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Wind-Based Multi-Regional Modelling and Control of Wind Turbines Generation

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Abstract

Modelling is important in studying systems. It shows the system from different angles, help in analysing and understanding the system, analysis the causes and effects, can discover the defects in the system and treat it, illustrates the alternatives and studies their effects. Research looks for appropriate models of low, medium, high and very high wind speed. ARMA can be used in making time series models. It can get models with similar properties of original data. This research develops several ARMA models for wind speed data classified according to its value in four groups. The least mean square error (MSE) is the criteria to choose between models, for each wind speed model gets the appropriate wind turbine model that tells the predicted output power. The original data is taken to its group according to its value and taken to its appropriate power model. Turbine stops for low and very high speed. MPPT is used for medium speed. High speed models need pitch angle control. The model is implemented to Zafranaa wind speed data. It is divided into three groups. There were no data points for fourth group, Max point was 17m/s. Third group has appropriate amount of data and most of data are in second group, Finally the implementation procedure has demonstrated the applicability of the preferred method only

Keywords: ARMA, low, medium, high and very high speed, MPPT, turbine pitch control

List of abbreviations

ANN	Artificial Neural network
ANSIF	Artificial neuro-fuzzy inference system
ARIMA	Autoregressive integrated moving average
BPNN	back propagation neural network
BT	Bootstrap tree
CGM	Combined Grey model
CNN	Convolution neural network
DGM	Discrete Grey Model
EE	Envelop Elliptic
ELM	Extreme Learning Machine
ICEEMDAN	Improved complete EMD adaptive noise
IF	Isolated forest
GM	Grey model
LSTM	Long short term memory neural network
MLP	Multi-layer perception neural network
NESN-MP	Nonlinear Echo State Network with Multiple Polynomial
NWP	Numerical weather predictions
MAE	Mean absolute error
MPPT	Maximum power point tracking
MSE	Mean square error
PCA	Principal component analysis
RPF	Radial Basic function
RF	Random forest
SDE	Standard deviation of error
SDSE	Standard deviation of square error
SSA	Singular spectrum analysis
SVR	Support vector regression
SVM	Supportive vector machine
SWT	Stationary wavelet transform
VMD	Variational mode decomposition
WNN	Wavelet neural network

1. Introduction

Wind power is one of most important renewable energy that take attention of the world. It has promising future. But there are some factors affect its performance. It has many variables and intermittent, that add more challenges to control the wind turbine, predict wind power and optimise wind farm that effect on power reliability, secure and power system stability. So, researchers are interested with studying wind speed prediction, wind power prediction and different types of wind turbine control.

Time series analysis and prediction has many approaches in research. Different models are using for prediction Pre-processing technique has important role in prediction accuracy. each technique makes different results. Decomposition is used as pre-processing analysis. The original signal is divided into sub signals to reduce nonlinearity and nonstationary in the original signal using different decomposition methods and apply prediction model in each signal alone. EMD divide it to several IMFs and residual [1,2,3]. Each IMF satisfy some conditions residual of data that can't satisfy these conditions take separately group VMD is similar to it in the data but different in conditions that divide the data [1,3,4,5,6,7,8]. WT analysis the signal with several levels of band pass filter [4]. It reduces the noising effect in the signals SWD [1,2] decompose the signal according to several low pass and high pass filters ICEEMDAN modify EMD to do better with noising in the data [6,9]. SSA is also used for decomposition [1]. It consists of both the multivariate statistic and the probability theory.

For power prediction there are two approaches first deal with it as single time series and predict it as wind speed time series or use both wind speed data and wind power data to make power curve model. filtering data such as six sigma, K-mean, IF and others. Segmentation [10] are used as pre-processing techniques. Some research use segmentation for power curve and apply model for each part alone. Partition [11] is used for this by dividing n-objects into equal parts and then apply the same module on it while bagged tree [12] dividing them to equal parts and make each part with the same number as original data by replace from it then applying different module on each tree and finally take the average of all modules. K-mean and k-medoid [13] are also used for segmentation.

Several methods are used for prediction modelling. ANNs with different types (BPNN, CNN, RPF, elc), BPNN has contribution as it adjusts its weights using the back propagation error [1,14,15,4,8]. WNN has the same structure as BPNN but it combines wavelet analysis and ANN [1,9]. LSTM is a member of recruitment neural network that use last states to determine new states Its nodes consist of three gates forget gate, input gate and output gate. Each node has two outputs: output cell and memory cell [3,6]. ELM is a fast Single-hidden Layer Feedforward Neural [1,16] ARIMA are preferred to time series modelling, SVR is preferred for power curve modelling.

Researchers uses different kernel functions such as Linear [12], polynomial [5,12,17], Gaussian or RPF [5,15,12,17], Multi task Gaussian [18], Tanh or sigmoid, Wavelet, Multi regression [5], Spline [16], also RF and CCM are used for modelling. fig. (1) shows various techniques for wind prediction and fig. (2) illustrates the techniques for wind power prediction

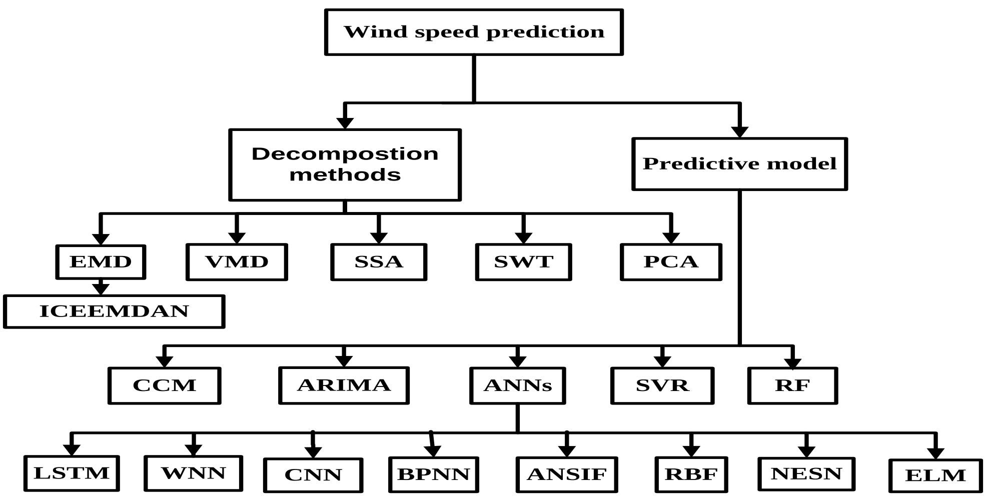

Fig. (1) Review of various techniques for wind speed prediction.

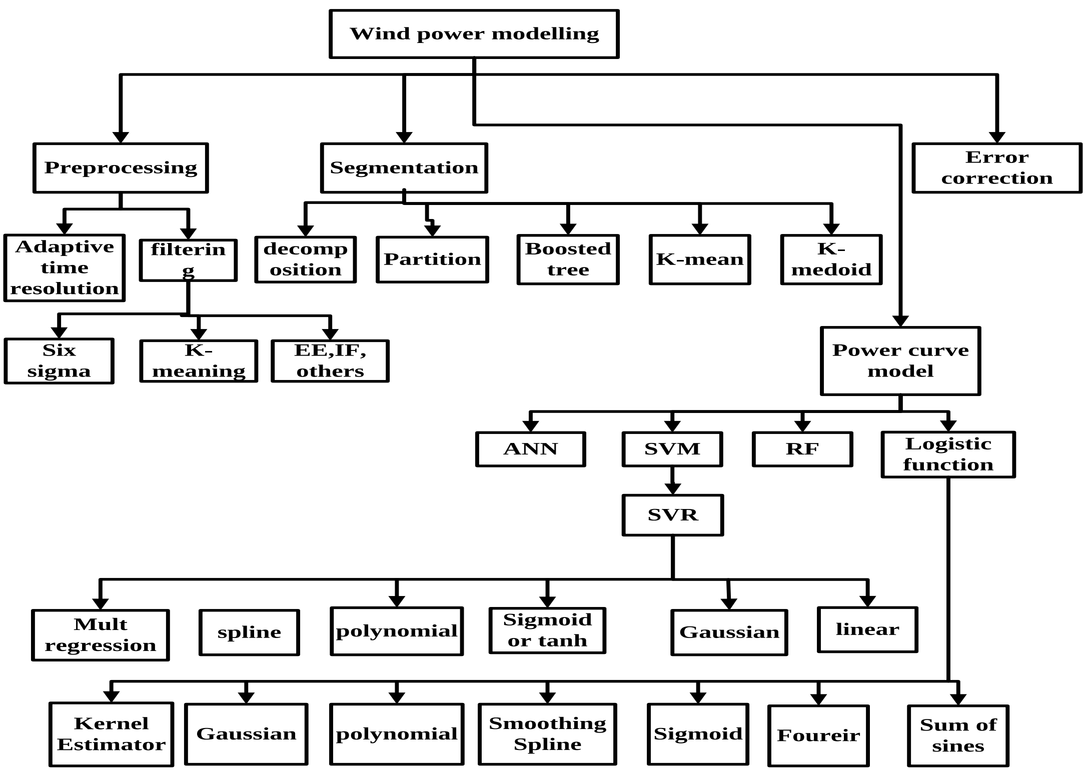

Fig. (2) Various techniques for wind power prediction.

When the wind speed exceeds the cut in speed the turbine becomes able to get output power. In this region the system aims to capture maximum power, so pitch angle is set to zero and input generator torque is controlled to get wr (turbine speed equal optimal speed to get maximum Cp. There are two methods to control torque First OT (optimal torque) [19,20] Second TSR use controller with rotor feedback to compare wg (generator speed) with wopt (optimal angular speed) as input of Tg.d. But in third region when the wind power exceeds the rated wind speed, the system (full load model) aims to keep the generator speed and output power at their rated values. It controls the pitch system to change the turbine efficiency. and to prevent steady state error in power value use also power controller.

Different types of controllers are used for these missions. PI controller is more popular controller than PID. Some researchers improve these controllers by using different algorithms.to choose the best gain of their controller ACO is used [21] to choose the gain of PI controller that achieve the minimum cost for TSR method for speed in second region. different types of optimization algorithm of open loop transfer function (OLTR), Error performance index (EPI) and ultimate cycles (UC) methods are applied to choose gains of PID controller [22]. Ziegler– Nichols (ZN-1) from open loop transfer function methods give the best performance (zero overshoot and small rising time and settling time).

More complicated methods are also used such as Adaptive Fuzzy that has two inputs error and the derivative of error are used in different ways. One of them [23] is to use fuzzy as main controller with 49 rules in addition to model predictive power that illustrate the system behaviour and another way uses it to modify the gain of classic PID controller [24]. Fractional order fuzzy PID [25] combined fuzzy with fractional order PID. In this method fuzzy has two inputs the error signal and fractional derivative of error. Its output determines gains of fractional order PI that gives the result

FFR_OPPT is used to control the speed in second and third region .It takes into account large moment of inertia of turbine rotor so in addition to OPPT method for second region and PI controller for pitch angle in third region, it is modified by visual inertia factor [26] in case of OPPT the value of kopt is modified with this factor and it also used for pitch angle control, it adds controller of virtual inertia factor signal to reference PI controller signal, and the change of pitch angle signal [27] sliding mode control is introduced instead of PID controllers and its schedule gains it produces formula that achieves two conditions in the same time so it move in sliding path for the pitch angle to track the reference angular velocity

Contribution of this study can be summarized as firstly classify the wind speed data according to its value into four groups low, medium, high and very high speed, Use ARMA make models for the three groups then take each model to its appropriate wind turbine model that illustrate the power that can out from each mode.

2. Objective

According to power curve fig. (3), the wind speed can be divided into four zones respect to its value. The data of each zone can be collected and make model represent each group. Each model will go to its appropriate wind turbine model and illustrate the output power that can

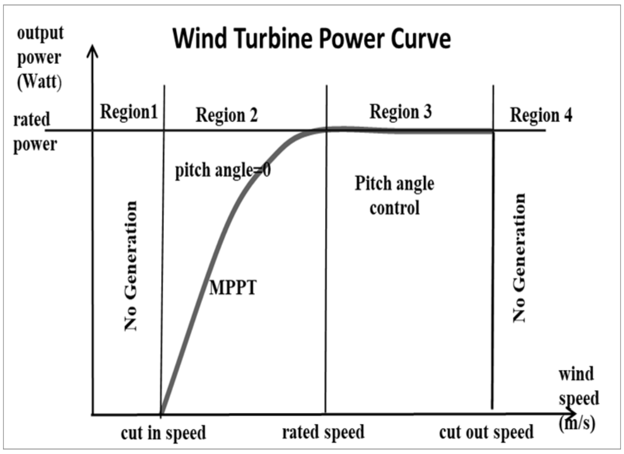

Fig. (3) Multiregional classification of wind turbine operation.

get out from this type of speed that makes it easier to study its effect on the grid and help studying the challenges related to power reliability and power system stability that occur due to wind intermittent

3. Methodology

Wind speed can be classified accordingly to fig. (3) into four regions and make four groups low, medium, high and very highly and make model represent each group. An autoregressive moving-average process (ARMA process) of order (p, q). ARMA Model has simple form and can get similar properties: similar mean similar correlation, similar standard deviations and similar probability distribution function. It can be good representor about historical time series [28]. It is a good choice for inaccurate data that has some missing value and problems related to sensor defects

To find appropriate model, proposed method changes the orders of AR (p) and MA(q) from 1to 10 and use likelihood method to estimate its parameters, then compare original data and simulated with each other, and calculate error signal and square error signal and their standard deviations. (MAE), (SDE), MSE and SDSE are the meters that represent the criteria of choosing the orders of ARMA, Models that give the least MAE, SDE, MSE, and SDSE are chosen as best models, then each model goes to its appropriate wind turbine model. Supervisory control stops wind turbine in both Zone1 that has low speed and Zone4 that has very high speed. Turbine operates in other two regions

In Zone2 maximum power point tracking method is the desired method. rotor speed should get the optimal rotor speed which give optimal turn speed ratio and get maximum efficiency, but Zone3 makes pitch angle control. Pitch angle changes to reduce C_p to set rotor speed at its dated value and set the power at rated power.

fig. (4) shows the steps of methodology and fig. (5) illustrates the wind turbine model for each zone.

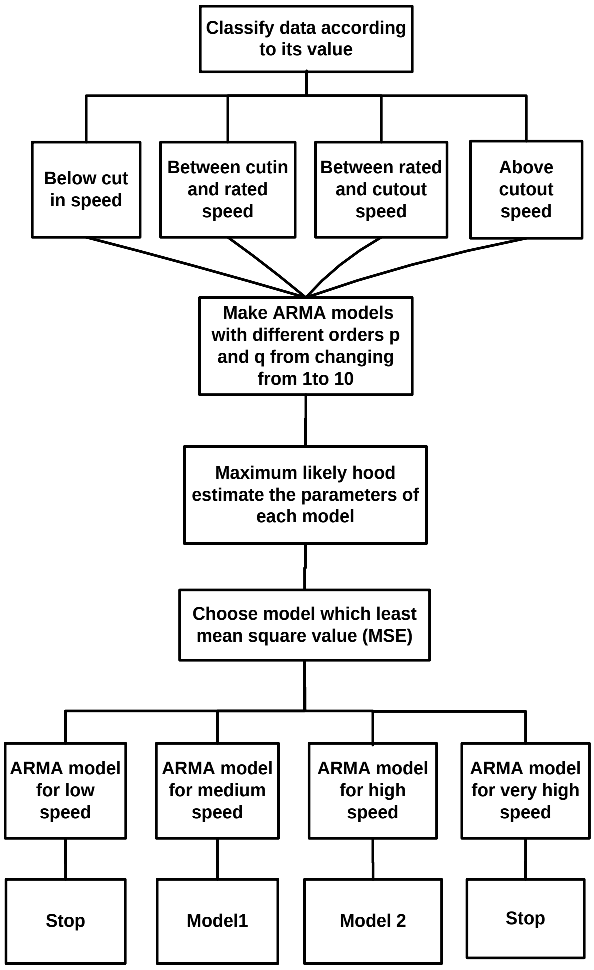

Fig. (4) Developing of low, medium, high and very high speed ARMA models of wind speed generation.

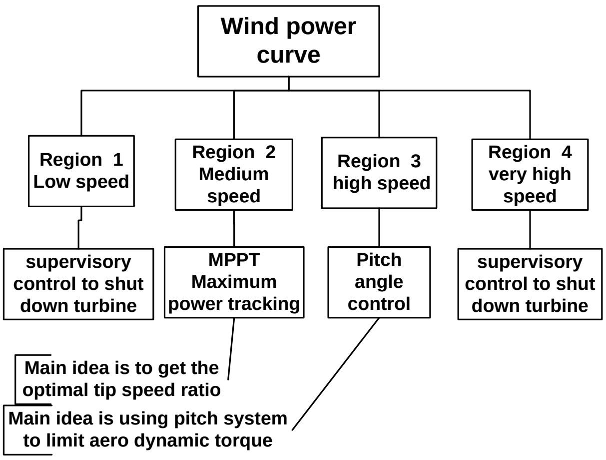

Fig. (5): Various techniques of Wind turbine controllers.

4. Proposed Wind Speed and Power Model

ARMA model that used to represent the data can be illustrated by this equation

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-1} + \cdots + \phi_p X_{t-p} + \theta_0 Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} + c \qquad (1)$$

Where X_{t-1}, X_{t-2}, X_{t-3},… are previous value of time series and Z_t, Z_{t-2},Z_{t-3},… are white noise representing the moving average of time series value. ϕ_1, ϕ_2, ϕ_3,…, θ_0, θ_1, θ_2, …. , and C are constants determine by fitting the model into the data using maximum likelihood method first deduce the unconditional disturbances from the regression model. deduce the residuals of the ARIMA error model using conditional density can be given

$$f(X_t|X_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_t^2}} exp(-\frac{(x_t-\mu)^2}{2\sigma_t^2}) \qquad (2)$$

Use the distribution of the innovations to build the likelihood function for T number of samples that can be represented by

$$L(\mu,\sigma|x) = f(x_1,x_2,\dots,x_T)\prod_{t=1}^{T} f(x_t|X_{t-1}) \qquad (3)$$

And its log-likelihood function will be

$$logL(\mu,\sigma|x) = -\frac{T}{2}log2\pi - \frac{T}{2}\,log\sigma^2 + \frac{1}{2}\sum_{t=1}^{T} - \frac{(x_t-\mu)^2}{2\sigma^2} \qquad (4)$$

Maximize the loglikelihood function with respect to the parameters using ordinary least square method. The mean absolute error (MAE), absolute error standard deviation (SDE), mean square error (MSE) and square error standard deviation (SDSE) can use them as criteria to determine the orders of ARMA, choose models which give least values

$$MAE = \frac{1}{T}\sum_{i=1}^{T}|X_i - X_i^m| \qquad (5)$$

$$SDE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left((X_i - X_i^m) - \frac{1}{T}\sum_{i=1}^{T}(X_i - X_i^m)\right)^2} \qquad (6)$$

$$MSE = \frac{1}{T}\sum_{i=1}^{T}(X_i - X_i^m)^2 \qquad (7)$$

$$SDSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left((X_i - X_i^m)^2 - \frac{1}{T}\sum_{i=1}^{T}(X_i - X_i^m)^2\right)^2} \qquad (8)$$

Wind turbine model can be illustrating by different system; aerodynamic mechanical, pitch angle and converter systems. Aero dynamic system of is main system that wind turbine is founded accordingly. The aero dynamic output power can be expressed as

$$P_{aer} = \frac{1}{2}A\rho\, C_p(\lambda,\beta)v^3 \qquad (9)$$

where A is the swept area, ρ is the air density, v is wind speed and C_p is the power efficiency. Its value depends on two factors pitch angle and tip speed ratio. Tip speed ratio is the ratio between the linear speed of tip blade which can be expressed as $\lambda = \frac{\omega_r R}{v}$ where w_r is the rotor angular velocity and R is the radius of the blade C_p can be represented by

$$c_p = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{\frac{-21}{\lambda_i}} + 0.0068\lambda \quad (10)$$

where

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + .08\beta} - \frac{0.035}{\beta^3 + 1} \quad (11)$$

The aerodynamic torque can be calculated from

$$T_{aer} = \frac{P_{aer}}{\omega_r} = \frac{1}{2}A\rho R\, C_q(\lambda,\beta)v^2 \quad (12)$$

where

$$C_q(\lambda,\beta) = \frac{C_p(\lambda,\beta)}{\lambda} \quad (13)$$

Characteristics of wind turbine can be illustrated by power curve fig. (3) can divide wind speed accordingly into four zones with special operation for each of them

First region below cut in speed. In this region the output power can't overcome the losses in the system. The turbine is shut down in this region.

Second region when the speed exceeds the cut in speed but still below rated speed, the system tries to capture maximum wind power. It tries to track maximum efficiency C_{pmax}. Maximum efficiency achieved when Pitch angle is set to zero and rotor angular speed becomes optimal rotor angular velocity (wopt). It can be represented by $\varpi_{opt} = \frac{\lambda_{opt} V}{R}$, Torque control has either optimal torque (OT) method with assume the desired torque is function of squared rotor speed or by Tip Speed Ratio (TSR) method by comparing the optimal rotor speed with actual rotor speed and using it as error signal to different types of controllers that determine the value of torque illustrated by fig. (6).

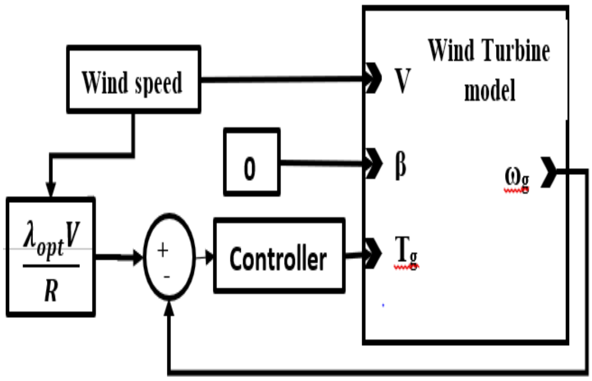

Fig. (6) Tip speed ratio (TSR) method of wind turbine.

In third region when wind speed exceeds the rated speed. Wind power that can be extracted exceeds the rated of turbine, so the system tries to reduce power coefficient C_p to set the output power at rated value and prevent the rotor speed from exceeding its rated value. Speed controller or power controller or both in some applications are used. Its main idea to change beta to track the reference rotor speed and rated power. sometimes power didn't match the rated power, so power controller is used to improve steady state error illustrated by fig. (7)

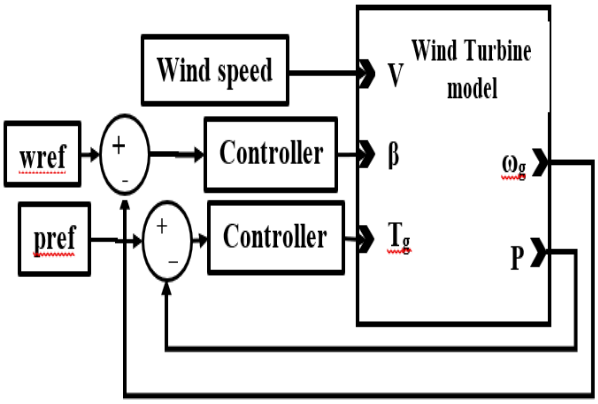

Fig. (7) Wind turbine full load control.

5. Application

Historical wind data used in this paper belongs to Zafaranaa which located in Red Sea region in Egypt. Data is taken from weather underground website It was recorded in June 2014 with 10 min horizon around 4321 samples. Missing data is calculated by mathematical algorithm. Maximum point in the data is 17 m/s. There aren't any points for fourth region, so there aren't any ARMA models that done for this region. ARMA models is done for three Zones. Wind turbine data are radius (R) is 34.5 m, three blades, swept area 3,739.2 m², max rotor speed 2.61 rad/s, rated power 1.5MW, rated speed 11.1, and air density(ρ) is1.225. Optimal tip speed ratio assumed to be 8.1.

For low speed the output power is very low, so the turbine is shut down the search doesn't make power model for low-speed models. Second models for medium speed go to MPPT as their wind turbine model. This model tries to get maximum power efficiency $C_p = 0.48$, so it sets pitch angle to zero β=0 and make rotor angular speed equal optimal angular speed to achieve optimal Tip speed ratio. The output power has wide range of variation. It changes from approximately zero to rated power 1.5e6 illustrated by fig. (8). Third models for high speed when speed exceed the rated value aim to fix angular rotor speed at its rated value 2.61 which decrease the tip speed ratio as wind speed increases. The power efficiency C_p is changing to keep output power at rated value 1.5MW by changing the value of pitch angle. It has low band of variation around the rated values. This region is illustrated by fig. (9). Wind turbine shut down for speeds in fourth region when wind speed exceeds cut-out speed.

Table (1) Best models results for Low-speed models

Error	Error.std	MSE	SE.std	P	Q
-0.00481	1.66027	2.746569	3.889226	6	2
0.696854	1.462791	2.617639	3.370598	7	3
0.156013	1.498418	2.261491	3.168116	6	9
0.026456	1.608415	2.578361	3.037089	3	10
-0.029	1.579451	2.486499	3.286755	1	4
0.011656	1.763498	3.098836	4.314837	5	2
-0.31854	1.57635	2.577379	3.203313	5	3
0.725502	1.522386	2.835647	3.887012	2	10
-0.14575	1.542786	2.39284	3.1665	1	10

Table (2) Best models results for medium speed models

Error	Error.std	MSE	SE.std	P	Q
0.00368	1.955316	3.822035	5.117032	2	1
-.00077	2.148688	4.615362	5.709494	2	9
0.002686	2.172236	4.717087	6.130802	3	9
0.113354	2.0334709	4.146512	5.6232165	6	1
0.003938	2.057771	4.233063	6.083199	8	10
0.023722	2.028364	4.113491	5.963173	2	3
0.063216	2.066407	4.27265	5.552986	3	7
-0.19567	2.027527	4.147819	5.439338	10	5
0.002468	2.27076	5.154683	6.752608	10	2

Table (3) Best models results for high-speed models

Error	Error.std	MSE	SE.std	P	Q
0.30334	1.548168	2.486342	3.352032	1	10
0.00056	1.792192	3.208602	5.089342	5	10
-0.06124	1.678329	2.817603	3.696689	2	4
-0.49743	1.587952	2.7664	3.53315	3	4
0.063216	2.066407	4.27265	5.552986	3	7
-0.05033	1.65854	2.750419	3.948215	2	7
0.285996	1.65209	2.808347	3.544647	3	10
-0.57939	1.674196	3.135703	3.787585	8	5
0.000913	1.859339	3.453537	4.582283	9	7

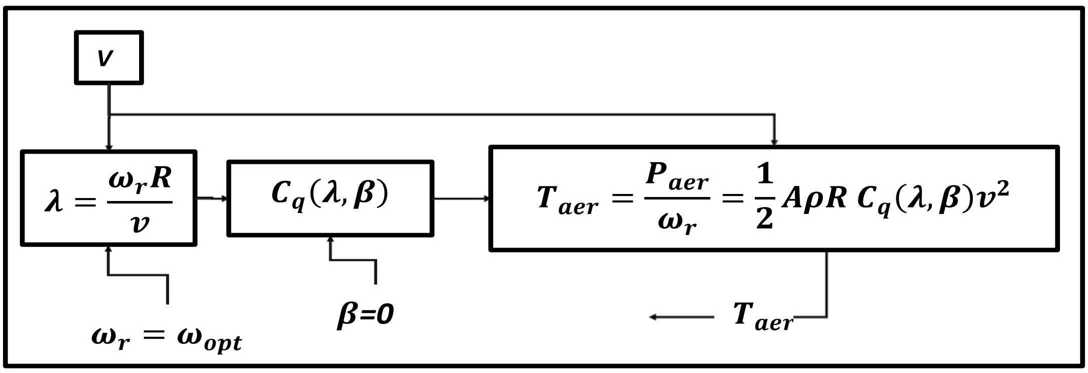

Fig. (8) Second wind turbine operation region control (β=0, ω_r=ω_opt).

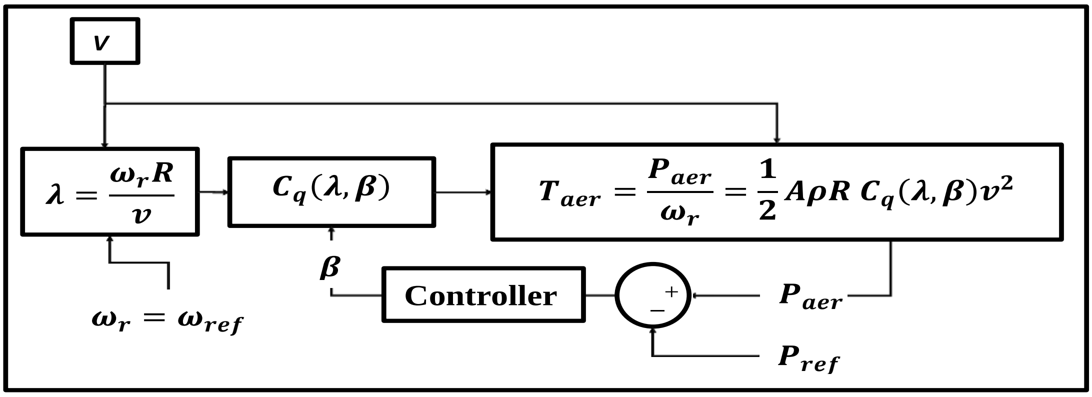

Fig. (9) Third wind turbine operation region control (β changing, $w_r = w_{ref}$).

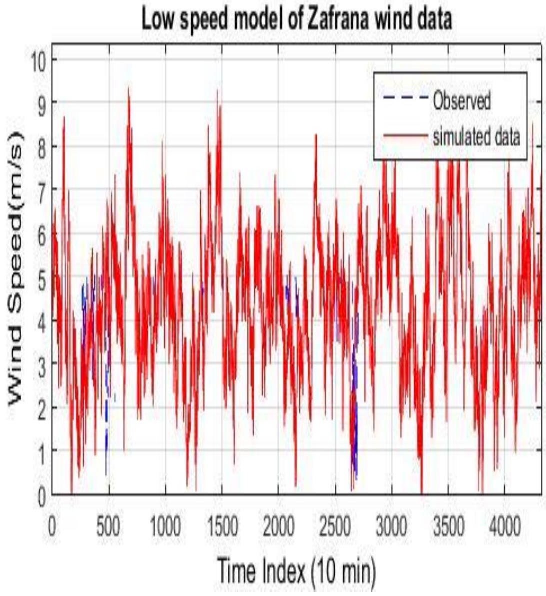

Fig. (10) Least MSE model for low wind speed region.

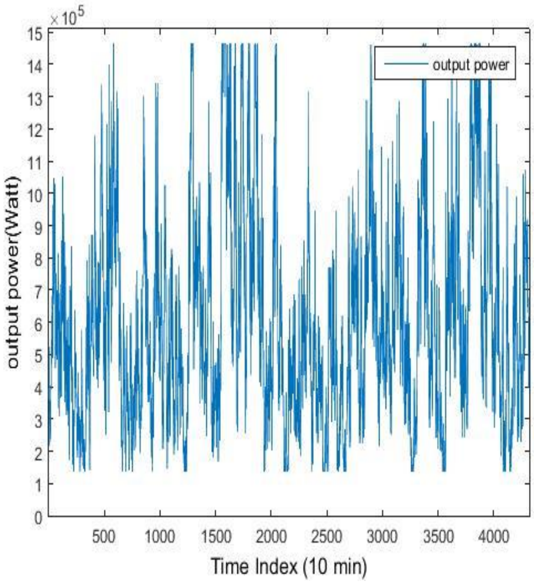

Fig. (12) Predicted output power from medium speed model.

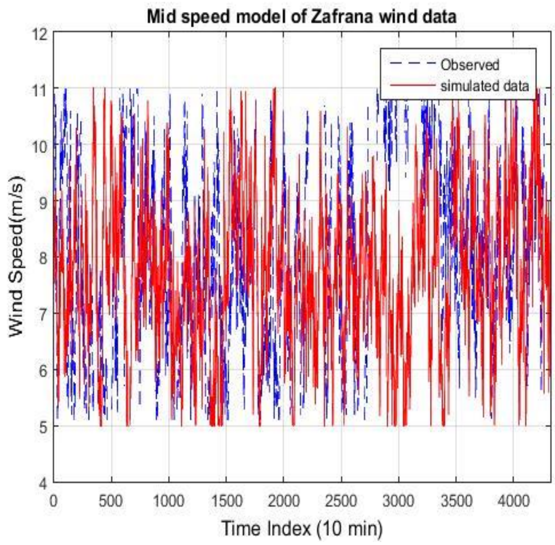

Fig. (11) Least MSE model for medium wind speed region.

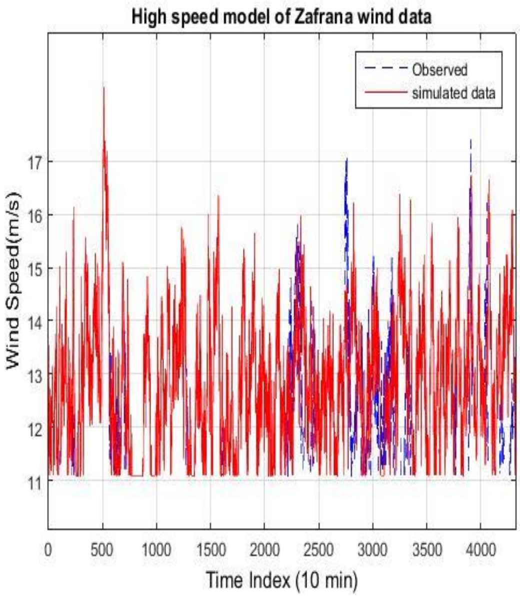

Fig. (13) Least MSE model for high wind speed region.

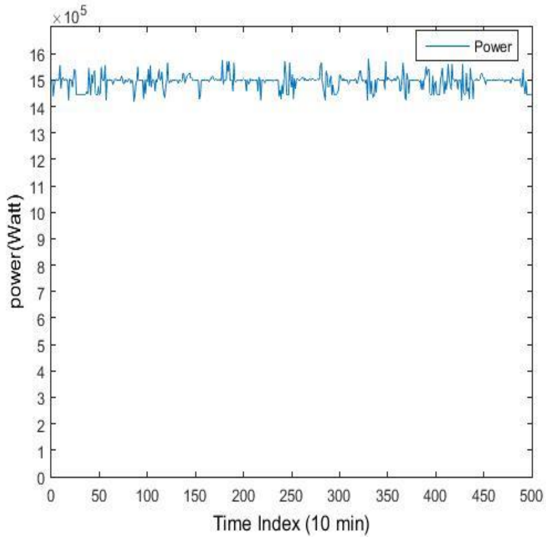

Fig. (14) Predicted output power from high-speed model for first 500 samples.

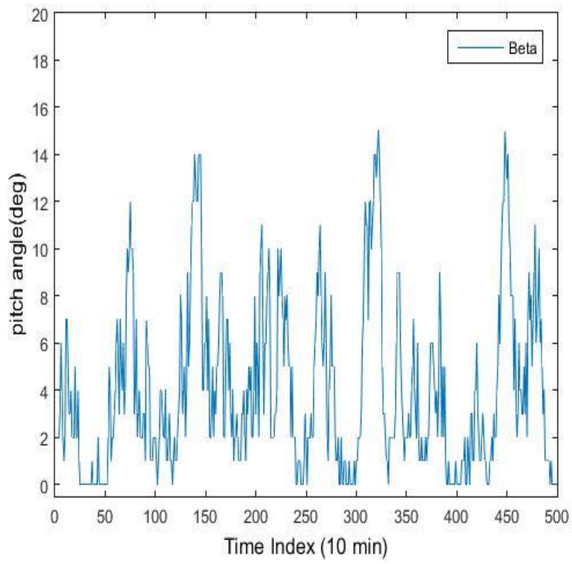

Fig. (15) Desired pitch angle signal for first 500 samples.

6. Conclusion

The ARMA model has simple form contain similar properties (mean, standard deviation, probability distribution function, elc). the research can be concluded in these points

- Data are classified according to its value into three groups.
- ARMA makes model to each group separately and use likely hood method to calculate the model parameters, The chosen model gives the least (MSE).

Each model has different control techniques,

- For low-speed model the output power is variable time series like medium speed model, but it is low and can't overcome the losses of the system. It isn't considered effectible, so supervisory control is used to stop the turbine in this model
- Second model for medium speed torque control is used to follow MPPT (maximum power point tracking). Angular rotor speed follows the optimal speed that achieve optimal tip speed ratio with zero pitch angle signal to get maximum efficiency.
- Output power, torque and rotor speed signal are variable time series as its speed model signal, as speed value changes the power value changes
- Third model for high-speed constant output power and torque zone. Pitch angle control is used to follow rated rotor speed, rated torque in contrast to medium model
- Output power, torque and rotor speed signals has narrow band of changing and it settles at its rated value in many periods, but pitch angle signal has large variable time series signal. Each speed value has a certain different pitch angle

The implementation is carried out using Zafaranaa data and the results has demonstrated the applicability of the proposed methodology

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