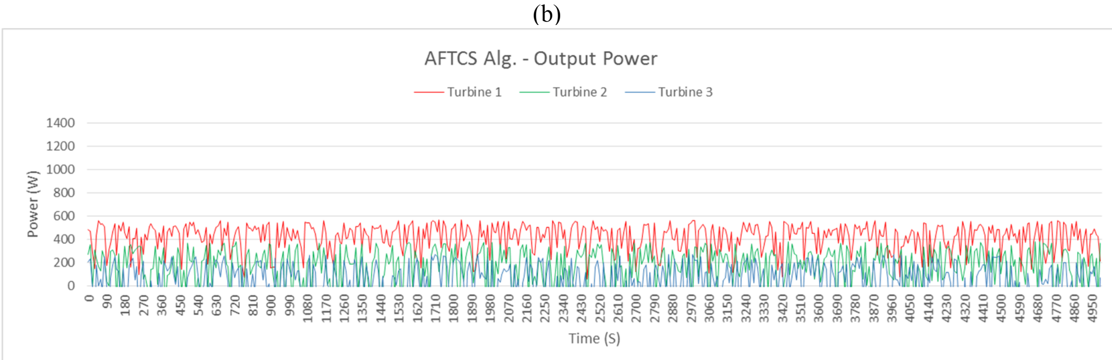
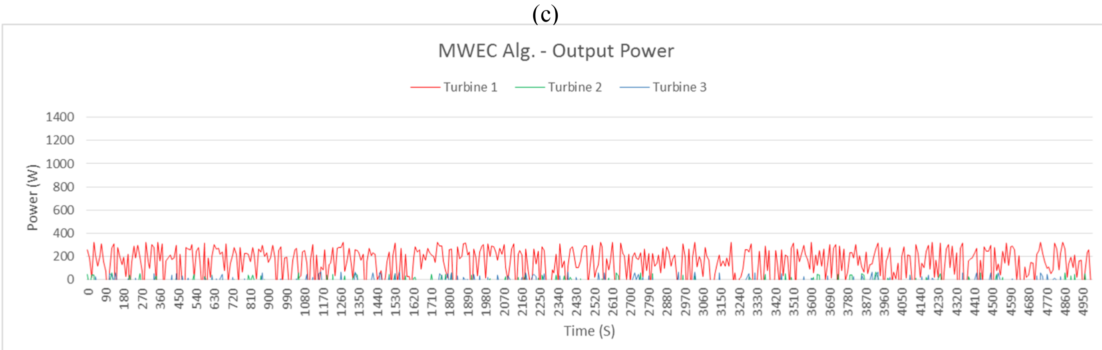


(b)



(c)



(d)

Fig. 5. An example of the results obtained in the third scenario: (a) the simulated wind and the obtained power by using (b) the proposed method, (c) AFTCS algorithm, (d) MWEC algorithm.

Table 2. Comparison of performances of the examined algorithms in different scenarios.

Algorithm	Evaluation Parameters	Simulated Scenarios		
		First	Second	Third
Proposed Algorithm	Power level (W)	1742	1331	1107
	Variance (W)	18.14	68.29	88.07
	Wind Estimation Error (%)	8.17	18.31	44.75
AFTCS Algorithm	Power level (W)	1720	1030	600
	Variance (W)	26.80	294.81	364.70
	Wind Estimation Error (%)	14.20	78.19	182.10
MWEC Algorithm	Power level (W)	1698	870	370
	Variance (W)	39.18	360.92	458.14
	Wind Estimation Error (%)	17.31	153.79	207.25
Proposed Algorithm	Power level (W)	First	Second	Third
	Variance (W)	1742	1331	1107
	Wind Estimation Error (%)	18.14	68.29	88.07

In the second scenario, the power levels of the proposed, AFTCS and MWEC algorithms fell to 411, 690 and 828 Watts (e.g. 23.59%, 40.11%, and 48.7%) compared to their values in the first scenario. The reductions were 6.18%, 20.82% and 37.21% for variance and 10.14%, 63.99%, 136.48% for wind estimation error. Despite these reductions, the mean power of the generated electricity by using the proposed algorithm showed typically 301 and 461 Watts (e.g. 22.6%, 34.6%) superiority compared with the alternative algorithms. Similarly, the variance of the obtained electricity by using the proposed algorithm showed 226 and 292 Watts superiority compared with the other algorithms. Furthermore, wind estimation error of the proposed method was typically 59.2% and 135.4% better than AFTCS and MWEC algorithms. These superiorities are considerably more than which obtained from the previous scenario. In the third scenario, the existence of eddy currents caused the parameters to fall more dramatically.

In the presence of eddy current, the power levels of the proposed, AFTCS and MWEC algorithms fell by 635, 1120 and 1328 Watts (e.g. 36.4%, 65.1%, 78.2%) compared to the first (e.g. the normal) scenario. These declines were 15.2%, 59.7% and 85.1% for variances and 36.5%, 167.9% and 189.9% for wind estimation error. The mean power of the generated electricity by using the proposed algorithm shows typically 507 and 737 Watts superiority compared with two other algorithms. Similarly, the variance of obtained electricity by using the proposed method was 276 Watts and 370 Watts better than the two other algorithms. Finally, the wind estimation error of the proposed method was typically 137.35% and 162.5% better than those of AFTCS and MWEC algorithms.

6. Conclusions

In this paper, a new method was introduced for optimum energy harvest from wind farms. In the proposed method firstly stochastic process was utilized to model the behavior of the blowing wind. By using this stochastic process the fault measurements of turbine sensors were determined. Then fuzzy-logic concept was utilized for modeling and controlling turbines of the wind farm. To evaluate the performance of the proposed algorithm, three scenarios were carried based on the real wind blowing conditions in wind farms. The first scenario belonged to normal conditions in which wind blows with turbulences bellow 10% and speed less than 12 m/s containing no eddy current. In the second scenario, the wind had the turbulence and speed more than 80% and 12 m/s respectively and containing no eddy current. In most complex scenario, several eddy currents were added to the simulated winds of the second scenario. In all scenarios, the performance of the proposed algorithm was compared with two existing methods (e.g. AFTCS and MWEC) using their harvested power, uniformity, and wind estimation error. By exploiting the above parameters the better performance of the proposed algorithm was proved. Results showed that the generated power by using the proposed algorithm in the first scenario was at least 22 Watts more than other examined methods. In the same manner, its uniformity and wind estimation also showed at least 8.66 Watts and 6.03% better than those of other examined methods. In the second scenario, performances of all algorithms fell considerably compared with normal wind conditions (e.g. at least 23.59%, 6.18% and 10.14% for generated power, uniformity and wind estimation, respectively). In parallel with these reductions, the superiority of the performance of the proposed algorithm became more considerable compared to the previous scenario. In this scenario, the generated power, uniformity and wind estimation of the proposed algorithm obtained at least 301 Watts, 226 Watts and 59.2% better than the results of the other examined methods.

The combination of high turbulence wind and eddy currents in the final scenario caused the greatest performance degradations compared with normal wind conditions (e.g. at least 36.4%, 15.2% and 36.5% for generated power, uniformity, and wind estimation, respectively). In this scenario, the generated power, uniformity, and wind estimation of the proposed algorithm had at least 507 Watts, 276 Watts, and 137.35% better than the results of the other examined methods.

These superiorities are excellently more than which obtained in both previous scenarios. Therefore, it may be concluded that as the blowing wind becomes more complicated, the performance of the proposed method shows more gain against the other algorithms and therefore, it may be used as a suitable alternative method for managing wind farms especially at high turbulence or eddy contained wind blowing.

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