Vector control of wind turbine on the basis of the fuzzy selective neural net

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Abstract. An article describes vector control of wind turbine based on fuzzy selective neural net. Based on the wind turbine system’s state, the fuzzy selective neural net tracks an maximum power point under random perturbations. Numerical simulations are accomplished to clarify the applicability and advantages of the proposed vector wind turbine’s control on the basis of the fuzzy selective neuronet. The simulation results show that the proposed intelligent control of wind turbine achieves real-time control speed and competitive performance, as compared to a classical control model with PID controllers based on traditional maximum torque control strategy.

Introduction

At the present time, because of ecological problems and due to limitation of natural energy sources the renewable energy becomes more popular. The wind energy is the most developing technology of the alternative clean energy sources. Modern wind turbine stations and windmill farms compiles the complex system for electricity generation. In recent years, a number of advanced control schemes have been proposed, but most of them lack the capacity to address the multi-objective problem since they concentrate only on particular objectives while disregarding others [1]. However, the controller did not take into account the fluctuation of structural loads. In this paper three–phase Permanent Magnet Synchronous Generator (PMSG) that will be used to generate electrical energy driven by wind turbine is simulated by Matlab.

There are many classical control strategies for wind turbine such as most common decoupling algorithm & maximum power point tracking (MPPT) and traditional maximum torque control strategy. One of the most common control strategies is the Proportional-Integral-Derivative (PID) controller due to its simplicity and applicability [2]. However, wind turbine systems are non-linear and commonly suffer from restrictions imposed by the uncertainty of the environment as a result of sudden variations in the wind speed. Therefore unstable dynamics must be confronted when designing control systems to track maximum power point quickly – in order to provide stability, disturbance attenuation. But the PID controllers for non-linear wind turbine system have slow response times to changing reference commands, take considerable time to settle down from oscillating around the MPP state, must often be designed by hand, and require extensive analysis of the system and dynamics. This process is generally difficult because it is hard to anticipate all operating conditions. The control model must coordinate the non-linear wind turbine system properly, generating robust behavior to negotiate disturbance attenuation effectively while maintaining stability. Moreover, the non-linear wind turbine system should be robust to different environmental conditions, in order to reliably generate maximum power.

Therefore, automatic design methods utilizing intelligent techniques such as neural network and fuzzy logic are a promising alternative [2-6]. For real-life wind turbine applications, the wind turbine system behavior can change; system parameters can exhibit random variations; the wind speed can fluctuate. Hence neural-network based solutions have been proposed to overcome these difficulties. But the network needs to become more adaptive.

¹This work is supported by Russian Foundation for Basic Research (grant №16-48-190912)
Adaptive behavior can be enabled by modifying the network to have fuzzy units which respond to the changing behavior of the wind turbine system. Therefore, wind turbines are best modeled as hybrid systems since their behaviors result from the interaction between continuous and discrete dynamics. Several methods have been developed to overcome the aforementioned difficulties. The most important approaches are those that combine the classical control strategy with the intelligent models, which are neural network and fuzzy logic. This paper presents the vector control of PV system on the basis of the fuzzy selective neuronet.

1. Wind turbine control model based on PID controllers
The aim of the Field Oriented Control is to perform real time control of the torque demand, to control rotor mechanical speed and to regulate phase currents. To perform these controls, the electrical equations are projected from a 3 phase non-rotating frame into a two co-ordinate rotating frame [1].

Using Clarke–Park transformations voltage and torque equations of the PMSG in d-q rotor reference frame can be given by (18)-(22), where the q-axis goes ahead 90 degrees from the d-axis with respect to the direction of rotation.

\[
\begin{align*}
\Psi_{sd} &= R_s i_{sd} + \frac{d}{dt} \Psi_{sd} - w_r \Psi_{sq} \\
\Psi_{sq} &= R_s i_{sq} + \frac{d}{dt} \Psi_{sq} + w_r \Psi_{sd} \\
T_e &= \frac{3}{2} p (\Psi_{sd} i_{sq} - \Psi_{sq} i_{sd})
\end{align*}
\]

where \( \Psi_{sd} \) is the d-axis stator flux linkage, \( \Psi_{sq} \) is the q-axis stator flux linkage.

\[
\begin{align*}
\Psi_{sd} &= L_s i_{sd} + \Psi_m \\
\Psi_{sq} &= L_s i_{sq}
\end{align*}
\]

where \( u_{sd} \) and \( u_{sq} \) are voltages in d-q axis , \( R_s \) is the stator resistance, \( L_s \) is the stator inductance, \( w_r \) is the electrical rotational speed, \( \Psi_m \) is the permanent magnet flux constant provided by the magnets, and \( p \) is the number of pole pairs. In this paper we ignore losses and can write equation for the dc-link dynamics as follows:

\[
\begin{align*}
i_{gen} &= i_c + i_{grid} \\
i_{gen} &= \frac{P_{gen}}{v_c} \\
P_{gen} &= \frac{3}{2} (u_{ds} i_{ds} + u_{qs} i_{qs}) \\
i_c &= C \frac{dv_c}{dt}
\end{align*}
\]

where \( P_{gen} \) is the generator output power, \( i_{gen} \) is the generator output current flowing towards the capacitor bank and the grid side, \( i_{grid} \) is the current drawn by the grid side from the dc bus, \( v_c \) is the capacitor voltage across the DC-link.

Vector control used a field-oriented theory controls space vectors of magnetic flux, current, and voltage. A traditional maximum torque control strategy has the rotor flux oriented frame. In this frame the q-component reference of the stator current is generated from a speed controller while the d-component reference is set to zero.

Vector control presents following benefits: speed control over a wide range, precise speed regulation, fast dynamic response, and operation above base speed.
2. Vector control of wind turbine system on the basis of the fuzzy selective neuronet

In this paper, the function approximation capabilities of fuzzy selective neural net are exploited to approximate a nonlinear control law of maximum power point tracking. The proposed fuzzy selective neural net is capable of handling uncertainties in both the wind turbine system parameters and the environment.

As formed, the fuzzy selective neural net creates the effective control signal, and identifies the system’s state. To make the vector control of wind turbine system on the basis of the fuzzy selective neuronet become adaptive, it needs to have some idea on how the actual wind turbine system’s behavior is differing from its expected behavior, so that the fuzzy selective neural net can recalibrate its behavior intelligently during run time, and try to eliminate the constant maximum power point tracking error. Hence the input signal of the fuzzy selective neural net will be non-zero, and it will give useful feedback for telling the model how to adapt to the dynamically changing wind turbine system’s conditions.

In this research we used experiment’s data \( Z = (X, y = (u_1, u_2)) \), where \( i = 1.10^7 \), \( X \in \mathbb{R}^{21} \) – represent the wind turbine’s input and some output data, stator current torque \( -i_{sd} = u_j \) and flux \( -i_{sq} = u_2 \). We did dimensionality reduction of data \( X \in \mathbb{R}^{21} \) from 21 to 5. This dimensionality reduction is developed through Principal Component Analysis. This step forms training data set \( \{x, u_j\} \) for the selective neural network \( u \), \( x \in \mathbb{R}^5 \). The statistical features \( x = (i_{sao}, i_{sd}, i_{sc}, \Delta P_{gen}, P_{gen}, \) electromagnetic moment, speed of rotor \( ) \) extracted from the data \( Z \) are used as inputs to fuzzy selective neural network. The selective neural net is trained based on the data

\[
\varepsilon' = (x', y')
\]

where \( i = 1.10^7 \), \( x \) – input signal of fuzzy selective neural net; \( y \) – control signal and output signal of fuzzy selective neural net.

First, sets \( AN_j^s (j = 1, ..., n^s, j = 1..10) \) formed using GNG’s (Growing Neural Gas [7]) clustering of the data (1); then, fuzzy sets \( AN_j^s (j = 1, ..., n^s, j = 1..10) \) with membership function \( \mu_j^s (x) \) formed using Fuzzy c-means of the data (1) (the sets \( AN_j^s \) was input for Fuzzy c-means); in order to effective obtain the wind turbine’s dynamic the fuzzy sets \( A_j (j = 1, 2, 3) \) with membership function \( \mu_j (x) \) determined according condition (2):

\[
\eta = \frac{1}{n^s} \sum_{u=1}^{n^s} \min_{i=1}^{n^s} \mu_j (x), \mu_{A_j} (x) \]

(2)

Second, for each \( j \) an identifier is constructed by a two-layer feed forward neural network. The data (1) have a training set of \( 9*10^4 \) examples, and a test set of \( 10^5 \) examples. Third, Formed as Simulink’s block if-then rules are defined as:

\[
\text{IF } x \text{ is } A_j \text{ THEN } u = f_j (x).
\]

Thus, the fuzzy selective neural net for the wind turbine’s control was carefully designed to correctly tackle the control task under uncertainty of the wind turbine system and of the environment.

In this research the fuzzy selective neuronet is used for vector control of wind turbine. The vector wind turbine’s control on the basis of the fuzzy selective neuronet elaborates following steps:

- Measure the generator quantities (phase voltages and currents),
- Transform the quantities into a stationary 2-phase \( (a, b) \) system using Clarke transformation,
- Calculate the rotor flux space vector magnitude and position angle, input \( x \),
- Aggregation antecedents of the rules (3) maps input \( x \) into their membership functions and matches data with conditions of rules. These mappings are then activates the \( k \) rule, which indicates the \( k \) wind turbine’s state \( k = 1.3 \),
- Transform stator currents into the \( d-q \) coordinate system using Park transformation,
- The stator current torque \( -i_{sd} = u_1 \) and flux \( -i_{sq} = u_2 \) producing components are created by neural net \( f_k \)
- The stator voltage space vector is transformed back from the \( d-q \) coordinate system into the two-phase system and fixed to the stator by inverse Park transformation.
This vector wind turbine’s control on the basis of the fuzzy selective neuronet does provide a more intelligent method of implementing the control signal. The proposed scheme with the fuzzy selective neural was implemented using MATLAB/Simulink software.

3. Simulation and results

In this section, simulation studies are accomplished to clarify the applicability and benefits of the proposed vector wind turbine’s control on the basis of the fuzzy selective neuronet. All the simulations for this study are implemented in MATLAB, Simulink. The simulation of the traditional maximum torque control strategy is obtained considering the expressions presented in sections 1. The simulation of the intelligent control of wind turbine is obtained fulfilling the fuzzy selective neuronet presented in sections 2. Boost converter and control algorithms are also implemented and included in Simulink models. In this comparison study, the performance of the vector wind turbine’s control on the basis of the fuzzy selective neuronet is compared against the standard control model with PID controllers based on traditional maximum torque control strategy, under the same conditions. Figures 1 to 2 show the simulation’s results. Figure 1 shows that the intelligent control of wind turbine provided a reduction in the steady-state and transient wind turbine’s rotor speed as compared with the standard control model with PID controllers.

**Figure 1.** Plot of wind turbine’s rotor speed provided by intelligent control of wind turbine and control model with PID controllers based on traditional maximum torque control strategy respectively

Figure 2 shows that the intelligent control of wind turbine provided a reduction in the steady-state and transient PMSG torque as compared with the standard control model with PID controllers. Figure 3 shows that the proposed intelligent control of wind turbine provides energy saving due reduction in the steady-state and transient PMSG torque compared with the control model with PID controllers based on traditional maximum torque control strategy.

**Figure 2.** Plot of PMSG torque provided by intelligent control of wind turbine and control model with PID controllers based on traditional maximum torque control strategy respectively
The vector control of wind turbine on the basis of the fuzzy selective neuronet is more robust and provided more power (Fig. 3) in comparison with the control model with PID controllers based on traditional maximum torque control strategy.

![The vector control of wind turbine on the basis of the fuzzy selective neuronet is more robust and provided more power in comparison with the control model with PID controllers based on traditional maximum torque control strategy.](image)

**Figure 3.** Plot of wind turbine’s power provided by intelligent control of wind turbine and control model with PID controllers based on traditional maximum torque control strategy respectively.

The aforementioned dynamic simulation results performance and robustness of the proposed vector control of wind turbine on the basis of the fuzzy selective neuronet are confirmed as compared to control model with PID controllers based on traditional maximum torque control strategy respectively. The use of the fuzzy selective neural net provides a more suitable approach to the MPPT problem, with the pointing accuracy. Extensive simulation studies on Simulink model have been carried out on different initial conditions, different disturbance profiles and variation in the wind speed levels parameters. It shows consistent performance has been achieved for the proposed fuzzy selective neural net with good stability and robustness as compared with the standard control model with PID controllers based on traditional maximum torque control strategy.

4. Conclusions

It is shown that the vector control of wind turbine on the basis of the fuzzy selective neuronet is robust to the wind turbine’s control system uncertainties. Unlike popular control model with PID controllers based on traditional maximum torque control strategy, a fuzzy selective neural net is used to approximate the control law, and not the system nonlinearities, which makes it suitable to handle a wide range of nonlinearities. Compared to standard control model with PID controllers based on traditional maximum torque control strategy, the vector control of wind turbine on the basis of the fuzzy selective neuronet produces MPPT, good response time, and performance. Simulation comparison results for the wind turbine’s control system demonstrate the effectiveness of the vector control of wind turbine on the basis of the fuzzy selective neuronet as compared with standard control model with PID controllers based on traditional maximum torque control strategy.

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