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A review of estimation of effective wind speed based control of wind turbines

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A R T I C L E I N F O

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This paper provides a comprehensive literature review on the estimation of effective wind Speed (EEWS), and EEWS based control techniques applied to wind turbine (WT). Several numbers of good publications have reported the EEWS based control of wind turbine. Wind speed is a driving force for the wind turbine system. In general wind speed measurement is carried out by anemometer which is located at the top of the nacelle. The optimal shaft speed is derived from the exact measurement of wind speed to extract the optimal power output at below rated wind speed. The wind speed provided by the anemometer is measured at a single point of the rotor plane which is not the accurate effective wind speed. At the same time anemometer increases the overall cost, maintenance and reduce the reliability of the overall system. So an accurate EEWS based control technique is required for WT systems to get the optimal power output. In this paper, a detailed description and classification of EEWS and some EEWS based control techniques have been discussed which is based on control strategy and complexity level of WT system. All most all previous work estimates the wind speed using EEWS techniques such as Kalman filter (KF), extended Kalman filter (EKF), neural network (NN) etc., and then different control techniques are applied. In the last section of this paper integral sliding mode control (ISMC) of a WT at below rated speed region is considered. Operating points are determined by proper estimation of effective wind speed, and modified Newton Raphson (MNR) is employed to estimate this. Finally simulation results are presented with a comparison between proposed ISMC, sliding mode control (SMC) and classical controllers such as aerodynamic torque feed forward (ATF) and indirect speed control (ISC).

Contents

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1. Introduction

The burning of fossil fuels has the significance influence on global climate change [1]. Wind energy is one the fastest growing and environment-friendly renewable energy sources. Past two decades the sizes of the wind turbines have been developed from 20 kW to 2 MW, even large wind turbines are also designed and tested [2]. Wind energy is playing an important role in future national energy scene [3–5]. Greenpeace states that, about 10% electricity can be supplied by the wind by the year 2020. Wind turbines convert the kinetic energy of the wind to electrical energy by rotating the blades. Modern wind turbines are classified into two types, i.e. fixed speed and variable speed wind turbine. Compared with fixed speed WT, variable speed WT are more reliable. Measurement of exact wind speed is required to control the variable speed WT (VSWT) at below rated wind speed for maximum power extraction. Generally a number of anemometers are placed at some distance to measure the wind speed at different points. The effective wind speed is defined as the spatial average of the wind field over the rotor shift area with the wind stream being unaffected by the wind turbine. WT anemometer cannot measure the exact shift area wind speed, due to which the overall performance of the system reduces. The other demerit is that the initial cost and maintenance of the anemometer is high. Exact estimation of effective wind speed is required to control the WT at above and below the rated wind speed which cannot be measured by using the anemometer. Several EEWS and control are reported in the literature [6–50]. In this review, an attempt has been made to compare the EEWS and control techniques on the basis of their advantages, disadvantages, control strategy, types of generator and operation of the WT at different regions. This paper provides a comparative review on most of the EEWS and control techniques. The contribution of this paper is the approximation of aerodynamic torque power coefficient to a 5^{th} order polynomial and estimation of the wind speed using MNR. Based on this estimated wind speed proposed ISMC based controller was found suitable in terms of the maximum power capture and reduced transient load compared to existing ATF, ISC, and SMC.

This paper is organized as follows. Section 2 explains polynomial based EEWS, Section 3 describes the NN based EEWS, Section 4 describes the nonlinear estimation with Newton Raphson (NR), Section 5 describes the unknown input based estimation, Section 6 describes the iterative algorithm/estimator based EEWS, Section 7 describes the nonlinear observer based EEWS, Section 8 describes the nonlinear estimation without NR, Section 9 describes the particle filter based EEWS, Section 10 describes the statistical model based EEWS, Section 11 describes the data fusion based EEWS, Section 12 describes the EEWS based fault diagnosis and finally Section 13 describes the proposed EEWS and comparison of various control performances. Finally, a conclusion is drawn in Section 14.

2. Polynomial based estimation

2.1. First- and second-order polynomial

When the generator is operated in speed control mode (below rated speed) the wind speed is estimated from the turbine output power (P_{wt}) by using the second order polynomial given in Eq. (1) [6].

$$\hat{\omega}_{s,low} = a_1 + a_2 P_{wt} + a_3 P_{wt}^2 \tag{1}$$

$\hat{\omega}_{s,low}$ is the estimated wind speed at below rated wind speed.

a_1, a_2, a_3 are the coefficient of the second order polynomial of Eq. (1).

When the wind speed is above the rated speed, pitch angle is used for estimating the wind speed by using first order polynomial given in Eq. (2).

$$\hat{\omega}_{s,high} = b_1 + b_2 \beta \tag{2}$$

$\hat{\omega}_{s,high}$ is the estimated wind speed at above rated wind speed, and b_1 and b_2 are the coefficient of the first-order polynomial. Then the estimated wind speed is low pass filtered as given in Eq. (3).

$$\begin{aligned}\frac{d\hat{\omega}_s}{dt} &= \alpha_{\omega_s}((1-k_{tr})\hat{\omega}_{s,low} + k_{tr}\hat{\omega}_{s,high} - \hat{\omega}_s) \\ &= \alpha_{\omega_s}\left((1-k_{tr})(a_1 + a_2 P + a_3 P^2) + k_{tr}(b_1 + b_2\beta) - \hat{\omega}_s\right)\end{aligned} \tag{3}$$

where $\hat{\omega}_s$ estimated wind speed, α_{ω_s} is the bandwidth of the estimator and k_{tr} is a transition parameter.

2.2. nth-Order polynomial

In [7,8] based upon the shaft speed and power output of the turbine, the wind speed is estimated by using the nth order polynomial. The characteristic of the power coefficient of the wind turbine is normally expressed in terms of tip speed ratio λ given as

$$C_P(\lambda) = C_{P0} + C_{P1}\lambda + C_{P2}\lambda^2 + \cdots + C_{Pn}\lambda^n \tag{4}$$

Nomenclature

R	turbine rotor radius (m)
ω_r	rotor speed (rad/s)
ω_g	generator speed (rad/s)
υ	wind velocity (m/s)
ν_p	tip speed ratio of the blade
C_p	performance coefficient of the WT
λ_{opt}	optimal tip speed ratio
P_{wt}	power output of the wind turbine
J	turbine inertia
P_e	generator Power
ω	synchronous electrical frequency
β	pitch angle (deg)
J_r	rotor inertia (kg/m^2)
J_g	generator inertia (kg/m^2)
K_r	rotor external damping (N m/rad/s)
K_g	generator external damping (N m/rad/s)
T_g	generator torque (N m)
T_{em}	generator electromagnetic torque (N m)
T_a	aerodynamic Torque (N m)
n_g	gear ratio
J_t	turbine total inertia (kg/m^2)
K_t	turbine total external damping (N m/rad/s)
T_{em}	generator (electromagnetic) torque (N m).
T_{hs}	high-speed shaft torque (N m).
T_{ls}	low-speed shaft torque (N m).
θ_g	generator-side angular deviation (rad).
θ_{ls}	gearbox-side angular deviation (rad).
θ_t	rotor-side angular deviation (rad)

where $C_P(\lambda)$ is the power coefficient of the wind turbine which depends on the particulars of the blade design. The tip speed ratio λ can be derived from the rotor speed and wind speed, given in Eq. (5).

$$\lambda = \frac{\omega_r R}{\upsilon} = \frac{\upsilon_p}{\upsilon} \tag{5}$$

Power output of the turbine is related to the cube of the wind velocity can be written as

$$P_{wt} = \frac{1}{2}\rho\pi C_p(\lambda) R^2 \upsilon^3 \tag{6}$$

By substituting wind speed from Eq. (5) in Eq. (6) we will get

$$P_{wt} = \frac{1}{2}\rho\pi C_p(\lambda) R^5 \frac{\omega_r^3}{\lambda^3} \tag{7}$$

The difference between the right- and the left-hand side of Eq. (7) can be taken as a function of λ which is represented as $F(\lambda)$, given in Eq. (8).

$$F(\lambda) = P_{wt} - \frac{1}{2}\rho\pi C_P(\lambda) R^5 \frac{\omega_r^3}{\lambda^3} \tag{8}$$

By subsisting the value $C_P(\lambda)$ given in Eqs. (4) and (8) we will get

$$F(\lambda) = P_{wt} - \frac{1}{2}\rho\pi R^5 \omega_r^3 \left[C_{P0}\lambda^{-3} + C_{P1}\lambda^{-2} + C_{P2}\lambda^{-1} + \cdots + C_{Pn}\lambda^{n-3}\right] = 0 \tag{9}$$

$$\frac{\partial F(\lambda)}{\partial \lambda} = -\frac{1}{2}\rho\pi R^5 \omega_r^3 \left[-3C_{P0}\lambda^{-4} - 2C_{P1}\lambda^{-3} - C_{P2}\lambda^{-2} \cdots - (n-3)C_{Pn}\lambda^{n-4}\right] \tag{10}$$

Iterative method such as Newton Raphson (NR) or Bisection method is used to determine the roots of the polynomial i.e. λ. Substituting λ in Eq. (5) the wind speed is estimated. As the optimal tip speed ratio λ_{opt} is a known quantity, with the estimation of wind speed the optimal rotor speed is determined by using Eq. (11).

$$\omega_{r_{opt}} = \frac{\upsilon\lambda_{opt}}{R} \tag{11}$$

Substituting λ_{opt} and C_{pmax} (it is a known quantity) and the ω_{ropt} in Eq. (7) the optimal turbine output power P_{wt}^{max} is calculated. The estimated maximum output power of the electrical generator P_t^{max} can be obtained by using the following relationship.

$$P_t^{max} = \eta_{max}^{DFM} P_{wt}^{max} \tag{12}$$

where η_{max}^{DFM} maximum DFM (doubly fed machines) efficiency.

3. Neural network based estimation

3.1. Multi-layer perceptron neural network (MLPNN)

MLPNN based estimation has mainly two applications. (1) NN based wind velocity estimator and (2) NN based pseudo-power curves to compensate the potential drift of the wind turbine power coefficient [9,10].

Fig. 1 shows a NN based training scheme for wind speed estimator. In this scheme, sampled data of the turbine power (P_{wt}) is obtained from turbine power equation with pre-selected rotor speed and wind velocity samples. As shown in Fig. 2, both P_{wt}

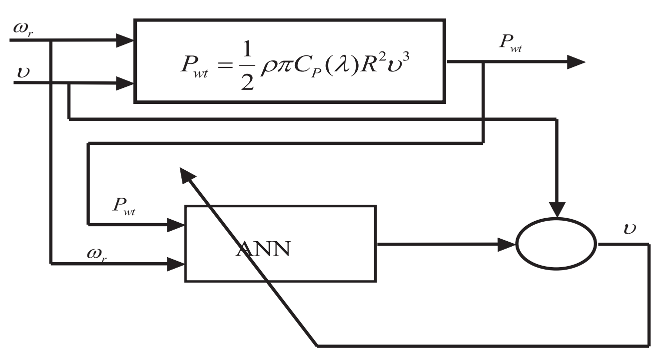

Fig. 1. NN based training scheme for wind velocity estimator [10].

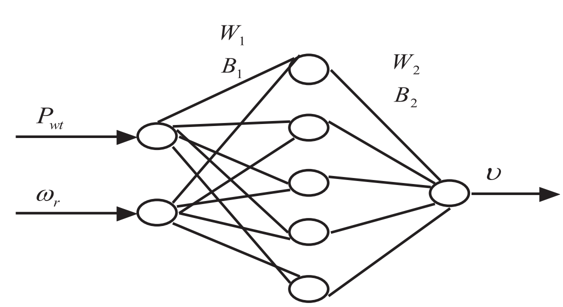

Fig. 2. NN based wind velocity estimation with five tan-sigmoid neurons and one linear neuron [10].

and ω_r samples are used as an input vector to the given NN, and the wind velocity acts as a target vector to train the NN. The NN is configured with two linear neurons in the input layer, five tan-sigmoid neurons in the hidden layer, and one linear neuron in the output layer.

A supervised NN is used to implement the high precision wind speed estimation in [10]. This training scheme of the NN that estimates wind speed ν is shown in Fig. 3. The inputs of the NN are generated from the generator power P_e and synchronous electrical frequency ω which is given in Eqs. (13) and (14), respectively.

$$\omega_r = \frac{2}{P}\omega \tag{13}$$

$$P_{wt} = J\omega_r\frac{d\omega_r}{dt} + P_e \tag{14}$$

To avoid the noise sensitivity in Eq. (14) the derivative operation is implemented via the "Approximate Derivative" and the electrical power P_e is derived from stator currents and voltages. With estimation of wind speed by using NN, maximum power point tracking (MPPT) is obtained with help of the rotor speed reference. This rotor speed reference is generated through the gain $K = (\lambda_{opt}/R)$ as shown in Fig. 3. Fig. 3 shows the NN based control of wind turbine rotor speed.

The drift error may occur in the power coefficient because of time and varied environment. When a drift error occurs, the compensation should be done in the control system. In Fig. 4, for maximum tracking a compensation function is used, instead of K. This function has been derived from the collection of data in pseudo power curves by using NN. The PI controller is used to control the actual rotor speed to the desired value by varying the switching ratio of the pulse width modulated (PWM) inverter. Fig. 5 shows the block diagram of small wind turbine driven by permanent magnet synchronous generator (PMSG) and PI controller.

NN based wind speed estimator for variable speed WT is presented in [17] where multilayer feed forward neural network (MLFFNN) with added momentum is adopted as a neural network paradigm. The neural network has three inputs i.e. mechanical power, rotor speed and blade pitch angle and the output is wind speed. The authors [17] discussed about a NN-based sensor less control which is having the following drawbacks. (1) requires more memory space, (2) requires more complex and time-consuming calculations, and (3) not accurate for real time control. The authors have proposed a multilayer feed forward network with so-called back propagation with momentum algorithm which is a gradient descent algorithm of the performance function. In order to achieve the maximum wind power extraction the optimal DFIG rotor speed command is determined from the estimated wind speed.

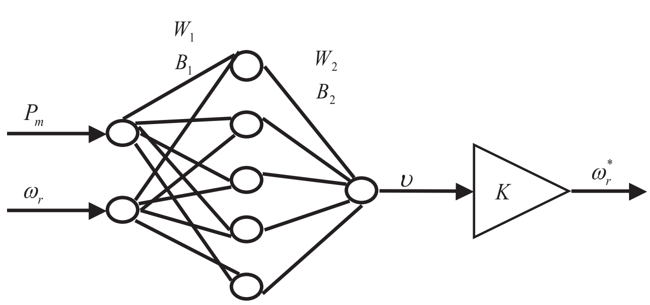

Fig. 3. NN based control of wind turbine rotor speed [10].

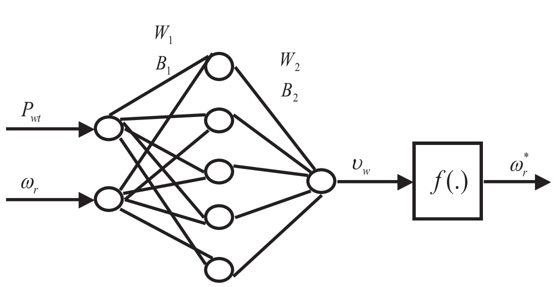

Fig. 4. NN-based control module of rotor speed with compensated function [10].

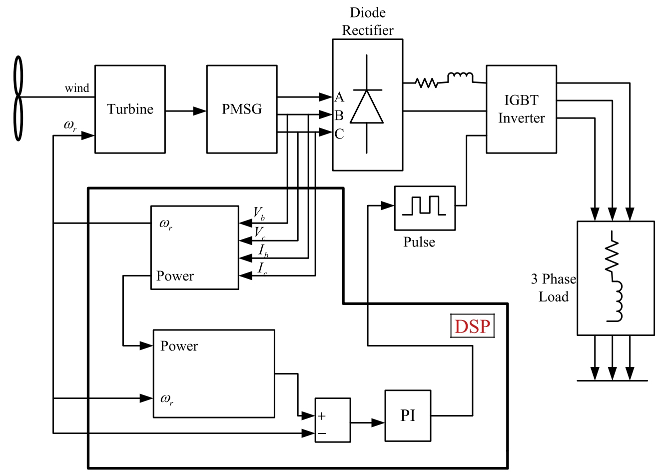

Fig. 5. Block diagram of small wind turbine driven PMSG and PI controller [10].

Simple back propagation artificial neural network (BPANN) is used to estimate the wind speed by using the rotor speed and mechanical power [20]. To determine the optimal rotor speed or power reference to the permanent magnet generator (PMG) the estimated wind speed is used. Three layered BPANN provides a nonlinear mapping between input and output where the input to the NN are mechanical power and rotor speed and output is estimated wind speed.

3.2. Soft sensor based support vector machine

In [11], estimation of effective wind speed is based on modeling of soft sensor by utilizing the support vector machine (SVM). This gives the estimation with high precision compared to other KF techniques. In general, soft sensor technique gives a nonlinear relation between the measured (secondary) and measurable (estimated) variable. The estimated value is obtained from the measured variable through a transformation and computation of the measurable variable. The mathematical model of the soft sensor is built from group of measured variable (secondary variable) associated with estimated variable (master variable), where measured variable acts as input and estimated variable acts as output. The mathematical model of the soft sensor can be derived from the secondary variable and optimal estimation of master variable.

In [11] the secondary variables are considered as rotor speed, generator output power and pitch angle, and master variable is the effective wind speed. Based on optimization theory the estimation process is performed. Black box modeling is used for soft sensor modeling, where SVM approximates the mapping between the input and output variables. Wind turbine acts as an anemometer to estimate the wind speed. Effective wind speed is a nonlinear function of rotor speed (ω_r), generator output power (P_e) and pitch angle (β), given in Eq. (15).

$$\upsilon = f(\omega_r, P_e, \beta) \tag{15}$$

The modeling of soft sensor is done by the nonlinear function f and finding the associated output. By using nonlinear mapping function $\varphi(.)$, the trained data set is mapped to high dimension feature space (Hilbert space). Because of this transformation the nonlinear system identification problem is transformed in to linear function in high dimension feature space. Fig. 6 shows the soft sensor of SVM. The inputs to the SVM soft sensor are the measurable variable X, the control variable u and measurable output y, finally the output of SVM soft sensor is optimal estimated value $\hat{X}$.

The soft sensor modeling steps based on SVM can be summarized as

(1) To determine the input and output variables.
(2) To collect the data samples and normalize it.
(3) Defining the input parameter set for training SVM.
(4) To validate the SVM.
(5) To select the optimal combination parameter for creating the SVM model and predict it.

Advantage of this method is that it can handle the problems like small sample, nonlinearity, high dimension, and local minimum.

3.3. Gaussian radial bias function network (GRBFN) based wind speed estimation

In [12,18] wind speed estimation is based on GRBFN which is used to provide a nonlinear input–output mapping for the wind turbine aerodynamic characteristics. The wind speed is estimated by taking the measured electrical power with losses, and nonlinear dynamics of the shaft system. Fig. 7 shows the GRBFN based wind speed estimation.

In practice the variation of the wind speed is fast and random, but due to the inertia of the wind turbine its response is relatively slow. So, to achieve a smooth rotor speed command to the turbine a low pass filter is necessary. Fig. 8 shows the Block diagram of the GRBFN based sensor less maximum wind power tracking.

In order to track the optimal rotor speed of the generator for maximum power extraction PI controller is employed for both rotor side control (RSC) and grid side control (GSC) [12]. The stator oriented flux vector control is applied in [18].

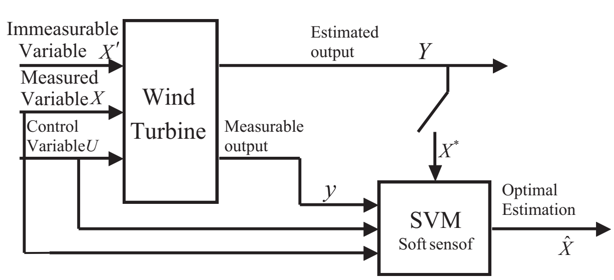

Fig. 6. Basic structure of SVM soft sensor [11].

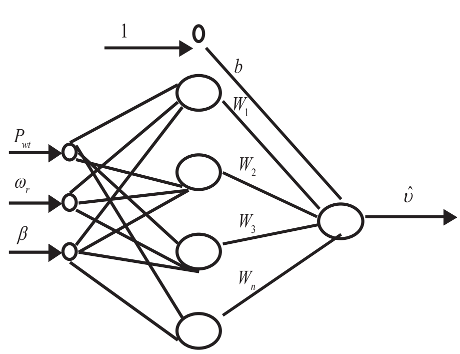

Fig. 7. GRBFN-based wind speed estimation [12].

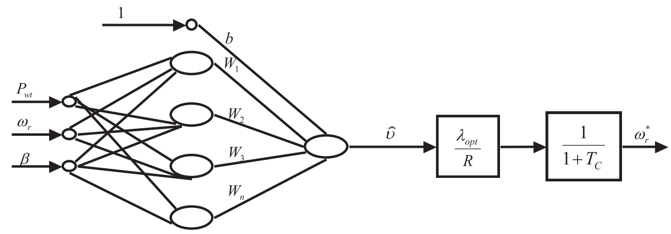

Fig. 8. Block diagram of the GRBFN-based sensor less maximum wind power tracking [12].

3.4. Support vector regression (SVR) based wind speed estimation

The relationship between the system input and output from the available samples or training data can be obtained by using regression method. It is desirable that the relationship should be determined in such a way that minimizes the error between the system output and real value i.e. the system output should match the real value as close as possible. The inputs of the SVR are wind turbine power and rotational speed. Then the wind speed is determined online from the instantaneous input [13–15]. The rotor speed and turbine power are input to the SVR and the output is estimated wind speed.

Let x_i and y_i denote the input and output spaces respectively and n is the dimension of training data. The general function of SVR estimation can be expresses as

$$f(x) = (w \times \phi(x)) + b \tag{16}$$

where w is a weight matrix, b is a bias term, φ denotes a nonlinear function transformation from n dimension space to higher dimension feature space. By solving Eq. (16) in regression risk we get

$$R_{reg}(f) = \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n}\Gamma(f(x_i) - y_i) \tag{17}$$

Subject to

$$|y_i - w\phi(x_i) - b| \le \varepsilon + \xi_i \quad i = 1, 2, \ldots, n. \quad \xi_i, \xi_i^* \ge 0$$

Eq. (16) can be solved by minimizing the regression risk given in Eq. (17). Where ξ_i, and ξ_i^* are the unpredictable error on the target vector, $\Gamma(.)$ is a cost function, ε is a permissible error and c is a constant which determines the tradeoff between minimizing training errors and minimizing the model complexity $\|w\|^2$. The radial basis function used is

$$K(x_i, x) = \exp\left\{-\frac{|x_i, x|^2}{\sigma^2}\right\} \tag{18}$$

where σ is a parameter known as center of the radial basis function. The polynomial kernel function and radial basis function are used in [15] for approximating $f(x)$ but in [13,14] only radial basis function is used.

3.5. Echo state network (ESN) based real time wind speed estimation

In [16] the nonlinear dynamical electrical power wind speed characteristics of the wind turbine systems are approximated by an ESN. By using the dynamical ESN model the wind speed is directly estimated from measured wind turbine power output. The wind turbine is controlled by using the estimated wind speed in real time [16]. Fig. 9 shows the principle of wind speed estimation.

The wind turbine aerodynamic model is represented by the conversion of wind energy to turbine mechanical power (P_{wt}). The turbine mechanical power is represented as a nonlinear function of wind speed ν, shaft speed ω_r and blade pitch angle β. The mechanical power is transferred to the generator and the generator converts the mechanical power to the electrical power, losses are also taken into account (referred to the generator side). ESN helps in involving the approximate inverse model for getting the estimated wind speed. In this case the inputs to the inverse model are P_m, β and ω_r. The major advantage of this method is no need for complex mathematics for developing a model. Using neural network the turbine generating system consider as a black box containing the nonlinear dynamics from (ν,β,ω_r) to P_e. Then ESN is used to estimate the wind speed ν in real time from the measured data $(P_e,\omega_r,\ \beta)$. Fig. 10 shows the estimation of wind speed by using ESN.

3.6. Extreme learning machine (ELM) based wind speed estimation

The authors in [19] have discussed the estimation of wind speed for variable speed variable pitch generation system. The mapping between the nonlinear input–output is done by using the ELM which gives more accuracy because of the variable pitch. This proposed method is independent of the environmental air density, so the ELM based wind speed estimation is robust to air density variation. MPPT control of variable speed variable pitch generation system is achieved by determining the optimal rotor speed from the estimated wind speed. Whenever the wind turbine operates more than rated speed, an ELM pitch control is applied. This control is much faster than the conventional pitch control systems. The input vectors to the NN are the turbine power (P_{wt}), the rotational speed (ω_r) and the blade pitch angle (β) and the output is estimated wind speed. This is the one of the technique for estimation of wind speed where pitch control system is also activated. In above rated wind speed the generated power exceeds its rated value, an ELM based pitch angle controller is used to limit the captured power by activating the pitch control system. Fig. 11 shows the entire sensor less control scheme for variable pitch PMSG wind turbine power generation system (WTPGS).

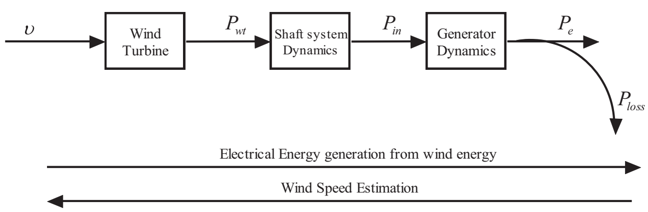

Fig. 9. The principle of wind speed estimation [16].

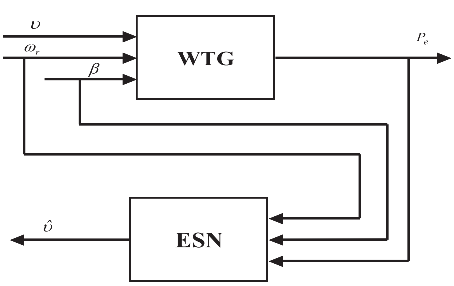

Fig. 10. Wind speed estimation using an ESN [16].

3.7. Adaptive neuro fuzzy inference systems (ANFIS)

In [52] the estimation of wind profile is done by the clustering algorithm based ANFIS. In that the wind speed is estimated up to a height100 m based on the knowledge of 10, 20, 30, 40 m. In this paper ANFIS contains five layers. First layer is called input layer, which is used to map the crisp input to membership function. Second layer performs the connective AND operation. Third layer performs the normalized operation and fourth layer performs the fuzzy rule which is adaptive with output. Finally fifth layer deals the weighted average of all rule outputs. ANFIS architecture contains four inputs, one output and five fuzzy rules. Finally the estimated wind speed from the model output is compared with the real wind speed at 40 m height and the mean absolute error was found to be within 3%.

In [55], ANFIS is used to estimate the effective wind speed. The inputs to the ANFIS are wind turbine power coefficient, rotational speed and blade pitch angle and the output is effective wind speed. NN is used to adjust the membership function in fuzzy logic. After training the ANFIS model is used for online and

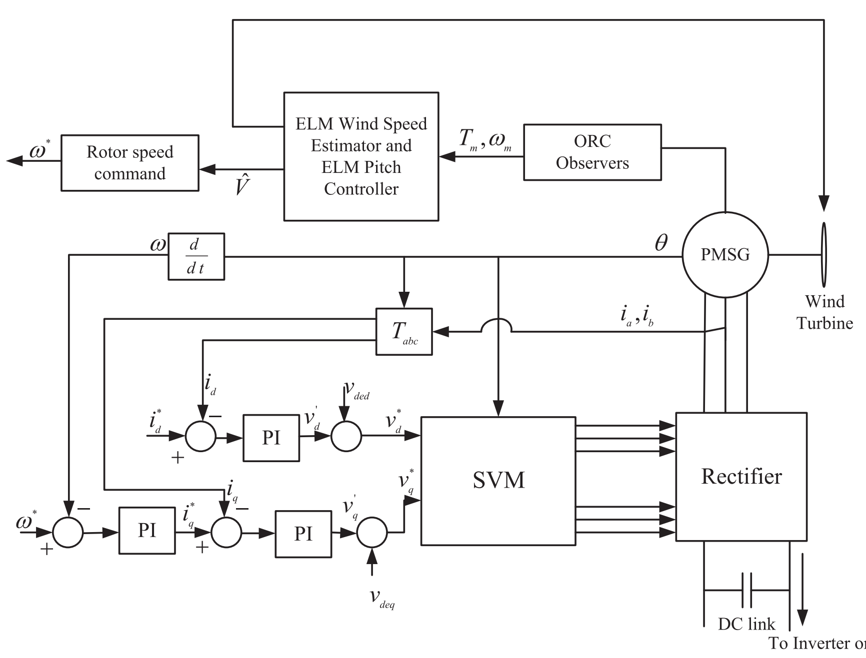

Fig. 11. Entire sensor less control scheme for variable-pitch PMSG WTPGS [19].

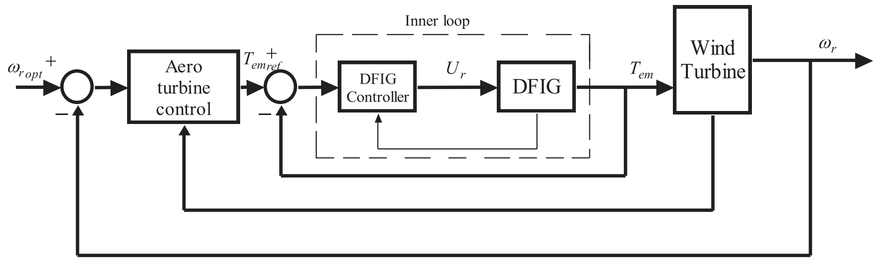

Fig. 12. WT control.

performance of the model is evaluated by root mean square error and correlation coefficients.

4. Nonlinear estimator with Newton Raphson

4.1. Kalman filter with Newton Raphson

A classical approach of linear quadratic regulator (LQR) controller is discussed in [22], where the KF is used to estimate states and NR is used to estimate the wind speed. LQR and PI controller regulates the pitch for above rated wind speed by maintaining the generator torque constant. Fig. 14 shows the LQR control of wind turbine. In [23] KF is used to estimate the aerodynamic torque and rotor speed. The generator torque control is achieved by ATF control and Fuzzy control.

Modern power systems having large multi-megawatt machines need very large rotor diameters. To allow the rotor to grow larger and capture more energy, independent torque and pitch control systems must be developed. Generally variable speed WT has two region of control i.e. below rated speed and above rated speed. In below rated speed the objectives are to maximize the energy capture from the wind and reduce the drive train oscillations. Fig. 12 shows the WT control schemes. From this figure it is clear that WT has two control loop i.e. inner and outer loop. The inner control loop consists of electrical generator with power converters. The outer loop having the aero turbine control which gives the reference to the inner loop is shown in Fig. 2. Classical vector control is used to control the double fed induction generator (DFIG) and it is connected to the grid.

The block diagram shown in Fig. 12 represents the estimation of aerodynamic torque and rotor speed from measured rotor speed and control input i.e. generator torque (T_g) for single mass model. For a two mass model the estimation of aerodynamic torque, rotor speed and generator speed are estimated from measured generator speed and control input i.e. electromagnetic generator torque (T_{em}). The inputs to the NR block are the estimated variables i.e. rotor speed and aerodynamic torque and output of the block is the estimated effective wind speed. The KF based estimation of aerodynamic torque is discussed in [22–29,31]. The aerodynamic torque T_a is considered as an extended state which is driven by white noise. Generally the process and measurement noise are considered as stationary.

In [22,24–29] the authors have determined the optimal rotor speed based on EEWS. This optimal rotor speed is taken as reference rotor speed for controlling the generator torque. The control technique used is the static and dynamic nonlinear feedback control for getting the maximum power [24–26,28]. The static feedback control technique is not robust for higher order dynamics. To track the higher order dynamics a dynamic state feedback linearization is used. In [26,28] two mass models are considered for EEWS, where the generator torque is controlled with static and dynamic nonlinear state feedback control. The estimator used is the KF. Fig. 13 shows the nonlinear static and dynamic state feedback control with estimator control scheme.

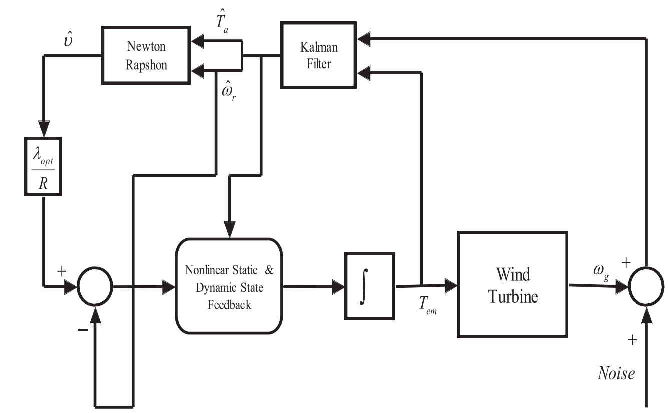

Fig. 13. Nonlinear static and dynamic state feedback control with estimator control scheme [28].

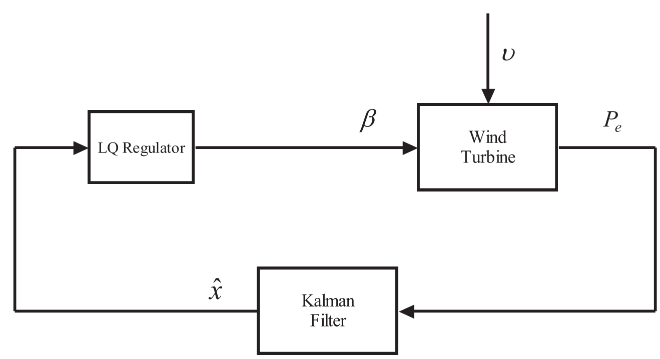

Fig. 14. LQR control of wind turbine [21].

In [24–26,28] a nonlinear static and dynamic state feedback with higher order tracking dynamics is introduced. Even if this can reject the input disturbance the only disadvantage is the complex control law and higher order derivatives. In [27] the controller used is based on the classical PI controller with nonlinear state feedback applied to a linearized wind turbine system. Fig. 15 shows the nonlinear state space feedback linearization with PI controller and wind speed estimator.

In multi-megawatt (MW) wind turbine the dynamic response of the turbine to sudden change in wind speed is usually slow because of slow pitch control system. Fig. 16 shows the feed forward pitch control with estimator and 3D lookup table for multi MW wind turbine. In this case, the estimated aerodynamic torque, pitch angle and the rotor speed acts as an input to the lookup table and the output is the estimated wind speed [31]. The pitch angle is calculated from the knowledge of estimated wind speed and rotor speed.

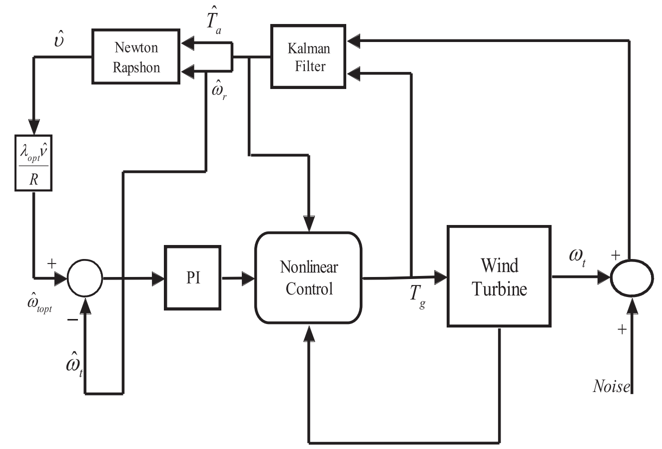

Fig. 15. Nonlinear state space feedback linearization with PI controller and wind speed estimator [25].

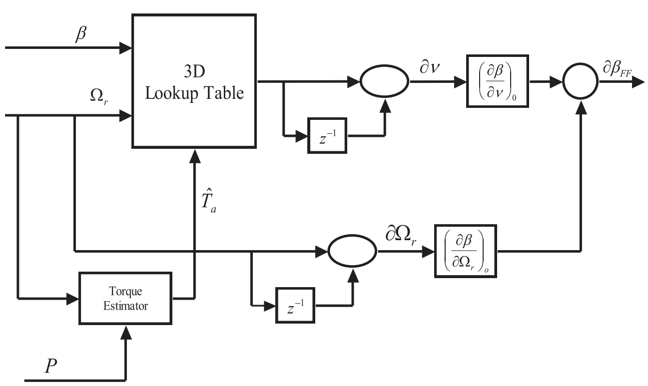

Fig. 16. Feed forward pitch control with estimator and 3D lookup table [31].

4.2. Kalman filter with Q and R estimation

In [29] KF is used for estimation of states such as rotor speed and aerodynamic torque, and NR is used to estimate the wind speed. NR is used to find the wind speed from the estimated aerodynamic torque. The choice of speed controller for the required torque can be any one of PI, LQG or H_∞, which don't affect the estimation algorithm. In [29] the noise covariance matrix Q and R are separately estimated in each iteration unlike [24–28], where Q and R are having fixed covariance. As the wind changes continuously, for estimation of wind speed the estimation algorithm should be self-adaptive to the changing wind condition and unknown measurement noise. Fig. 17 shows the control scheme based on aerodynamic torque and effective wind speed estimation.

In [30] rotational speed reference is achieved by aerodynamic torque estimation using KF. Adaptive optimal fuzzy control for rotational speed is presented on the basis of equation of mechanical and electrical parts of wind turbines. This has two parts, (i) Nonlinear approximation using system identification based fuzzy identifier (ii) Fuzzy controller.

4.3. Least square method

In [32] the mechanical drive train system is considered as the simple first order dynamical system. The estimation of wind speed is done by two steps. First aerodynamic torque is estimated from the electrical torque and rotor speed; second the estimation of wind speed by using the aerodynamic model. Aerodynamic torque is considered as the unknown input. The aerodynamic torque is periodic with perfectly known period where, periodicity is directly

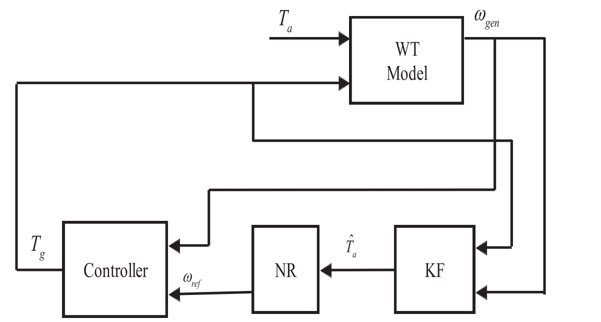

Fig. 17. Control scheme based on aerodynamic torque and effective wind speed estimation [29].

linked with rotation of the wind turbine. Reconstruction of the aerodynamic torque has been done by estimating its Fourier expansion coefficients. The main advantage of this method is Fourier coefficients of the decomposition are constant and this gives the good decomposition for estimation purpose. Wind speed estimation has been done in two steps. First the aerodynamic torque is estimated from the electrical torque and rotor speed by using the time varying Luenberger type observer. Then the wind speed is estimated from the estimated aerodynamic torque by using the least square method. This is achieved by solving the following equation:

$$\hat{\upsilon} = \arg \upsilon \left[\min \left(\hat{T}_a - C_q \left(\frac{R\omega_r}{\upsilon}, \theta \right) \frac{1}{2} \rho \pi R^3 \upsilon^2 \right) \right] \tag{19}$$

4.4. Maximum likelihood estimator

In [53] the estimation of wind speed is achieved by the maximum likelihood estimator (MLE) with the presence of observation noise. In that wind turbine power coefficient and total turbine inertia of the rotor are known. Wind speed is formed as one of the state variable which is estimated by the maximum likelihood estimator and it is verified by the simulation and experimental data with the presence of noise.

5. Unknown input based estimation

In [22–29,31] aerodynamic torque has been taken as an augmented state for estimation of wind speed. In unknown input based estimation instead of taking the aerodynamic torque as an augmented state, it is taken as an unknown input. In [33–37] authors have discussed about KF based estimation and input observer based estimation for estimating the aerodynamic torque. From this estimated variables together with measured pitch angle is used to calculate the effective wind speed. Fig. 18 shows the block diagram of the observer with PI based estimation. The differentiation based estimation of aerodynamic torque is explained in [33]. As the method based on differentiation, which amplifies the measurement noise a first order low pass filter is used to smoothen out the estimation. Fig. 19 shows the block diagram of differentiation based estimator. In [33–34,36] the estimation of rotor speed and aerodynamic torque together with measured pitch angle is used to calculate the effective wind speed. The torque equation given in Eq. (20) can be written in the form of Eq. (21) under the assumption the air density are known and all variables in the left hand side are known.

$$T_a \omega_r = \frac{1}{2} \rho \pi \frac{R^5 \omega_r^3}{\lambda^3} C_p(\beta, \lambda) \tag{20}$$

$$\frac{2T_a}{\rho \pi R^5 \omega_r^2} = \frac{C_p(\beta, \lambda)}{\lambda^3} \tag{21}$$

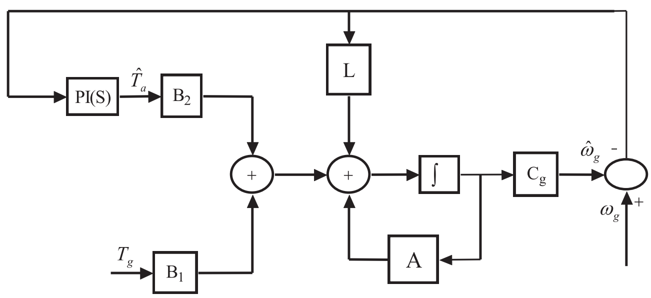

Fig. 18. Block diagram of observer with PI based estimation [33].

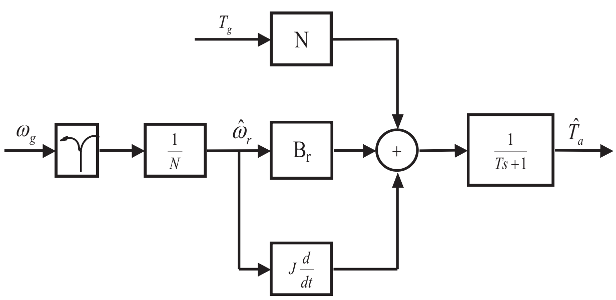

Fig. 19. Block diagram of differentiation based estimator [33].

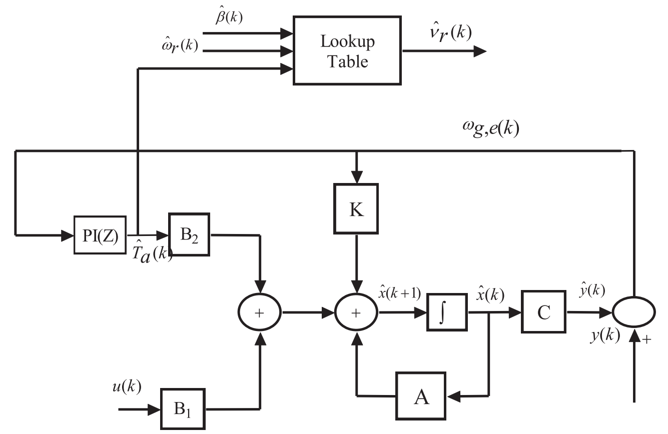

Fig. 20. Block diagram of lookup table based wind speed estimator [35].

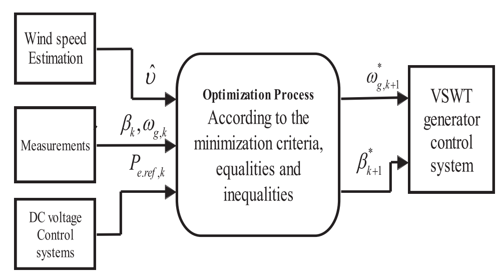

Fig. 21. Block diagram of optimization process [36].

In Eq. (20), $C_p(\lambda,\beta)$ for particular β is denoted by $C_{p,\beta}(\lambda)$, which is a known quantity. By solving the above equation for λ the effective wind speed can be calculated by using the relation $\upsilon=\omega_r R/\lambda$. To solve the λ the monotonicity property can be written as $C_{p,\beta}(\lambda)\times\lambda^{-3}$.The right hand side of Eq. (21) is not invertible for some pitch angles. So, knowledge about operation of the wind turbine is used to calculate the most likely λ that would solve Eq. (21). The monotonicity can occur in the stall region because of positive slope in $C_{p,\beta}(\lambda)$, this monotonicity cannot occur in the nominal operating region because the algorithm is designed for pitch controlled wind turbine. For some situations like gust or other fault the turbine may operate in stall region. In this case, a largest tip speed ratio to satisfy Eq. (21) is based on the assumption that the wind turbine is operating nearer to the rated speed.

In [33,34,36], the authors approach is somehow different than [35,37] where instead of using monotonicity the estimation of effective wind speed is calculated by using the look up table provided pitch angles are known. Fig. 20 shows the block diagram of lookup table based wind speed estimator.

In [36] the wind speed estimation is done on the same way given in [33,34]. But the authors have used an optimization approach for selection of appropriate reference pitch angle and rotor speed. As shown in Fig. 21 the input to the optimization algorithm are estimated wind speed, measurements of the actual pitch angle and the rotating speed. The outputs are reference of pitch angle and rotor speed.

In [56] control based observer is used for estimation of effective wind speed at partial load region using three mass model. The input estimation is done based on the output tracking which can be achieved by the high gain control loop. The wind speed is considered as unknown input to the WT system. Based on the state feedback and relocation of poles which is five to ten times larger than the initial one used to derive the effective wind speed. A state observer is designed basing on the nonlinear model of WT, is used to estimate the unknown wind speed from measured states [57]. In general WT model is nonlinear so that Takagi–Sugeno (TS) model structure is used. This nonlinear model structure is represented by the linear sub models that can be derived by using local Taylor linearization or sector nonlinear approach. The rotational and torsional degree of freedom are included in the observer. The effective wind speed estimation is done by adding the wind speed as a state in the state observe and by considering the dynamics of the wind without white noise.

In [56] three mass model and [28] two mass model based estimation of effective wind speed are proposed. In three mass model shaft torsion, tower bending and flapping are considered to create the mass model but in two mass model rotor and generator speed masses are considered. In model wise comparison three mass model increase the complexity and order of the system, and also it's more useful for short time phenomenon such as transient stability analysis and faults condition. But in estimation based control two mass model is enough to accommodate the WT dynamics for maximum power capture. Generally wind speed estimation depends on three parameters i.e. aerodynamic torque, rotor speed and pitch angle. In [28] estimation of effective wind speed is derived from estimation of aerodynamic torque and rotor speed. From these estimated quantities the effective wind speed is obtained by applying NR method. But in [56] the aerodynamic torque is linearized around the operating point which depends on the low shaft speed and wind speed. The wind speed is estimated by unknown input based estimation.

6. Iterative algorithm/estimator

In [38] the authors have discussed the estimation of effective wind speed by using NR, KF and EKF. In NR method the rotor power is assumed as a generated electrical power which gives more estimation error. KF and EKF give more accurate results than NR but it requires whole knowledge of the system and mean wind speed.

7. Nonlinear observer based estimation

For fixed pitch wind turbine the torque produced is a function of blade profile, pitch angle, rotational speed and radius of the blades [39]. Eq. (22) shows the aerodynamic torque equation as a function of tip speed ratio and wind speed.

$$T_a(\lambda,\upsilon)=\frac{1}{2}\rho\pi C_t(\lambda)R^3\upsilon^2 \tag{22}$$

The dynamics of the wind turbine is described by

$$J\frac{d\omega_r}{dt}=T_a(\omega_r,\upsilon)-B\omega_r-T_g \tag{23}$$

where J is the system inertia, T_g is the generator torque and B is the friction coefficient. Variation of wind waveforms can be represented as some basic combination of linear function. Wind profiles are not known completely and the statistical representation is not useful estimating the wind velocity. Wind model can be generated by the linear combination of some basic functions as given in the following equation:

$$\upsilon(t)=\sum_{i=1}^{N}C_i g(t) \tag{24}$$

C_i is the linear weighting coefficients are completely unknown.

Using standard transformation this can be represented in state space form as given in Eq. (25).

$$\dot{z}=Hz+\delta(t) \tag{25}$$

$$\upsilon=Gz \tag{26}$$

where H and G are known matrices and the elements of $\delta(t)$ are completely unknown sequences of random intensity random occurring isolated delta functions. Wind speed estimator is designed by combining Eqs. (21) and (23). The authors have taken ν as an output variable instead of a state variable and X considers for state variable.

$$X=\begin{bmatrix}\omega_r\\ z\end{bmatrix} \tag{27}$$

$$Y=\upsilon \tag{28}$$

Observer equation is

$$\dot{\hat{X}}=A\hat{X}+\begin{bmatrix}T_a(\hat{x})\\ 0\end{bmatrix}+\begin{bmatrix}T_g\\ 0\end{bmatrix}+K(y-C\hat{X}) \tag{29}$$

If T_a satisfies the Lipschitz condition

$$\|T_a(X_1)-T_a(X_2)\|\le k_T\|X_1-X_2\| \tag{30}$$

Feed forward pitch control of pitch angle is addressed by the author of [40,51] which consists of following steps.

(i) Reconstruction of aerodynamic torque.
(ii) Wind speed estimation.
(iii) Pitch angle setting.

Reconstruction of aerodynamic torque is given by the following equation.

$$\tilde{T}_a=\hat{J}_t\times\dot{\tilde{\omega}}_r+\left(\tilde{P}_r^f/\tilde{\omega}_r^f\right)+\hat{T}_1 \tag{31}$$

$$\hat{C}_q(\tilde{\theta}^f,\hat{\lambda})\times\frac{1}{2}\hat{\rho}\pi\hat{R}^3\times(\overline{\upsilon})^2=\hat{T}_a \tag{32}$$

By using the above two equations the effective wind speed is calculated using NR method.

$$\hat{\upsilon}^{(k)}=\hat{\upsilon}^{(k-1)}-\frac{(\tilde{T}_a-\hat{T}_a^{(k-1)})}{\left(d\hat{T}_a/d\hat{\upsilon}\right)_{\hat{\upsilon}^{(k-1)}}} \tag{33}$$

The aerodynamic torque coefficient is approximated as a 2D polynomial function. In case of sudden wind gusts the optimized turbine power can be obtained by the additional pitch control action which is based on estimated wind speed.

8. Nonlinear estimator without NR

In [41] a direct estimation of wind velocity by means of the nonlinear EKF is used without estimating the aerodynamic torque. The idea consists of using a time dependent Riccati like equation to construct a robust continuous observer for estimating effective wind speed. It is capable of rejecting system perturbations and disturbances acting on the generator torque T_g. In [42,43] an EKF is used to estimate the wind speed and this estimated wind speed is used for finding the optimal point of the wind turbine. Uncertainties of the drive train system also considered. These uncertainties are considered as parametric uncertainties in the model and to implement the robust controller using DK iteration method. The sources of the uncertainties are drive train stiffness, damping factor and linearized model. The review of estimation of rotor effective wind speed is given in [58] which is completely based on linear and nonlinear state /input estimation techniques. Five major estimators are discussed i.e. Power balance estimator, EKF based estimator, KF based estimator, DAC (disturbance accommodating control) based estimator, Unknown input estimator and finally immersion and invariance (I&I) estimator. A comparison has been made among the estimators in that KF, I&I and power balance estimator are giving better results. From the field test analysis it is found that EKF based estimator at lower turbulence, power balance estimator at high turbulence and I&I based estimator at all turbulence intensities gives best results.

9. Particle filter

In [44] fuzzy control is proposed for aero turbine control which gives the optimal power at below rated wind speed. Effective wind speed is not available for direct measurement, so a wind speed estimator based on sequential Monte Carlo technique is developed. From the knowledge of aerodynamic torque T_a and measured rotor speed ω_r, the estimation of effective wind speed is done by sequential Monte Carlo estimator particle filter. The main advantage of particle filter is that, it is not depend on any local linearization or functional approximation like EKF at the same time, it can estimate in nonlinear non Gaussian scenarios [44]. The dynamic state estimation based on Bayesian approach is depend on a posterior probability density function for all state variable which is based on available information that includes the set of received measurements. This density function having the complete statistical information about the dynamic state, so it may possible to have a complete solution to the estimation problem [45,46].

10. Statistical model based estimation

In [47] autoregressive statistical model is used for wind speed prediction and sensor less control to maximize the power of the wind turbine generator. Generally the prediction model requires previous set of time frame captured by the wind system which is used for the next time frame set. In [42] two wind speed ranges are considered namely 30 s or 60 s wind speed prediction. Fig. 22 shows the sensor less wind energy conversion system (WECS) based control.

In [48] the wind speed is estimated from the linear time invariant transfer function relating to ω_r and T_g. This transfer function is obtained from the MATLAB identification tool. The signals used in the identification process are wind speed at hub height, rotor speed and generator torque. After removing the mean from those signals an auto regressive exogenous (ARX) model was obtained from identification tool. The estimated wind speed time series compared with real wind speed and found to 79.75% fit.

11. Data fusion

Anemometer accuracy is poor because of response speed of an anemometer and some susceptible factors such as the wind turbulence, tower vibration, wind shear, and the roughness of ground. In general the static accuracy of generator signal is good. But the dynamic response of this generator signal is slow due to large lag and delay of the rotator. The characteristics of these two signals i.e. anemometer data and the generator power are complementary in frequency domain. The estimation error will reduce by fusion of those two signals for estimating the effective wind speed. So by combining the two sensors the effective wind speed can be calculated with higher accuracy as shown in Fig. 23.

In [49] the estimation of effective wind speed is based on the data fusion technique. The spectrums of measurement of anemometer and generator power are analyzed. From the analysis it was found that the two signals are complementary in the frequency domain. To design an observer for estimation of effective wind speed frequency domain data fusion is discussed. Fig. 23 shows the schematic diagram of the effective wind speed filter.Fig. 24

12. Estimation of wind speed applied to fault diagnosis and other prediction

In paper [50] the major issues of fault diagnosis are considered that is high noise in wind speed measurement, nonlinearities in the aerodynamic torque and uncertainties of the parameters. In

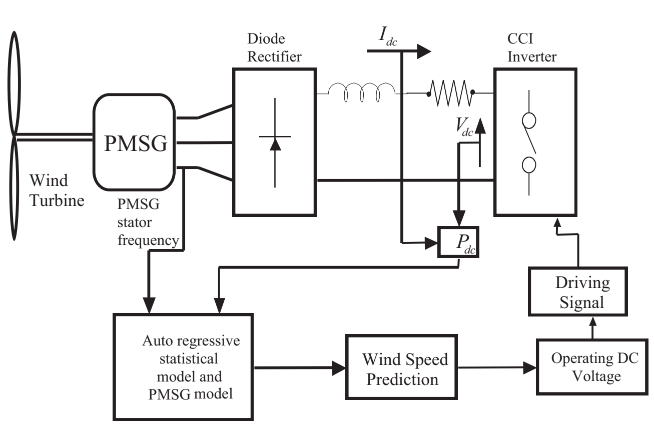

Fig. 22. Block diagram of the wind prediction sensor less WECS-controlled system [47].

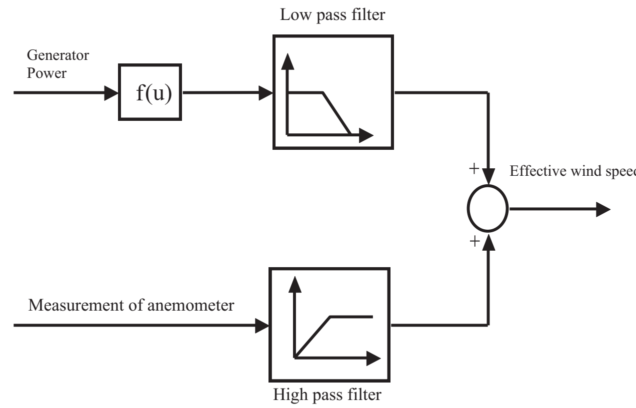

Fig. 23. Schematic diagram of the effective wind speed filter [49].

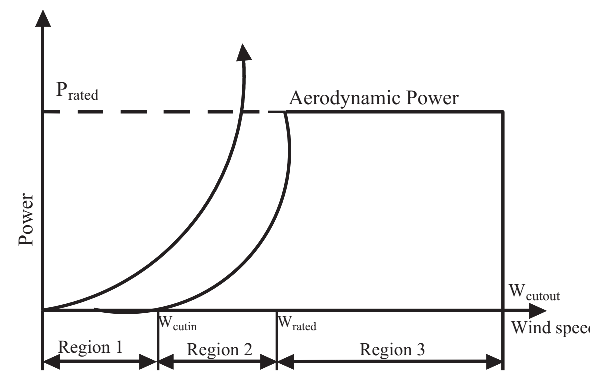

Fig. 24. Power operating region of wind turbines.

this approach a set membership that contains all states consistent with past measurement. If the current measurement is not consistent with this set, a fault is detected. The advantage of this method is no need for threshold design.

13. Proposed EEWS and control

In general the variable speed wind turbine operations are classified into three regions. Region 1 reports the starting speed when the wind speeds are below cut-in speed. Region 2 reports the wind speed between cut-in speed and rated speed. In this region the main objective is to maximize the amount of energy capture from the wind provided the pitch angles are approximately constant and generator torque is used to vary the rotor speed. In Region 3 the wind speed is between rated speed and cut-out speed. In this region the main objective is limit the output power to rated value by adjusting the pitch angles. In this work we concentrated only the Region 2 that is to extract the maximum power at below rated wind speed.

In order to achieve the maximum power at below rated speed, the turbine shaft speed should be adjusted according to the variable wind speed. Wind speed data is used to control the turbine rotor speed. Generally, anemometer is used to measure the wind speed. Anemometers are placed surrounding to the wind turbine to provide the wind speed data. As anemometers are used for measuring the wind speed at single point, accurate information of wind speed is not available from the anemometer. These mechanical sensors increase the cost and reduce the overall efficiency of the wind turbine system. In order to get the accurate control action over the wind turbine, we need to exact estimation of effective wind speed and control.

13.1. Wind speed estimator

The aero dynamic torque is approximated with 5th order polynomial given in Eq. (7) and rotor speed is measurable. Estimation of effective wind speed depends on aerodynamic torque and rotor speed with the pitch angle at optimal value.

$$F(\upsilon) = T_a - \frac{1}{2}\rho\pi R^3 \frac{C_P(\lambda)}{\lambda}\upsilon^2 \tag{34}$$

The MNR algorithm is used to solve Eq. (34). This equation has unique solution at below rated region. With known υ the optimal rotor speed ω_{ref} is defined in Eq. (35).

$$\omega_{ref} = \frac{\lambda_{opt}R}{\upsilon} \tag{35}$$

13.2. Sliding mode control (SMC)

To achieve the maximum power at below rated wind speed sliding mode based torque control is proposed in [54]. The main objective of this controller is to track the reference rotor speed ω_{ref} for maximum power extraction.

The WT single mass model can be rearranged and given in Eq. (36).

$$\dot{\omega}_r = \frac{1}{J_t}T_a - \frac{K_t}{J_t}\omega_r - \frac{1}{J_t}T_g \tag{36}$$

For speed control a sliding surface is defined as

$$S(t) = \omega_r(t) - \omega_{ref}(t) \tag{37}$$

The reference rotor speed is defined in Eq. (35). Taking the time derivative of Eq. (37) we will get Eq. (38).

$$\dot{S}(t) = \dot{\omega}_r(t) - \dot{\omega}_{ref}(t) \tag{38}$$

By substituting $\dot{\omega}_r$ in the above equation we will get

$$\dot{S} = \frac{1}{J_t}T_a - \frac{K_t}{J_t}\omega_r - \frac{1}{J_t}T_g - \dot{\omega}_{ref} \tag{39}$$

In order to evaluate the stability of the SMC by using Lyapunov candidate function

$$V = \frac{1}{2}S^2 \tag{40}$$

Taking the time derivative of the above equation

$$\dot{V} = S\dot{S} = S\left[\frac{1}{J_t}T_a - \frac{K_t}{J_t}\omega_r - \frac{1}{J_t}T_g - \dot{\omega}_{ref}\right] \tag{41}$$

if $\dot{V}$ is negative definite

$$\frac{1}{J_t}T_a - \frac{K_t}{J_t}\omega_r - \frac{1}{J_t}T_g - \dot{\omega}_{ref}\left\{ \begin{array}{l} <0 \text{ for } S>0 \\ >0 \text{ for } S<0 \end{array} \right\} \tag{42}$$

Stability of the controller is achieved provided the torque control satisfies Eq. (43).

$$T_g \left\{ \begin{array}{ll} < T_a - K_t\omega_r - J_t\dot{\omega}_{ref} & \text{for} \quad S>0 \\ > T_a - K_t\omega_r - J_t\dot{\omega}_{ref} & \text{for} \quad S<0 \end{array} \right\} \tag{43}$$

Finally the torque control structure is given in Eqs. (44) and (45)

$$T_g = T_a - K_t\omega_r - J_t\dot{\omega}_{ref} + J_t k \,\mathrm{sign}(S) \tag{44}$$

$$T_g = T_a - K_t\omega_r - J_t\dot{\omega}_{ref} + J_t k \tanh\left(\frac{S}{\varphi}\right) \tag{45}$$

where k is the sliding gain, sign is signum function and φ thickness of the boundary layer.

The major drawback in the signum function is it has the discontinued value between +1 and −1, because of this it introduces the chattering phenomenon. So the signum function is changed by a smooth function i.e. saturation (sat) and hyperbolic tangent (tanh) with boundary layer (φ). The chattering phenomenon is eliminated by the boundary layer. For robust control the boundary layer thickness is small, but if it is too small it increases the chattering. In order to select the boundary layer thickness it is necessary to know about the system behavior inside the boundary layer

13.3. Proposed sliding mode control with integral action (ISMC)

The conventional sliding mode control sliding surface generally depends on error and derivative of the error signal is given in Eq. (46).

$$S(t) = \left(\lambda + \frac{d}{dt}\right)^{n-1} e(t) \tag{46}$$

where λ is the positive constant and n is the order of the uncontrolled system.

To improve the sliding surface and overcome the steady state error the integral action is included in the sliding surface.

A sliding surface is defined as

$$S(t) = \left(\lambda + \frac{d}{dt}\right)^{n-1} e(t) + K_i \int_0^{\infty} e(t)\, dt \tag{47}$$

where K_i is the integral gain.

The order of the system $n=1$ then the sliding surface modified as

$$S(t) = e(t) + \int_0^{\infty} e(t)dt \tag{48}$$

The major objective of the controller is the tracking error $e(t)$ should converge to zero. The stability of the controller is determined by using the Lyapunov candidate function is already defined in Eq. (40) with $V(0)=0$ and $V(t)>0$ for $S \neq 0$.

By taking the time derivative of Eq. (48),

$$\dot{S}(t) = \dot{e}(t) + K_i e(t) \tag{49}$$

$$\dot{V} = S\dot{S} = S\left[\frac{1}{J_t}T_a - \frac{K_t}{J_t}\omega_r - \frac{1}{J_t}T_g - \dot{\omega}_{ref} + K_i e(t)\right] \tag{50}$$

Generally the SMC have two parts i.e. equivalent control U_{eq} and switching control U_{sw}. By combining these two controls minimizes the tracking error and satisfies the stability of the controller.

$$U(t) = U_{eq} + U_{sw} \tag{51}$$

The Switching control is defined in two ways

$$U_{sw} = k \,\mathrm{sign}\left(\frac{S}{\varphi}\right) \tag{52}$$

or

$$U_{sw} = k \tanh\left(\frac{S}{\varphi}\right) \tag{53}$$

Finally the torque control structure is given in Eq. (54).

$$T_g = T_a - K_t\omega_r - J_t\dot{\omega}_{ref} + J_t k_i e(t) + J_t k \tanh\left(\frac{S}{\varphi}\right) \tag{54}$$

13.4. Result and discussion

Fig. 25 shows the test wind profile of the WT. Generally wind speed consists of two parts i.e. mean and turbulent component. From this figure it is clear that wind speed having the data 10 min and it is applied to a WT. Fig. 26 shows the rotor speed comparisons for different control strategy such as SMC and ISMC. From this figure it is clear that ISMC is almost tracking the reference rotor speed without any turbulence. Fig. 27 shows the comparison of generator torque for different control strategy. In order to analyze the controller performance the following objectives are considered.

(1) Optimization of electrical and aero dynamic efficiency.
(2) Maximum generated torque and its standard deviation (STD).
(3) Control algorithm tested with model uncertainty and different wind profiles.

By referring to Table 1 it is clear that SMC and ISMC are almost having the same electrical efficiency which ensures the maximum power capture than other conventional controllers such as ATF and ISC. But according to oscillation in the drive train ISMC having minimum STD i.e. 1.26 kN m compared to all other controllers. This indicates less drive train oscillation and smoothness of control action.

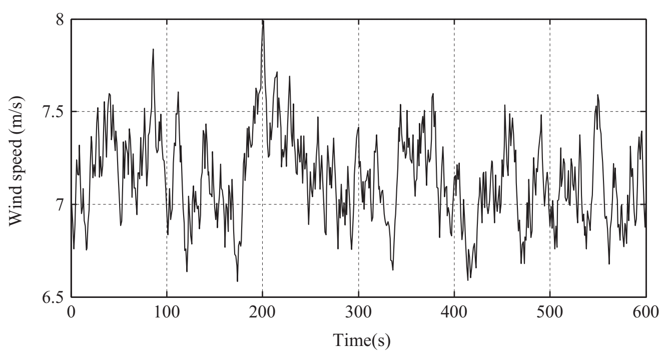

Fig. 25. Wind profile of mean 7 m/s.

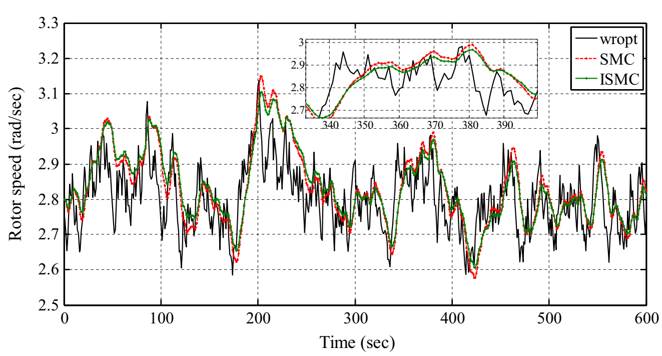

Fig. 26. Rotor speed comparison of different control strategy.

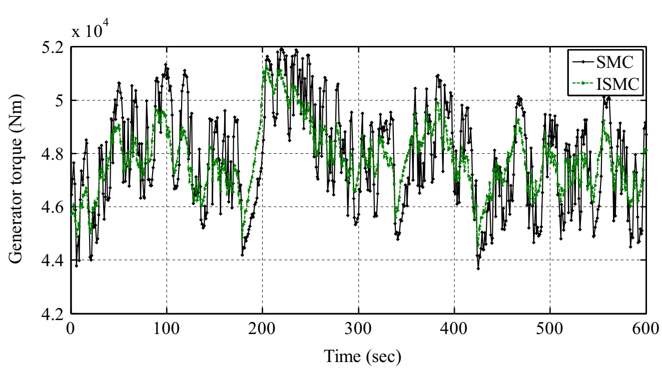

Fig. 27. Generator torque comparison of different control strategy.

In order to analyze the robustness of the controllers a parameter uncertainty is introduced in the WT system parameters i.e. turbine inertia J_t and turbine damping K_t. The WT parameter is varying between $+30\%$ of its nominal values. Table 2 gives the controller performance with the presence of the parameter uncertainty. From this table it is found that for the proposed ISMC control the STD of the generated torque T_g (2.219 kN m) is less than the STD of T_g (3.471 kN m) in SMC control with acceptable

Table 1
Comparison of different control strategy.

Control strategy	ATF	ISC	SMC	ISMC
STD (T_g) kN m	2.42	2.12	1.928	1.260
η_{ele} (%)	89.43	89.37	91.10	91.06
η_{aero} (%)	91.6	91.56	93.23	93.21
Relative variation T_g (%)	30.41	25.30	17.25	14.04

Table 2
Different control strategy with $+30\%$ uncertainty.

Control strategy	SMC	ISMC
STD (T_g) kN m	3.471	2.219
η_{ele} (%)	90.46	90.40
η_{aero} (%)	93.23	93.19
Relative variation T_g (%)	29.26	22.34

Table 3
Comparison of different control strategy with mean wind speed of 8 m/s.

Control strategy	ATF	ISC	SMC	ISMC
STD (T_g) kN m	2.719	2.623	2.542	1.384
MAX (T_g) kN m	67.18	67.12	67.04	67.72
η_{ele} (%)	89.42	89.39	91.45	91.48
η_{aero} (%)	91.66	91.65	93.38	93.43
Relative variation T_g (%)	30.71	28.31	15.65	13.54

Table 4
Comparison of different control strategy with mean wind speed of 8.5 m/s.

Control strategy	ATF	ISC	SMC	ISMC
STD (T_g) kN m	2.785	2.747	2.426	1.424
STD (T_g) kN m	73.59	73.65	74.69	74.94
η_{ele} (%)	89.56	89.53	91.83	91.79
η_{aero} (%)	91.66	91.65	93.6	93.58
Relative variation T_g (%)	26.09	25.72	14.46	12.56

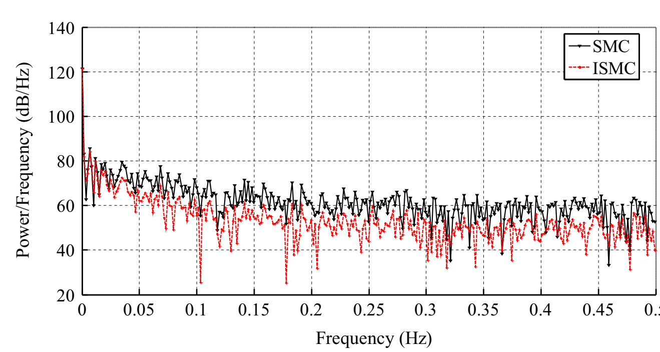

Fig. 28. Power spectral density of generator torque.

Table 5
Comparison of various EEWS techniques.

Methods for EEWS	Subclass	Merits	Demerits	Control strategies	Type of generator used and control techniques	Operation of the wind turbine
Polynomial	First order polynomial	– Generator is operated in speed control mode, power is used for WS estimation	– Power and pitch angle both are control variable, so estimation of wind speed is difficult	SC	Only estimation no control over it	VSWT
	Second order polynomial	– Pitch angle is used to control the speed of the turbine, pitch angle is used for WS estimation		PC		VSWT
	n^{th} order polynomial	– Simple model based approach – Increases the overall power output of the generation system with a minimal increase in controller complexity	– Power loss and above rated WS are not mentioned – It is complex and time consuming calculation – If the WS suddenly changing, the relatively slow search and may not make the maximum power extraction – Estimation accuracy depends on the size of the lookup table	SC	BDFM and MPPT	VSWT
Neural Network	Multi-layer perceptron neural network (MLPNN)	– Highly precise and fast calculation – The time-consuming calculation is achieved in a simple way without losing accuracy	– Power loss is not considered – Significant memory space and and may result time consuming search	SC	PMSG and PWM control	VSWT
	Support vector machine (SVM)	– High estimation precision and good generalization	– It required complete data of secondary and master variable – More training is required	SC	Only estimation no control over it	VSWT
	Gaussian radial bias function NN (GRBNN)	– Power losses is considered – Speed controller is designed such that to effectively damp the low frequency torsional oscillation – Reactive power and voltage control also investigated	– Required knowledge of characteristics WTG. This may not accurate due to high complexity, nonlinearity and uncertainty of WTG – This method is not robust against the air density variations and no test is given when the pitch angle system is activated – Low pass filter introduce a time delay	SC and PC	DFIG and RSC, GSC	VSWT
	Support vector regression (SVR)	– High accuracy and fast transient performance – Relevant function can calculated by offline, so that output can be calculated directly by inputs	– It's too slow duo to large number of support vector is generated – Real time estimation cannot be guaranteed	SC	DC motor coupled with squirrel cage IG and MPPT	VSWT
	Echo state network (ESN)	– Approximate the nonlinear dynamic electric power-wind speed characteristics	– It gives variable performance due to randomly connected hidden layer	SC and PC	DFIG and RSC, GSC	VSWT
	Multi layer feed forward artificial neural network (MLFANN)	– Easy to implementation for NN – It has the back propagation with momentum algorithm – No need for significant memory, complex and time consuming calculation	– Losses is not considered	SC and PC	DFIG and RSC, GSC (IGBT PWM)	VSWT
	Extreme machine learning (ELM)	– Robust and independent of air density variation – Reduce the number of training and improve the estimation accuracy. – An ELM based pitch angle controller puts into operation to limit the captured power	– It takes more time to converge and local minima	SC and PC	PMSG and RSC, GSC	VSWT
	Newton Raphson method	– It is not necessary to know the whole system model and mean wind speed	– It gives more estimation error	SC	Only estimation no control over it	VSWT

Table 5 (*continued*)

Methods for EEWS	Subclass	Merits	Demerits	Control strategies	Type of generator used and control techniques	Operation of the wind turbine
Iterative algorithm/ estimator (NR/KF/ EKF)*	Kalman filter (KF) and extended Kalman filter (EKF)	– More accurate compare to NR	– It is required to know the whole system model and mean wind speed	SC		VSWT
Nonlinear estimator with NR (Q and R estimation)**	Kalman filter with NR	– Adaptive Q and R based KF is used	– It depends on local linearization – Only for Gaussian (Stationary) Noise disturbance – NR method take own time to estimate the WS	SC	DFIG and PI, LQR, H_∞, ATF, ISC, NSSFE, NDSFE	VSWT
Nonlinear estimator without NR	Extended Kalman filter (EKF)	– Don't require the linearization of the system equation of state – Direct estimation WS without estimate the aerodynamic torque	– It is only for Gaussian noise disturbance	SC	ATC, ISC	VSWT
Statistical model	Autoregressive model (ARX)	– 30 s and 60 s wind prediction	– It is not accurate for online MPPT control – Anemometer is used to measure the WS for MPPT	SC	PMSG and RSC, GSC	VSWT
Recursive Bayesian estimators	Particle filter	– It does not rely on any local linearization – technique or any crude functional approximation – It is applicable for nonlinear and Gaussian scenario	– High computation complexity – Particle depends on the model dimension	SC	DFIG and Fuzzy control	VSWT
Unknown input based	KF with PI control	– Input and state estimation based WS estimation	– The complexity is increased because of the choice of model for the unknown input and the weighting between state – estimation and input estimation	PC	DFIG and RSC, GSC	VSWT
Data fusion	Frequency domain data fusion	– Easy to implement	– Two filters are used, it may introduce a delay – Pitch control is not investigated	SC	Only estimation no control over it	FSWT

BDFM—Brushless doubly fed machine, MPPT—Maximum power point tracking, VSWT—Variable Speed Wind Turbine, FSWT—Fixed Speed Wind Turbine, SC—Stall Controlled, PC—Pitch Controlled. * These two methods only applicable for WT having high wind speed and nominal operating point around the output power.

** Adaptive Kalman filter with estimation of unknown process and noise covariance to keeping the filter closely tuned optimal behaviour.

tracking error. It is clear that ISMC is more robust compared to SMC with respect to parameter uncertainty.

To ensure the controller performance the simulation is carried out for different wind profiles with below rated wind speed. Tables 3 and 4 shows the proposed ISMC controller achieves the similar performance even though mean wind speed changes. From Tables 3 and 4 it is concluded that with the increase in the mean wind speed the generator torque increases at the same time STD of generator torque also becomes high.

Power spectral density (PSD) is used to make the frequency analysis of the drive train torque. Fig. 28 shows the PSD for different controllers. From this figure it is clear that ISMC gives the minimum excitation to the drive train because the PSD curve of ISMC is completely below the SMC curve. For a good controller a tradeoff should be made between the power capture and smooth control action. From the results it is clear that SMC and ISMC have almost same power capture in terms of electrical efficiency but the transient loads in the drive train is minimum for ISMC. This ensures smooth control action of the ISMC control over SMC control. It is also found from the results that, ISMC is the optimal controller with maximum power capture and reduced oscillation on the drive train in comparison with the conventional controllers such as ATF and ISC.

Table 5 includes the merits and demerits of the each EEWS techniques, control strategy and generator used for the WT.

14. Conclusion

In this paper, review has been carried out on the problem of effective estimation of wind speed. Almost all the important EEWS techniques and its implementation are thoroughly discussed. This review also provides EEWS based control of wind turbines at below and above rated wind speed. The following are the main focus from the studies analyzed.

- The control algorithm requires the exact estimation of the wind speed which is having potential benefits for wind turbines located at complex sites.
- Accurate estimation of wind speed found to be beneficial in terms of increase in energy capture.
- Reduction of transient loads on the drive train is also dependent on the accuracy of EEWS techniques.
- The inaccurate estimation of wind speed leads to unnecessary pitch control action at below rated wind speed.
- The WT performances such as power capture and load reduction can be enhanced by additional control features and action.

Finally this review includes the merits and demerits of each EEWS techniques, with its control strategy, and generator used for WT. In the last section proposed ISMC control has been introduced which combines with the modified Newton Raphson method for estimation of the wind speed. In comparison with the classical controllers and conventional SMC, proposed ISMC was found to be better in terms of maximum energy capture and reduction in transient load on the drive train.

Appendix A

Two mass model of the wind turbine

The dynamics of the rotor side are given by the first order differential equation which is driven by the aerodynamic torque (T_a)

$$J_t\dot{\omega}_r = T_a - T_{ls} - K_r\omega_r$$

where low speed shaft torque acts as a braking torque (T_{ls}) on the rotor. It gives the torsion and friction effects due to difference between (ω_r) and (ω_{ls}).

$$T_{ls} = B(\theta_r - \theta_{ls}) + K_{ls}(\omega_r - \omega_{ls})$$

The dynamics of the generator side are given by the first order differential equation which is driven by the high speed shaft torque (T_{hs}) and braked by the electromagnetic torque (T_{em})

$$J_g\dot{\omega}_g = T_{hs} - K_g\omega_g - T_{em}$$

Gearbox ratio is defined as

$$n_g = \frac{T_{ls}}{T_{hs}} = \frac{\omega_g}{\omega_{ls}}$$

Transforming the generator side dynamics into the low speed shaft side

$$n_g^2 J_g\dot{\omega}_g = T_{ls} - n_g K_g\omega_g - n_g T_{em}$$

If a perfectly rigid low-speed shaft is assumed, the dynamics of the rotor characteristics of a single mass wind turbine model can be expressed by a first-order differential equation given as

$$J_t\dot{\omega}_r = T_a - T_g - K_t\omega_r$$

where

$$J_t = J_r + n_g^2 J_g$$

$$K_t = K_r + n_g^2 K_g$$

$$T_g = n_g T_{em}$$

Appendix B

Two mass model parameters

Rotor radius	R=21.65 m
Air density	ρ=1.29 kg/m^3
Rotor inertia	J_r=3.25.10^5 kg/m^2
Generator inertia	J_g=34.4 kg/m^2
Shaft damping coefficient	K_{ls}=9500 N m/rad
Shaft stiffness coefficient	B_{ls}=2.691.10^5 N m/rad
Rotor friction coefficient	K_r=27.36 N m/rad/s
Generator friction coefficient	K_g=0.2 N m/rad/s
Gear ratio	$n_{g=}$43.165

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