Neurocomputing 000 (2017) 1–10

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Adaptive neuro-fuzzy algorithm to estimate effective wind speed and optimal rotor speed for variable-speed wind turbine

Aamer Bilal Asghar, Xiaodong Liu*

School of Control Science and Engineering, Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian 116024, P.R. China

A R T I C L E I N F O

Article history:
Received 4 April 2017
Revised 7 July 2017
Accepted 11 July 2017
Available online xxx

Communicated by H.R. Karimi

Keywords:
Wind turbine
Tip speed ratio
Rotor speed
Mechanical power
Power coefficient
ANFIS

A B S T R A C T

The precise measurement of effective wind speed is a crucial task and has huge impact on wind turbine output power, safety and control performance. In this study, a hybrid intelligent learning based adaptive neuro-fuzzy inference system (ANFIS) is proposed for online estimation of effective wind speed from instantaneous values of wind turbine tip speed ratio (TSR), rotor speed and mechanical power. The artificial neural network (ANN) adjusts the parameters of fuzzy membership functions (MFs) using hybrid optimization method. The estimated value of effective wind speed is further utilized to design the optimal rotor speed estimator for maximum power point tracking (MPPT) of variable-speed wind turbine (VSWT). Both estimators are implemented in MATLAB and their performance is investigated for national renewable energy laboratory (NREL) offshore 5 MW baseline wind turbine. The simulation results show the effectiveness of proposed method. The proposed scheme is computationally intelligent, easy to implement and more reliable for fast estimation of effective wind speed and optimal rotor speed.

1. Introduction

Wind power generation has grown very rapidly in last two decades due to its lower cost and environmental problems. Wind is considered as a most viable energy source to fulfill the world's future energy demands [1,2]. Therefore, advanced control techniques have been applied to improve the performance. However, wind is totally weather dependent and the most difficult parameter to measure accurately due to its intermittent and unpredictable nature [3]. The wind turbine output power mainly depends on wind speed. So, accurate estimation of wind speed is very important to optimize the operation and improve the efficiency of wind turbine [4].

The VSWTs are preferred due to their better efficiency, high power quality and lower aerodynamic load. When wind speed is below the rated value, the VSWT can extract maximum power if its rotor speed is adapted optimally according to the variable wind speed [5–8]. So, real time estimation of wind speed is necessary for rotor speed control [9]. Normally, wind speed is estimated by anemometer mounted at the top of nacelle. However, surrounded installed anemometer cannot give a precise value of wind speed. Anemometer measures the wind speed at a single point which does not represent the effect of wind speed on the whole rotor. In wind farms, many anemometers are installed at different places and an average wind speed is measured. But it also does not give a true picture of wind speed acting on individual wind turbine [10]. The anemometers not only increase the cost and compromise the measurement accuracy but also affect the wind turbine control performance [11]. As wind turbines are exposed to severe weather conditions, the mechanical wind speed sensor may become faulty and start malfunctioning. So, there is a need to replace the anemometer with soft computing based wind speed estimator which estimates the effective wind speed on the basis of wind turbine attributes [12,13]. The measurement of effective wind speed also increases the control performance by minimizing the effect of abrupt changes in wind speed.

The wind speed estimation methods are classified as: (a) statistical model based methods, (b) time-series models, (c) artificial intelligent methods and (d) hybrid intelligent models [14]. In [15] an autoregressive (AR) statistical model was used for wind speed estimation but this method involved complex computation and results were not accurate enough to use for rotor speed control of wind turbine. The statistical models rely on previous time series data of wind speed and forecast the future pattern. Some other time-series models which have been used by researchers for wind speed estimation are autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), seasonal ARIMA and fractional ARIMA [16–19]. These models perform well when there are

* Corresponding author.
E-mail addresses: aamerbilal92@hotmail.com (A.B. Asghar), xdliuros@dlut.edu.cn (X. Liu).

http://dx.doi.org/10.1016/j.neucom.2017.07.022
0925-2312/

Please cite this article as: A.B. Asghar, X. Liu, Adaptive neuro-fuzzy algorithm to estimate effective wind speed and optimal rotor speed for variable-speed wind turbine, Neurocomputing (2017), http://dx.doi.org/10.1016/j.neucom.2017.07.022

Nomenclature

C_P	power coefficient
β	pitch angle (°)
λ_{opt}	optimal value of tip speed ratio
v	wind speed (m/s)
P	incident wind power (MW)
R	rotor radius (m)
T_m	mechanical torque (Nm)
$\omega_r{}^*$	optimal rotor speed (rad/s or rpm)
P_{mMax}	maximum mechanical power (MW)
ANFIS	adaptive neuro-fuzzy inference system
VSWT	variable-speed wind turbine
MW	mega watt
AR	autoregressive
ARIMA	autoregressive integrated moving average
RBFNN	radial basis function neural network
SVM	support vector machine network
SVR	support vector regression
GA	genetic algorithm
BBSC	block-backstepping controller
ISMC	integral sliding mode control
FAST	fatigue, aerodynamics, structures and turbulence
RMSE	root mean square error
$C_{P\max}$	maximum value of power coefficient
λ	tip speed ratio
A	rotor swept area (m^2)
ρ	air density (kg/m^3)
P_m	mechanical power (MW)
ω_r	rotor speed (rad/s or rpm)
C_q	torque coefficient
$T_m{}^*$	maximum mechanical torque (Nm)
TSR	tip speed ratio
MF	membership function
NREL	national renewable energy laboratory
MPPT	maximum power point tracking
ARMA	autoregressive moving average
BPNN	back propagation neural network
EKF-NN	extended Kalman filter based neural
PSO	particle swarm optimization
AWNN	adaptive wavelet neural network
SMC	sliding mode control
T–S FIS	Takagi–Sugeno fuzzy inference system
ISA	international standard atmosphere
ANN	artificial neural network
LMI	linear matrix inequality

no rapid wind speed variations but have difficulties for high frequency changes. In [20] authors proposed the wavelet analysis for wind speed estimation. The artificial intelligent learning methods include back propagation neural network (BPNN), radial basis function neural network (RBFNN), extended Kalman filter based neural network (EKF-NN), support vector machine (SVM) and support vector regression (SVR) [21–28]. Some evolutionary techniques such as particle swarm optimization (PSO) and genetic algorithm (GA) have also been used to update weights during training process of ANNs [29,30]. The advantages of these soft computing techniques are their ability to deal with nonlinearities and less reliance on previous data. The hybrid intelligent techniques such as ANFIS [31], ARIMA-NN [32], adaptive wavelet neural network (AWNN) [33] and Bayesian method in combination with ANN [34] are becoming more popular because of their better performance and higher accuracy.

The mechanical power produced by wind turbine is proportional to area of the rotor, power coefficient (C_P) and wind speed. Power coefficient is a non-linear function of blade pitch angle (β) and TSR (λ). The value of TSR depends on turbine rotor speed and wind speed [35,36]. Power coefficient reaches to its maximum value ($C_{P\max}$) at optimum TSR (λ_{opt}). The wind turbine rotor speed at 'λ_{opt}' and '$C_{P\max}$' is called optimal rotor speed. Wind turbine extracts maximum power at optimal rotor speed. In [37] MPPT was achieved by using lookup table of power–speed curve. But lookup tables require a significant memory space. Researchers implemented stator flux oriented vector control [7], block-backstepping controller (BBSC) [22], sliding mode control (SMC), integral sliding mode control (ISMC) [25], fuzzy logic control [38,39], ANN and power converter [40] based methods to control rotor speed for MPPT.

The ANNs are very popular in modeling complex nonlinear systems. In [41] a multilayer perceptron ANN model was developed to estimate the fuel consumption of haul trucks in surface mines. The gross vehicle weight, the truck velocity and total resistance were selected as inputs of the ANN model. The system was trained for different number of nodes in the hidden layer. The results showed that the ANN system has best performance for 15 nodes in the hidden layer. The developed system was able to efficiently forecast the fuel consumption of haul trucks on the basis of haulage parameters.

The Takagi–Sugeno (T–S) fuzzy model has been implemented in many applications to approximate the behavior of nonlinear systems. Therefore, analyzing the stability of T–S fuzzy systems has always been a major concern. The linear matrix inequality (LMI) based approaches are widely preferred to investigate the stability of nonlinear systems but the major problem with this technique is the conservativeness of derived results. Many efforts have been made to derive more relaxed stability conditions using different type of Lyapunov functions. In [42] membership-dependent stability conditions were developed for T–S fuzzy systems using a newly proposed non-quadratic Lyapunov function. It was further shown with the help of two numerical examples that conservativeness of developed criteria decreases with the degree of Lyapunov function. Many power electronic and network control switched systems are composed of continuous/discrete time subsystems and discrete switching events. The common Lyapunov functions may provide conservative stability conditions for switched systems. Therefore, it is very important to design an efficient switching signal to stabilize a switched nonlinear system which is composed of all unstable subsystem. In [43] the stabilization of switched nonlinear systems with all unstable subsystems was investigated using average dwell time switching. A sufficient stability condition was derived on the basis of proposed switching signal. The T–S fuzzy modeling approach was applied on the system and some conditions were provided in LMI set to guarantee its asymptotic stability using a new multiple quadratic Lyapunov function approach.

The hybrid intelligent techniques are famous for their ability to realize the non-linear relationships between input/output data. ANFIS is also a hybrid intelligent scheme which is a combination of T–S fuzzy inference system (FIS) and ANNs. The ANNs embed learning capabilities in fuzzy systems by training fuzzy MFs to adopt the system behavior. Recently, researchers have used ANFIS in various applications such as controlling, forecasting, classifying and diagnosing [44–48].

In this paper, an effective wind speed estimator is proposed using adaptive neuro-fuzzy algorithm. An attempt is made to realize the relationship of wind speed with TSR, rotor speed and mechanical power. In order to design ANFIS, the input/output data samples are collected by conducting experiments during online operation of NREL offshore 5 MW baseline wind turbine. The ANN trains the input MFs by using least square method and back propagation