A Neural Network Based Adaptive Sliding Mode Controller for Pitch Angle Control of a Wind Turbine

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***Abstract*— In this paper the variable rotor speed and variable blade pitch wind turbine operation in regions with high wind speeds is investigated where the objective is limiting the turbine energy capture to the nominal power value. To aim regulation of the rotor speed to a constant nominal value, in the presence of uncertainties characterizing the wind turbine model, this paper proposes a second order sliding mode approach, implementing the blade pitch as control input, also to approximate the uncertainties of the turbine model neural network is implemented. A closed loop convergence has been proved for the complete control system. Finally to illustrate the effectiveness and performance of the proposed controller the proposed method is applied to a 5 megawatt wind turbine.**

***Keywords*— Wind Turbine, Sliding Mode Control, Neural-Network, Pitch Control.**

I. INTRODUCTION

Recently a great deal of attention has been paid to the renewable energies. Wind energy as a renewable energy is considered as a very attractive kind of energy resource. The wind energy can be harvested using Wind Energy Conversion System (WECS). However in wind turbines the efficiency can be affected adversely because of inevitable wind variations. Considering what has been discussed, it seems beneficial to use an appropriate control system for WECS that is able to increase the captured wind energy and turbine efficiency and also reduce the loads effect on the turbine itself [1, 2].

Based on the wind speed, maximum acceptable rotor speed and rated power, different operating regions can be considered for the extraction of wind power using WECS. Three main operating regions can be considered for variable rotor speed and variable blade pitch wind turbines, with respect to wind speed [3-7]. The first operation region is where the turbine is starting up or is not moving at all. The second operation region is the operation mode that aims the maximizing of the captured wind energy. In the third operation region that includes high wind speeds, in order to make sure that the safe electrical and mechanical loads are not surpassed, the turbine needs to limit its captured wind power. The generator torque control that keeps the blade pitch constant at an optimal value in order to get the peak energy extraction usually is implemented in second region [8-13], whilst in the third region for the purpose of limiting the power for the turbine operating in that region, the control of blade pitch is implemented [14, 15].

The most implemented control strategy for the control of blade pitch is a feedback strategy based on the error between the actual output power and the rated power, which is equivalent to the actual rotor speed and the corresponding rated rotor speed. What makes the linear control approach to be poorly effective and robustly depending on a fixed operating point is the nonlinear relationship between aerodynamic power, rotor speed, wind speed and pitch angle along with the disturbances and model uncertainties. On top of that, even if there has been promises for providing real-time measurements of wind speed by advances in light detection and ranging systems (LIDAR), still parametric uncertainties and nonlinearities in the wind turbine model remains an issue to be solved, therefore a robust nonlinear control approach to solve this problem is needed [1, 14-18].

Adaptive or gain-scheduled controllers has been implemented to compensate for the dynamic behavior or variation in parameters, that the gains of control in which are adapted/scheduled based on the calculated or measured varying parameters, including the pitch angle in the third region and the generator velocity in the second region. Different approaches are implemented to deal with robustness, such as adaptive control, neural network based control, backstepping control, model predictive control and sliding mode control [1, 2, 16, 19-26]. In [34], sliding mode controller is used to regulate the wind turbine speed on the rated speed in the third region. Also some parametric uncertainties are considered and although the nonlinear relationship between the wind turbine model and the pitch angle is approximated so the model becomes affine with respect to the pitch angle. Considering what has been discussed, the sliding surface used in [34] is proportional and integral which can result in chattering phenomenon in the pitch angle so the dynamic stress on wind turbine increases and will be a cause for damage to the wind turbine. Also parametric uncertainties and unknown approximation nonlinear terms, increase the control effort. In order to overcome aforementioned problems second order sliding surface and neural network to approximate the nonlinearities can be utilized respectively.

In this paper by introducing an estimation of the power coefficient, which makes the producing of an effective and practical control law possible, the complexity of the wind turbine model which is a non-affine with respect to the pitch angle is reduced. A sliding mode controller based on the model corresponding to the aforementioned approximation is designed that based on the specific turbine features, guarantees the rotor speed regulation to its rated value that corresponds to a rated aerodynamic power. To estimate the nonlinear uncertainties and non-affine approximation error of pitch angle in the wind turbine model, a radial basis function neural network is used. To overcome the chattering phenomenon a second order sliding mode surface is employed and using adaptive control made the controller more flexible to the parametric uncertainties. The neural network approximation error bound is estimated by defining an appropriate adaptation law. Finally the asymptotically stability of the proposed controller is proved by using the Lyapunov theorem and it can guarantee that the tracking error of wind turbine speed converges to zero.

II. WECS DYNAMICS

The system model that was mentioned here is inspired by [21,29]. As it is clear, wind energy at first is transformed into mechanical energy using the WT blades and, finally, into electrical energy using the generator. The aerodynamic (mechanical) power that the wind turbine produces from the wind is introduced by the following equation [21,28]

$$P_a(t) = \frac{1}{2}\rho \pi r^2 C_p(\lambda,\beta) V^3(t) \qquad (1)$$

where ρ is the air density, r is the wind turbine rotor radius, V is the wind speed and the power coefficient Cp (λ, β) shows the turbine efficiency to transform the kinetic energy of the wind into mechanical energy [21] that is a function of the blade pitch angle β and of the tip speed ratio λ which is introduced as [30]

$$\lambda(t) = \frac{\omega(t)}{V(t)} r \qquad (2)$$

where ω(t) is the WT angular shaft speed. The substitution of (2) in (1) gives:

$$P_a = \frac{k_a r \omega(t) C_p(\lambda,\beta)}{\lambda(t)} V^2(t) \qquad (3)$$

by defining $k_a = \rho \frac{\pi}{2} r^2$, the torque that the wind turbine extracts from the wind can be expressed as follow

$$T_a(t) = \frac{k_a r C_p(\lambda,\beta)}{\lambda(t)} V^2(t) \qquad (4)$$

The power coefficient Cp (λ, β) which is a nonlinear function [30,31] depends on the blade aerodynamic design and the WT operating conditions. In [28], the following equation is proposed in order to model the power coefficient

$$C_p(\lambda,\beta) = k_5(k_1\gamma + k_2\beta + k_3)e^{k_4\gamma} \qquad (5)$$

$$\gamma = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \qquad (6)$$

The coefficients k_i, i=1 … 5, depend on shape and aerodynamic performance of the blade [3,28] and they are considered uncertain:

$$k_i = \bar{k}_i + \Delta k_i, \qquad i = 1,2,...,5$$

The nominal values $\bar{k}_i$, i = 1 . . . 5 obtained by fitting Eq. (5) with the values of Cp for the NREL 5 - MW wind turbine [33], are introduced by:

$$\bar{k}_1 = 7.022 \quad \bar{k}_2 = -0.04176 \quad \bar{k}_3 = -0.3863 \quad \bar{k}_4 = -14.52 \quad \bar{k}_5 = 6.909$$

It is assumed that the uncertainties Δk_i, i=1 … 5, are bounded with unknown bounds:

$$|\Delta k_i| \le \rho_{k_i} \qquad (7)$$

Accordingly, defining the following functions

$$h_1(\lambda,\beta) = (\bar{k}_1\gamma + \bar{k}_2\beta + \bar{k}_3)$$

$$h_2(\lambda,\beta) = k_5(\Delta k_1\gamma + \Delta k_2\beta + \Delta k_3) + \Delta k_5 h_1(\lambda,\beta)$$

$$\bar{C}_p(\lambda,\beta) = \bar{k}_5 h_1(\lambda,\beta) e^{\bar{k}_4\gamma}$$

$$\Delta C_p(\lambda,\beta) = \left[(\bar{k}_5 h_1(\lambda,\beta) + h_2(\lambda,\beta)\right]\left[e^{\bar{k}_4\gamma}(e^{\Delta k_4\gamma} - 1)\right] + h_2(\lambda,\beta) e^{\bar{k}_4\gamma}$$

the power coefficient Cp (λ, β) can be rewritten as:

$$C_p(\lambda,\beta) = \bar{C}_p(\lambda,\beta) + \Delta C_p(\lambda,\beta) \qquad (8)$$

The mechanical equation governing the turbine is the following [33]:

$$\dot{\omega}(t) = (\frac{1}{J})(T_a(t) - B\omega(t) - N_g T_e(t)) \qquad (9)$$

where, B is the viscous friction coefficient of the low-speed shaft, J is the inertia moment, N_g is the gearbox ratio and $T_e(t)$ is the electrical torque of the generator, which can be imposed designing voltages and currents of the generator stage. Similarly to parameters k_i, B and J are assumed to be uncertain with unknown bounds on the deviations with respect to the nominal values, i.e.:

$$B = \bar{B} + \Delta B, |\Delta B| \le \rho_B, J = \bar{J} + \Delta J, |\Delta J| \le \rho_J \qquad (10)$$

and $\bar{B}$ and $\bar{J}$ are the nominal values, and ρ_B, ρ_J two unknown positive constants.

As it is known, when the wind turbine is operating in region of high wind speeds, the power $P_a(t)$ should be kept at the rated value P_a^*. Therefore, the electrical torque $T_e(t)$ needs to be fixed at the value $T_e(t) = \frac{P_a^*}{\omega(t)}$ [27]. Using this latter condition and considering Eqs. (4), (8), (10) and Eq. (9) becomes:

$$\dot{\omega}(t) = (\frac{1}{\bar{J}})\left[\frac{k_a r}{\lambda(t)}\bar{C}_p(\lambda,\beta)V^2(t) - \bar{B}\omega(t) - N_g\frac{P_a^*}{\omega(t)} + \bar{d}(\lambda,\beta,V,\omega)\right] \qquad (11)$$

With:

$$\bar{d}(\lambda,\beta,V,\omega) = \left[\frac{k_a r}{\lambda(t)}\Delta C_p(\lambda,\beta)V^2(t) - \Delta B\omega(t)\right] - \frac{\Delta J}{\bar{J} + \Delta J}\left[\frac{k_a r}{\lambda(t)}C_p(\lambda,\beta)V^2(t) - B\omega(t) - N_g\frac{P_a^*}{\omega(t)}\right] \qquad (12)$$

The term $\bar{d}(\lambda,\beta,V,\omega(t))$ shows the overall system parametric uncertainty, depending on (7) and (10).

Intrinsic physical restrains of a real wind turbine points out that there are bounded ranges for wind speed, rotor speed and blade pitch angle. So, by taking into account (7) and (10), it can be assumed that there exists $\bar{d} > 0$ such that:

$$\left|\bar{d}(\lambda, \beta, V, \omega)\right| \le \bar{\delta} \tag{13}$$

III. SPEED CONTROL

In this section, it is assumed that the wind turbine operates above the rated wind speed and keeping the angular velocity ω(t) to a fixed value ω^*, corresponding to the rated value P_a^* of the captured wind power is the objective of the blade pitch control. In other words, β(t) in (11) is used as the control law to keep the wind turbine angular velocity ω(t) at the desired speed ω^* in the presence of uncertainties.

A. Power coefficient approximation

Wind turbine model in (11) has a non-affine relationship with control input β(t). So an approximation of the nominal power coefficient $\bar{C}_p(\lambda, \beta)$ will be proposed that makes the model in (11) affine with respect to β(t). Consider $\frac{0.08\beta}{\lambda(t)} << 1$ and $\frac{1}{\lambda(t)+0.08\beta} \ge \frac{0.035}{\beta^3+1}$, so the function γ in (5) can be approximated as:

$$\begin{aligned}\gamma &= \frac{1}{\lambda(t)+0.08\beta} - \frac{0.035}{\beta^3+1} \simeq \frac{1}{\lambda(t)+0.08\beta} \\ &= \frac{1}{\lambda(t)}\left(1+\frac{0.08\beta}{\lambda(t)}\right)^{-1} \simeq \frac{1}{\lambda(t)}\left(1-\frac{0.08\beta}{\lambda(t)}\right)\end{aligned} \tag{14}$$

The term $e^{(\bar{k}_4\gamma)}$, can be approximated by a linear regression as follow:

$$e^{(\bar{k}_4\gamma)} \simeq \alpha_1(\beta)\lambda + \alpha_2(\beta) \tag{15}$$

where coefficients $\alpha_1(\beta)$, $\alpha_2(\beta)$ are functions of the pitch angle β, which will be assumed bounded by known constants:

$$\alpha_1^{\min} \le \alpha_1(\beta) \le \alpha_1^{\max}; \ \alpha_2^{\min} \le \alpha_2(\beta) \le \alpha_2^{\max} \tag{16}$$

Finally, if we consider $\bar{\alpha}_1\lambda + \bar{\alpha}_2$ as a ''nominal'' linear regression, that $\bar{\alpha}_1$, $\bar{\alpha}_2$ are constant, and by defining:

$$g_1(\lambda) = \frac{\bar{k}_1}{\lambda(t)} + \bar{k}_3$$

$$g_2(\lambda) = \frac{0.08\bar{k}_1}{\lambda(t)^2} - \bar{k}_2$$

the power coefficient $\bar{C}_p(\lambda, \beta)$ can be rewritten as:

$$\bar{C}_p(\lambda, \beta) = \bar{k}_5[g_1(\lambda) - g_2(\lambda)\beta](\bar{\alpha}_1\lambda(t) + \bar{\alpha}_2) + \hat{d}(\lambda, \beta) \tag{17}$$

where $\hat{d}(\lambda, \beta)$ is the overall error due to the above simplifications.

Using (17), the wind turbine model (11) can be approximated as follows:

$$\dot{\omega}(t) = f_1(\omega, \lambda, \beta, V) + \frac{k_a r V^2(t)}{\bar{J}\lambda(t)}\bar{k}_5[g_1(\lambda) - g_2(\lambda)\beta](\bar{\alpha}_1\lambda(t) + \bar{\alpha}_2) \tag{18}$$

being:

$$f_1(\omega, \lambda, \beta, V) = -\frac{\bar{B}}{\bar{J}}\omega(t) - \frac{N_g}{\bar{J}}\frac{P_a^*}{\omega(t)} + \frac{k_a r V^2(t)}{\bar{J}\lambda(t)}\hat{d}(\lambda, \beta) + \bar{d}(\lambda, \beta, V, \omega) \tag{19}$$

B. Neural network approximation

The radial basis function neural network (RBFNN) is a general approximator of a nonlinear functions. An unknown and continues nonlinear function $f(\underline{x}) : \Omega_{\underline{x}} \subset \mathbb{R}^4$ can be approximated by RBFNN over a compact set $\Omega_{\underline{x}}$ as follows:

$$f(\underline{x}) = W^{*T}\underline{\Phi}(\underline{x}) + \varsigma(\underline{x}) \tag{20}$$

Where $W^* = [w_1^*, w_2^*, ..., w_l^*]^T \in \mathbb{R}^l$ is the optimal constant weight vector, ς is the minimum approximation error, $l > 1$ is the number of NN nodes and $\underline{\Phi}(\underline{x}) = [\varphi_1(\underline{x}), \varphi_2(\underline{x}), ..., \varphi_l(\underline{x})]^T$ is the activation function of NN and it is considered as Gaussian function in the following form:

$$\varphi_i(\underline{x}) = \exp\left(-\frac{\left\|\underline{x} - \underline{m}_i\right\|^2}{\sigma_i^2}\right), \quad i = 1, 2, ..., l \tag{21}$$

Also $\underline{m}_i = [m_{i1}, m_{i2}, m_{i3}, m_{i4}]^T$ and σ_i are centers vector and the width of the Gaussian function respectively. W^* and ς are bounded, i.e. $\left\|W^*\right\|_F \le \bar{W}$ and $\left|\varsigma(\underline{x})\right| \le \bar{\varsigma}$. By considering the compact set $\Omega_{\underline{x}} \subset \mathbb{R}^4$, the optimal weight vector W^* in (20) defined as:

$$W^* := \arg\min_{W^* \in \mathbb{R}^l}\{\sup_{\underline{x} \in \Omega_{\underline{x}}} |f(\underline{x}) - W^T\underline{\Phi}(\underline{x})|\} \tag{22}$$

C. Adaptive robust Controller design

In this section to regulate the speed of the wind turbine on its rated speed a neural network-based adaptive sliding mode controller is proposed. Nonlinear uncertain term in mechanical model of wind turbine is approximated with a neural network and on top of that to improve the performance of the proposed controller, the neural network approximation error is adaptively estimated. Also in order to make the controller more flexible against uncertainties an adaptive gain is designed.

To eliminate the chattering effect a second-order sliding surface is defined as follow:

$$\sigma(t) = \dot{s}(t) + \eta s(t) = k_p e(t) + k_i \int e(x)dx \tag{23}$$

Which the tracking error of speed is

$$e(t) = \omega(t) - \omega_r(t) \tag{24}$$

k_p and k_i are positive design parameters.

And $\omega_r(t)$ is the reference speed which is the rated speed ω^*. Also another controller input is the pitch angle which is designed as below

$$\beta = \frac{1}{q_2(\lambda,V)}(\beta_{SOSMC}(t)+\beta_{RBFNN}(t)+\beta_{ad}(t)) \quad (25)$$

$$\beta_{SOSMC}(t) = k_p\dot{\omega}_r - k_i\, e(t) - q_1(\lambda,V) - a_1\dot{s}(t) - a_2 s(t) \quad (26)$$

$$\beta_{RBFNN}(t) = -W^T \underline{\Phi}(\underline{x}) \quad (27)$$

$$\beta_{ad} = -\frac{\dot{s}(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t) - \hat{\varsigma}(t) \quad (28)$$

Which $\beta_{SOSMC}(t)$, $\beta_{RBFNN}(t)$ and $\beta_{ad}(t)$ are second order sliding mode pitch angle, the control input resultant of neural network and adaptive control input respectively.

To simplify the equations the two nonlinear functions $q_1(\lambda,V)$ and $q_2(\lambda,V)$ are defined as follow

$$\begin{aligned} q_1(\lambda,V) &= k_p \frac{k_a rV^2(t)}{\bar{J}\lambda(t)}\bar{k}_5(\bar{\alpha}_1\lambda(t)+\bar{\alpha}_2)g_1(\lambda) \\ q_2(\lambda,V) &= -k_p \frac{k_a rV^2(t)}{\bar{J}\lambda(t)}\bar{k}_5(\bar{\alpha}_1\lambda(t)+\bar{\alpha}_2)g_2(\lambda) \end{aligned} \quad (29)$$

The adaptation law for estimation of neural network approximation error is

$$\dot{\hat{\varsigma}} = \tau_1 \dot{s}(t) \quad (30)$$

and the adaptive gain is given as

$$\dot{\hat{\alpha}}(t) = \frac{\dot{s}^2(t)}{|\dot{s}(t)|+\mu} \quad (31)$$

the adaptation law for neural network weights vector is designed as

$$\dot{W} = \tau_2 \dot{s}(t)\underline{\Phi}(\underline{x}) \quad (32)$$

Theorem. The designed adaptive sliding mode controller based on input control law and adaptation laws (23)-(32) can guarantee the closed-loop stability of the system (18). In the next section, this theorem will be proved.

IV. STABILITY ANALYSIS OF PROPOSED ROBUST CONTROLLER

To proof the stability of the proposed controller the Lyapunov theorem is implemented.

The Lyapunov function candidate is defined as follow

$$V = \frac{a_2}{2}s^2(t) + \frac{1}{2}\dot{s}^2(t) + \frac{1}{2\tau_1}\tilde{\varsigma} + \frac{1}{2}\tilde{\alpha}^2(t) + \frac{1}{2\tau_2}\tilde{W}^T\tilde{W} \quad (33)$$

where s and $\dot{s}$ are defined in (21), $\tilde{\varsigma}$ is an estimation error of the neural network approximation error, $\tilde{\alpha}$ is the estimation error of the positive constant gain α and $\tilde{W}$ is the estimation error of constant optimal neural network weights vector W^* which is used to approximate a nonlinear function that will be defined later.

The derivative of V with respect to time is

$$\dot{V} = a_2 s(t)\dot{s}(t) + \dot{s}(t)\ddot{s}(t) + \frac{1}{\tau_1}\tilde{\varsigma}\dot{\tilde{\varsigma}} + \tilde{\alpha}(t)\dot{\tilde{\alpha}}(t) - \frac{1}{\tau_2}\tilde{W}^T\dot{W} \quad (34)$$

where $\tilde{\alpha}(t) = \alpha - \hat{\alpha}(t)$, $\tilde{\varsigma}(t) = \hat{\varsigma}(t) - \varsigma$ and $\tilde{W}(t) = W^* - W(t)$.

Using (23) and (18) $\ddot{s}(t)$ can be obtained as

$$\begin{aligned} \ddot{s}(t) = &-\eta\dot{s}(t) - k_p\dot{\omega}_r + k_i\, e(t) + W^{*T}\underline{\Phi}(\underline{x}) + \varsigma(\underline{x}) \\ &+ k_p\frac{k_a rV^2(t)}{\bar{J}\lambda(t)}\bar{k}_5(\bar{\alpha}_1\lambda(t)+\bar{\alpha}_2)g_1(\lambda) \\ &- k_p\frac{k_a rV^2(t)}{\bar{J}\lambda(t)}\bar{k}_5(\bar{\alpha}_1\lambda(t)+\bar{\alpha}_2)g_2(\lambda)\beta \end{aligned} \quad (35)$$

where $W^{*T}\underline{\Phi}(\underline{x}) + \varsigma(\underline{x}) = k_p f_1(\omega,\lambda,\beta,V)$ and $\underline{x} = [\lambda\, \beta\, V\, \omega]^T$.

By substituting (30) in (36)

$$\begin{aligned} \ddot{s}(t) = &-\eta\dot{s}(t) - k_p\dot{\omega}_r + k_i\, e(t) + W^T\underline{\Phi}(\underline{x}) + \tilde{W}^T\underline{\Phi}(\underline{x}) \\ &+ \hat{\varsigma}(\underline{x}) - \tilde{\varsigma}(\underline{x}) + q_1(\lambda,V) + q_2(\lambda,V)\beta \end{aligned} \quad (36)$$

By adding and subtracting $\frac{\dot{s}(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t)$ to (36) Eq. (38) can be given as follow

$$\begin{aligned} \ddot{s}(t) = &-\eta\dot{s}(t) - k_p\dot{\omega}_r + k_i\, e(t) + q_1(\lambda,V) \\ &+ \frac{\dot{s}(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t) + \hat{\varsigma}(t) + W^T\underline{\Phi}(\underline{x}) + \tilde{W}^T\underline{\Phi}(\underline{x}) \\ &- \tilde{\varsigma}(\underline{x}) - \frac{\dot{s}(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t) + q_2(\lambda,V)\beta \end{aligned} \quad (37)$$

By substituting (25)-(28) in (37) we have

$$\begin{aligned} \ddot{s}(t) = &-(\eta + a_1)\dot{s}(t) - a_2 s(t) + \tilde{W}^T\underline{\Phi}(\underline{x}) - \tilde{\varsigma}(\underline{x}) \\ &- \frac{\dot{s}(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t) \end{aligned} \quad (38)$$

So $\dot{V}$ is as follow

$$\begin{aligned} \dot{V} = &-(\eta + a_1)\dot{s}^2(t) + \dot{s}(t)\tilde{W}^T\underline{\Phi}(\underline{x})\dot{s}(t) - \dot{s}(t)\tilde{\varsigma}(\underline{x}) \\ &- \frac{\dot{s}^2(t)}{|\dot{s}(t)|+\mu}\hat{\alpha}(t) + \frac{1}{\tau_1}\tilde{\varsigma}\dot{\tilde{\varsigma}} + \tilde{\alpha}(t)\dot{\tilde{\alpha}}(t) - \frac{1}{\tau_2}\tilde{W}^T\dot{W} \end{aligned} \quad (39)$$

Using Eq. (31)-(33), (40) becomes

$$\begin{aligned} \dot{V} &= -(\eta + a_1)\dot{s}^2(t) - \frac{\dot{s}^2(t)}{|\dot{s}(t)|+\mu}(\tilde{\alpha}(t) - \hat{\alpha}(t)) \\ &= -(\eta + a_1)\dot{s}^2(t) - \frac{\dot{s}^2(t)}{|\dot{s}(t)|+\mu}\alpha \end{aligned} \quad (40)$$

Therefore if α be a positive constant it can be concluded that $\dot{V} < 0$.

Based on the Lyapunov theorem the system (18) under control and adaptation laws (25)-(28) and (30)-(32) is asymptotically stable.

V. SIMULATION RESULTS

In this section the proposed controller is applied to a 5-MW wind turbine introduced in [33]. In simulation process the rated angular velocity ω^* and the rated aerodynamic power P_a^* are considered 12.1 rpm and 5.29661-MW respectively. Except ω(0)=12 rpm and β(0)=14 deg, all other initial conditions are assumed to be zero.

Controller parameters are selected as $k_p = 0.02$, $k_i = 3$, $a_1 = 0.32$, $a_2 = 0.15$, $\tau_1 = 6$, $\tau_2 = 7.3$ and $\mu = 0.001$. Also neural network parameters are considered as $\sigma_i = 0.3$, l=8 and $\underline{m}_i\ (i = 1,2,..,l)$ evenly spaced in $[-2,2]\times[-2,2]\times[-2,2]\times[-2,2]$.

Simulation results are illustrated in Fig. 1. to Fig. 4.

Fig.1. shows the wind speed with the mean value of 17.5 m/s which is a high wind speed.

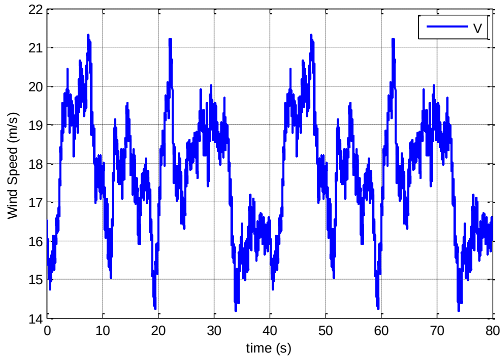

Fig. 1. Wind speed profile

Extracted aerodynamic power from wind turbine is shown in Fig.2. It's regulated around the desired nominal value P_a^*.

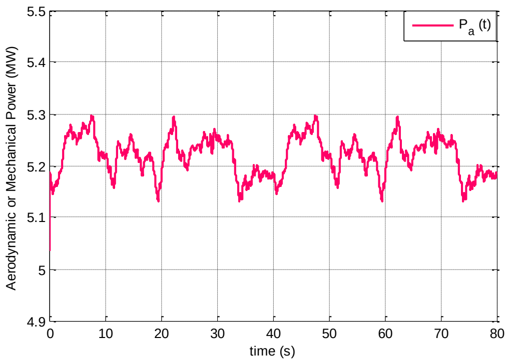

Fig. 2. Aerodynamic wind turbine power

The angular speed of rotor is shown in Fig.3. It is set on the rated speed value which has resulted in capturing of the nominal power.

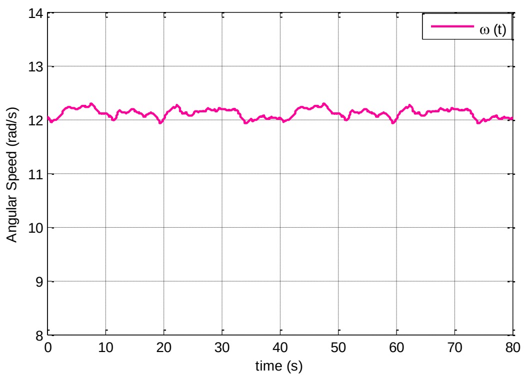

Fig. 3. Angular velocity of rotor

The pitch angle to control the rotor angle is illustrated in Fig.4.

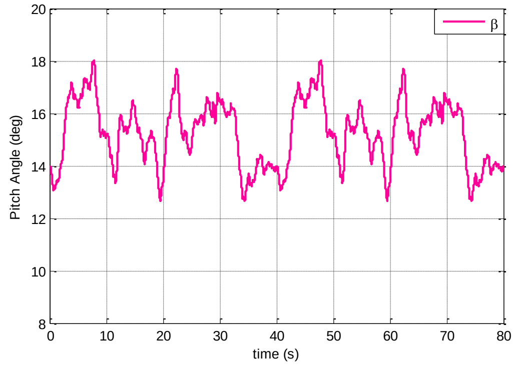

Fig. 4. Pitch angle of wind turbine

VI. CONCLUSION

In this paper a neural network-based adaptive second order sliding mode controller was proposed. To approximate the nonlinear uncertain terms in wind turbine model a RBFNN was implemented. Also adaptive control was used for a better performance of the controller against the parameters variation of wind turbine model.

The simulation results of the proposed controller strongly indicate that the controller performance despite model uncertainties was promising.

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