University College of Takestan

Volume6 ,Issue4

Available online at **http://UCTjournals.com**

UCT Journal of Research in Science, Engineering and Technology
UCT. J. Resea. Scien. Engineer. Techno. (UJRSET)

6-10 (2018)

ISSN 2382-977X

Wind Turbine Power Control Using Neural Control

Mohammadreza Ebrahimi[1], Mohammad Hosein Atazadegan[*2]

1&2.Department of Electrical Engineering, Islamic Azad University, Jahrom Branch, Iran

***Corresponding Author:** Email:Atazadegan1370@gmail.com*

Original Article:
Received 7 Nov. 2018 Accepted 1 Dec. 2018 Published 30 Dec. 2018

ABSTRACT

Wind is a good source of energy. Power generation in a variable speed wind turbine is an interesting topic. Because the wind energy converter systems have maximum operation at any speed. But this system needs its parameters to calculate the optimal turbine speed. In this research, a neural network based controller based on a backup machine is provided to control the power of the wind power converter system. In this study, the system for converting wind energy into a two-way inductive generator, connected to the grid with a rotor and a stator. The input of the control system is the difference between the desired generator speed and its actual speed. The optimal speed is the speed at which the generator receives the maximum power from the wind turbine. After performing simulations and designing a suitable neurologist for the system, it was found that the neural control method has a very good function in controlling the wind turbine system..

Keyword:

Wind turbine, Inductive induction generator, Nerve controller

*** Corresponding author:** **Mohammad Hosein Atazadegan**
Email: Email:Atazadegan1370@gmail.com

I. INTRODUCTION

These days, wind energy conversion systems (WECS) have gained considerable attention as suitable replacement for fossil fuels. Wind energy is known to be the most important and most applicable renewable energy in 21st century[1]. Therefore, stable and efficient utilization of wind energy and consequently evaluating WEC systems is being researched as an important subject[2]. The most important section of electricity generation system using wind energy is the generator. A wind turbine could be employed in a constant speed or variable velocity mode. For constant velocity, the velocity of turbine is kept at a constant value while in variable velocity mode, the rotational velocity of the rotor changes with any change in wind velocity.

There has been various evaluations and studies regarding the simulation and control of wind turbine systems. In [2,3], many methods for wind turbine MPPT have been introduced using doubly fed induction generator and the optimized rotational velocity has been found using a wind velocity related coefficient. In [4], theoretical analysis of doubly fed induction generator's dynamic behavior has been evaluated. A without sensor decoupled control method has been introduced in [5] and the obtained results highlights the efficiency of the performance. In [6], a wind turbine generator system has been fully implemented and a novel voltage control method has been used in order to control the system. In [7], they have attempted to designing a controller and evaluated its performance on controlling a wind turbine during harsh wind situations. In [8], classical control methods have been used and in [9,10], adaptive LQG control method was employed. Moreover, [11] used an observational control method in order to control the wind turbine. In [3,12], systematic evaluation, identification and optimized compensation in wind turbines have been discussed. In [3,13], long distance control of wind turbines has been attempted. Structural control proposed in [5,3], is another control method that has been implemented on wind turbine systems. In their work, wind turbines have been mathematically modeled and researched based on Euler-Lagrangian method. Based on that, doubly fed induction generator that is connected to the network by rotor and stator is the main considered model in this article. Given that the wind velocity is variable during a year or even a day, the considered structural control will aim to control the system performance during wind velocity changes such that the efficiency is maximized.

2- Simulations and Result Evaluation

2-1- Neural Network Design and learning for estimating $[Fst_{opt} \quad Vst_{opt}]$ for each P_{ref}

The first step is to specify the inputs and the outputs of the neural network. The neural network input is the wind velocity and required power and its output must be the estimation of voltage and optimized frequency couple that is fed to SVM in order to transfer the reference power P_{ref} from the generator to the load. Even then, the criteria for coupled generation is to minimize the THD voltage signal as well as providing P_{ref}. We consider a SVM network for estimating Fst_{opt} and another network for estimating Vst_{opt}.

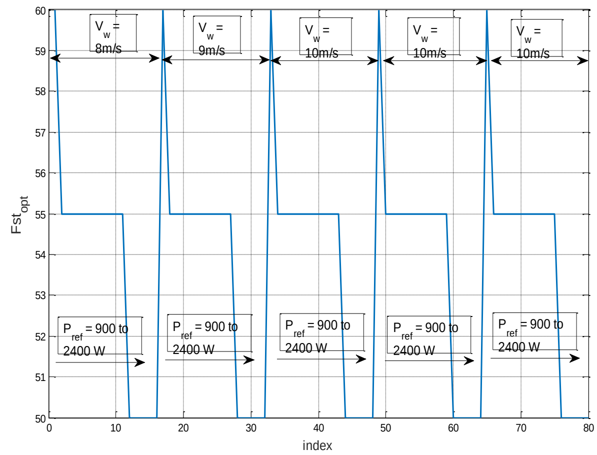

figure 1: optimized frequency for power generation $900 \leq P_{ref} \leq 2400$ **during different wind velocities**

We consider the neural network used for Fst_{opt} as a SVM network with 100 neurons in the

hidden layer. The activation functions for all of these neurons are assumed to be Gaussian.

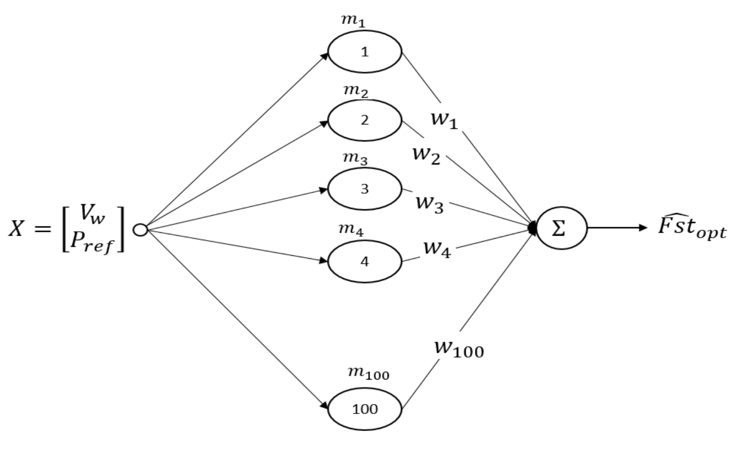

Figure 2: SVM neural network for $\mathbf{Fst_{opt}}$

In the above figure, $m_i\ , i = 1, \ldots , 100$ centers are all selected for the initiation of the training process for the neural network weights, at random and in the domain $[0 - 25 \quad 0 - 4200]$. These weights are calculated using method of least square error on the training data.

Figure 3 indicates that the neural network reasonably follows the output.

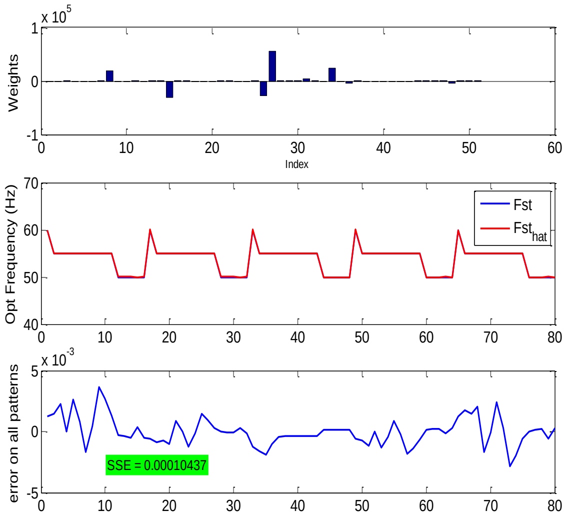

Figure 3: The outcome of training the SVM neural network for estimating $\mathbf{Fst_{opt}}$ from $\mathbf{V_w}$ and $\mathbf{P_{ref}}$

The trained weights are shown in the first section of the above figure. In the second section, Fst_{opt} and its estimation $\widehat{Fst}_{opt}$ are compared. Given that the curves are almost identical, it is challenging to differentiate them.

The third curve shows the training error related to each training data and the SSE could be obtained by squaring the data on this curve.

In order to estimate Vst_{opt}, we employ another SVM network that has 100 neurons in the hidden layer. The obtained results regarding the trained weights and the estimation error as well as the neural network's output and the real value of Vst_{opt} are shown in Figure 9.

As it can be seen in the figure, the value of SSE is quite low in this case and the two curves are almost identical.

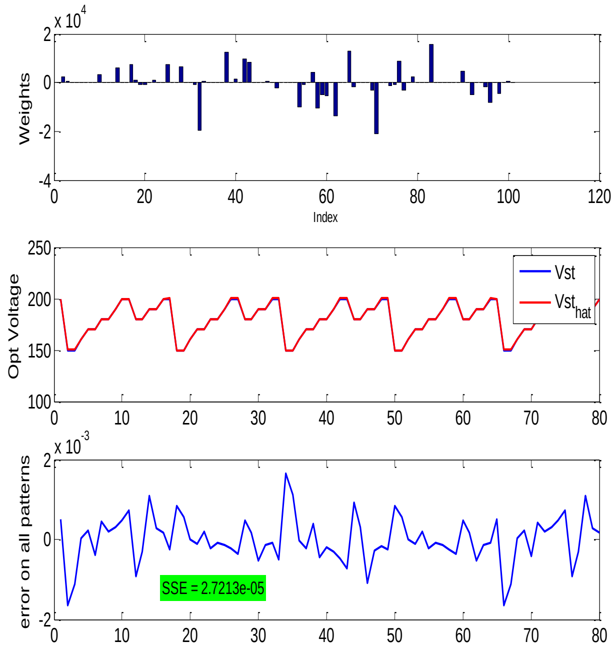

Figure 4: Result of training SVM neural network for estimating $\mathbf{Vst_{opt}}$ from $\mathbf{V_w}$ and $\mathbf{P_{ref}}$

The first section of figure 4 shows the trained weights by the SVM neural network. In the second section, the output of the neural network that is the Vst_{opt} estimation is compared to its actual value. Lastly, the estimation error and the SSE value are shown in the third section of the figure.

2-2 Using neural network for control active power generation by DFIG

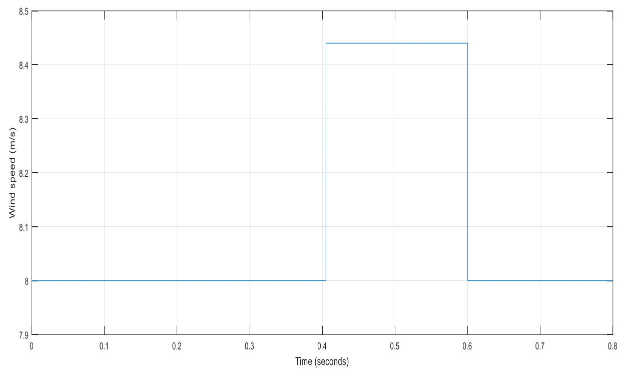

Figure 5: Velocity of the wind $\boldsymbol{V_w}$

The above figure indicates that the velocity of wind changes abruptly in 0.4 and 0.5s.

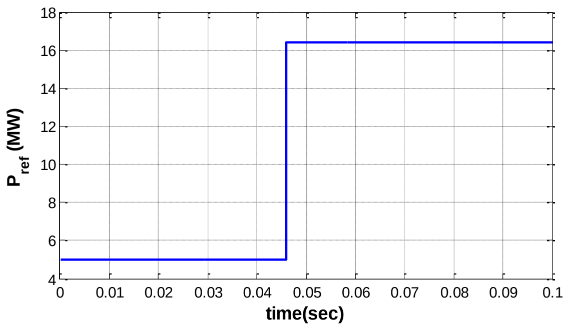

Figure 6: Reference Power $\mathbf{P_{ref}}$

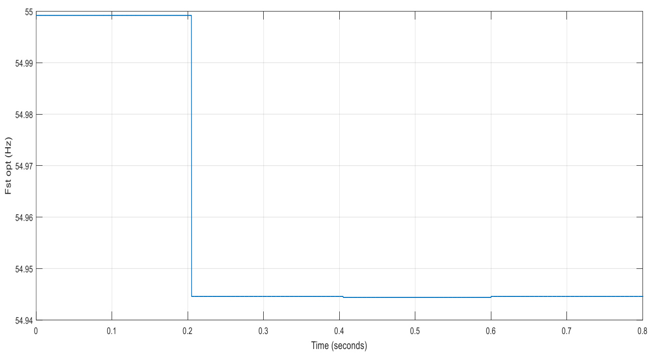

Figure 7: Optimized frequency for $\mathbf{P_{ref}}$ generation, from the POV of THD

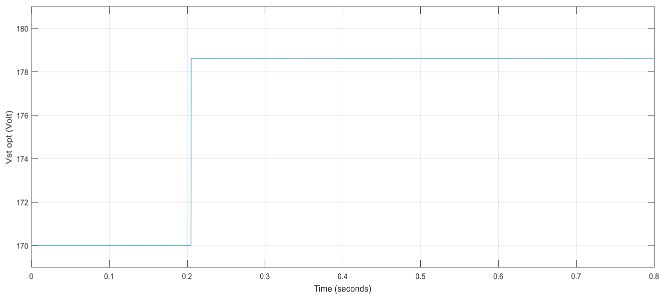

Figure 8: Optimized voltage related to minimized THD for P_{ref} generation

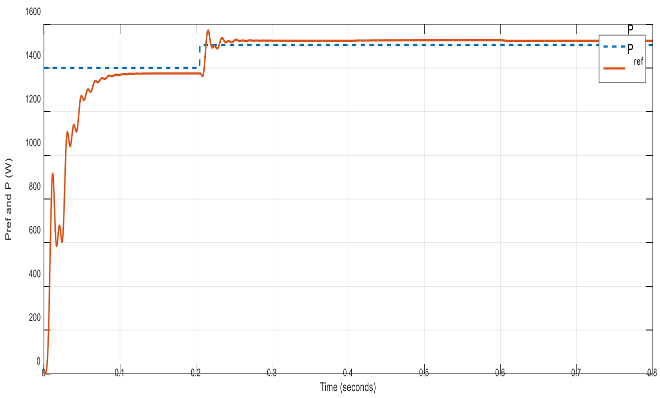

Figure 9: Active power P_{ref} tracing

Figure 9 indicated that even when there is a step change in the velocity of wind, the active power does not change considerably and it follows the required power in a reasonable way. The important point in the above figure is that there is a small diversion from the required state which is due to the initial data used for neural network training. In order to evaluate the employed method in this research, a comparison of neural control based on SVM with other methods is presented in Table 1.

Method	Time		
	0.1	0.5	1
RBF NN	0.4152	0.3516	0.3484
Fuzzy	0.3846	0.3411	0.3346
Adaptive	0.4202	0.3761	0.3600
Supervisory	0.2813	0.2711	0.2661
SVM NN	0.3149	0.2754	0.2507

Table 1: Comparison of active power tracing error for non-linear controllers

As it can be seen, the employed neural control based SVM shows mediocre performance compared to other method during the initial fractional time. As time increases, however, the performance of this method is superior to the others and the tracing error is lower.

3. Conclusions

In this paper, a highly efficient neural network control based on SVM neural networks was designed and implemented in order to control wind turbines intelligently and improve the performance of wind turbine systems. Moreover, it was considered that the doubly fed induction generator's model is available and the structure of the wind turbine is known. The design and implementation of the neural network control on the wind turbine and its desirable results highlights the highly efficient performance of the neural network controller. Given that the evaluated system in this work is highly non-linear, it can be concluded that non-linear systems can be decently controlled with accurate and reasonable design of neural network controllers with desirable performance.

Resources

1. Hau E. Wind turbines: fundamentals, technologies, application, economics. 2nd ed. Springer-Verlag Press; 2006.

2. Junyu Liang , Yongxing Qiu, "The modeling and numerical simulations of wind turbine generation system with free vortex method

3. and Simulink", Energy Conversion and Management 103 (2015) 762–777.
4. Tapia A, Tapia G, Ostolaza JX, et al. Modeling and control of a wind turbine driven doubly fed induction generator. IEEE Trans Energy Convers 2003;18(2):194–204.
5. López J, Roboam X, Marroyo L. Dynamic behavior of the doubly fed induction generator during three-phase voltage dips. IEEE Trans Energy Convers 2007;22(3):709–17.
6. Akel F, Ghennam T, Berkouk EM, et al. An improved sensorless decoupled power control scheme of grid connected variable speed wind turbine generator. Energy Convers Manage 2014;78:584–94.
7. Koa HS, Yoonb GG, Kyunga NH, et al. Modeling and control of DFIG-based variable-speed wind-turbine. Electr Power Syst Res 2008;78:1841–9.
8. Bekka H, Taraft S, Rekioua D, Bacha S. Power control of a wind generator connected to the grid in front of strong winds. J Electr Syst 2013;9(3):267–78.
9. Bianchi, F.D., De Battista, H., Mantz, R.J., 2010. Robust multivariable gain- scheduled control of wind turbines for variable power production. Int. J. Syst. Control 1 (3), 103–112.
10. Mateescu, R., Pintea, A., Stefanoiu, D., 2012. Discrete-time LQG control with disturbance rejection for variable speed wind turbines. In: 1st International onference on Systems and Computer Science—ICSCS 2012, Lille, France, August, pp. 1–6.
11. Boukhezzar, B., Lupu, L., Siguerdidjane, H., Hand, M., 2007. Multivariable control strategy for variable speed, variable pitch wind turbines. Renew. Energy 32, 1273–1287.
12. Ramadge, P., Wonham, W.M., 1984. Supervisory control of a class of discrete event processes. In: Bensoussan, A., Lions, J.L. (Eds.), Lecture Notes in Control and Information Sciences, vol. 63. Springer-Verlag, Heidelberg, pp. 475–498.
13. Atkinson DJ, Lakin RA, Jones R. A vector-controlled doubly-fed induction generator for a variable-speed wind turbine application. Trans Trans Inst Meas Control 1997;19(1):2–12.
14. Petersson A, Thiringer T, Harnefors L, et al. Modeling and experimental verification of grid interaction of a DFIG wind turbine. IEEE Trans Energy Convers 2005;20(4):878–86.