Sensorless maximum power point tracking systems in wind energy conversion systems

A review

*Enno Tchorz**

Münster University of Applied Sciences, Stegerwaldstraße 39, 48565 Steinfurt, Germany

Abstract

Wind energy conversion systems have attracted considerable attention as a renewable energy source due to depleting fossil fuel reserves and environmental concerns as a direct consequence of using fossil fuel and nuclear energy sources. The increasing number of wind turbines increases the interest in efficient systems. The power output of a wind energy conversion system depends on the accuracy of the maximum power tracking system, as wind speed changes constantly throughout the day. Maximum power point tracking systems that do not require mechanical sensors to measure the wind speed offer several advantages over systems using mechanical sensors. In this paper four different approaches that do not use mechanical sensors to measure the wind speed will be presented; the assets and drawbacks of these systems are highlighted, and afterwards the examined algorithms will be compared based on different characteristics. Finally, based on the analysis, an evaluation is made as to which of the presented algorithms is the most promising.

1 Introduction

The total installed capacity of wind power is growing tremendously in the global market. According to the statistics of the world wind energy association [1], the global wind power installation has reached 651 GW by the end of 2019. That is approximately double the amount of the wind power capacity by the end 2014, due to the increasing number of wind energy capacity the need of more efficient systems to determine the maximum power point (MPP) rises. Wind energy conversion systems (WECS) are usually equipped with mechanical sensors to measure wind speed, rotor shaft speed, generator position and speed for system monitoring, control and protection of the WECS. The use of this sensors increases the:

1. cost,
2. size,
3. weight,
4. hardware wiring complexity and
5. lowers the reliability of WECS [2].

Another drawback: anemometers typically used to measure wind speed from WECS are sensitive to icing. In many regions that have excellent wind resources but long winters, special models of anemometers with electrically heated shaft and cups are required [2]. To achieve high efficiency with MPPT systems in WECS, an accurate anemometer is required due to the gusts and turbulence of the wind. The use of an accurate anemometer adds extra cost to system, especially for small scale wind turbines [3]. The problems associated with using mechanical sensors to measure the wind speed can be solved by using sensorless maximum power point tracking (MPPT) systems.

2 Wind turbine modeling

The input of a wind turbine is wind and the output is mechanical power driving the generator rotor [4, 5]. The mechanical power can be expressed as:

$$P_m = \frac{1}{2}\rho A V^3 C_p(\lambda, \beta) \qquad (1)$$

where P_m is the power extracted from the wind (in Watts), ρ is the air density (in kg/m^3), A is the area swept by the rotor (in m^2), V is the wind speed (in m/s) and C_p is the turbine power coefficient (dimensionless). The turbine power coefficient C_p describes the power extraction efficiency of the wind turbine [6]. It is a nonlinear function of both the tip speed ration (λ) and the blade pitch angle (β). While its maximum theoretical is approximately 0.59, in reality it is between 0.4 and 0.45 [7]. The tip speed ratio is a variable expressing the ratio of the linear speed of the

*Corresponding author: et839266@fh-muenster.de.

https://doi.org/10.25974/ren_rev_2021_05

blade tips to the rotational speed of the wind turbine [8–10], and can be expressed by Eq.2:

$$\lambda = \frac{R\omega_m}{V} \tag{2}$$

where ω_m is the velocity of the rotor. Numerous different versions of fitted equations for C_p have been used in previous studies. One way to express C_p is [11]:

$$C_p(\lambda,\beta) = 0,5176(\frac{116}{\lambda_i} - 0,4\beta - 5)e^{-\frac{21}{\lambda_i}} + 0,0068\lambda \tag{3}$$

with

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0,08\beta} - \frac{0,035}{\beta^3+1} \tag{4}$$

3 MPPT control

3.1 Optimal Torque Control

The objective of the MPPT-Optimal Torque (OT) method is maximizing power extraction without wind speed measurements. This method is equivalent to tracking the maximum power conversion point of a filtered version for the wind, avoiding sudden changes of the torque, and consequently reducing mechanical stress in the shaft [12]. As shown in the block diagram Fig. 1, the OTC is reaching the maximum power point by adjusting the actual torque of the generator according to the reference torque. In order to determine the maximum power point without knowledge of the wind speed we substitute Eq.2 into Eq.1. The new expression yields:

$$P_m = \frac{1}{2}\rho\pi R^5 \frac{C_p}{\lambda^3}\omega_m^3 \tag{5}$$

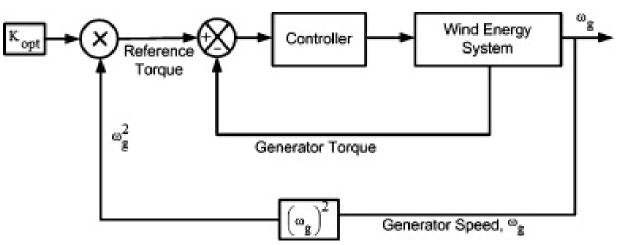

Fig. 1: Block diagram of the optimal torque control method [13]

If the rotor is running at $\lambda = \lambda_{opt}$, it will also run at $C_p = C_{Pmax}$. Thus Eq.5 also can be written as:

$$P_m = \frac{1}{2}\rho\pi R^5 \frac{C_{Pmax}}{\lambda_{opt}^3}\omega_m^3 = k_{opt}\omega^3 \tag{6}$$

Considering that $P_m = \omega_m T_m$, we reach our final expression:

$$T_m = \frac{1}{2}\rho\pi R^5 \frac{C_{Pmax}}{\lambda_{opt}^3}\omega_m^2 = k_{opt}\omega^2 \tag{7}$$

Eq.7 represents our analytical expression of the optimum torque curve, and Fig. 1, is a given as reference torque for the controller that is connect to the wind turbine.

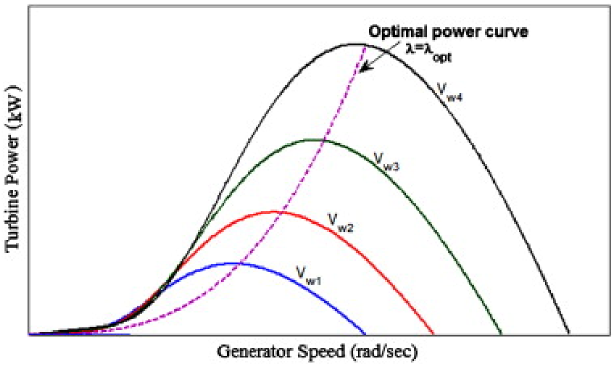

Fig. 2: Characteristics of turbine power as a function of the rotor speed for a series of wind speeds [13]

3.2 Hill Climb search

The hill-climb searching (HCS) method, is a mathematical optimization technique to determine the local maximum of a given function. Fig. 3 shows how the algorithm works. If the operating point of the function, in our case on the left side of the peak point P_{mpp}, the controller must move our operating point to the right so we can reach P_{mpp}. This happens with a perturbation of the control variable. If the perturb results in an increase of the power, the same perturbation is applied, otherwise the mathematical sign of the perturbation is reversed. To improve the efficiency and the accuracy of the conventional HCS method, modified variable step size algorithms have been proposed [13–15]. When using improved HCS algorithms, the step size is getting generated according the the operating point. When the system is far away from the tracking point, it speeds up the process by increasing the step size and speeding up the process of reaching the MPP. As the controller approaches the MPP, the step size decreases until it approaches zero. This way the oscillations occurring when using the conventional HCS algorithm are getting reduced. One way to increase efficiency and accuracy using an improved HCS algorithm is now explained. In the examined study [14], the distance from the actual generator speed (ω) to the optimal generator speed (ω^*),which is determined by the optimal power curve, was used to adjust the perturbation size at the end of each cycle[13].The Flowchart of the improved method can be found in [14]. There are three steps of operation. The features of the three modes are explained below:

- Mode 0: searching for k_{opt} to track the MPP. Once the initial conditions are satisfied, k_{opt} will

https://doi.org/10.25974/ren_rev_2021_05

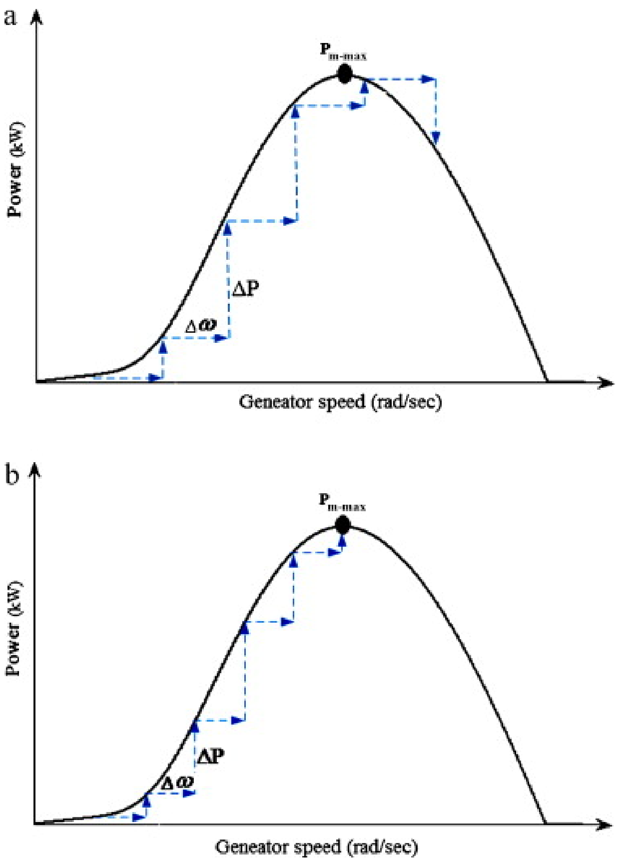

Fig. 3: HCS control (a) larger perturbation and (b) smaller perturbation [13].

be calculated through the measured power and rotational speed and the system is switched to Mode 1.

- Mode 1: the perturbation is set to zero to keep the system at the state reached in Mode 0. A change of wind speed is detected through change in rotor speed and leads to Mode 2.
- Mode 2: this mode implements the adaptive hill climbing according to the stored k_{opt}. The perturbation size is decided by the distance of the operating point from the $k_{opt} * w^3$ curve, shown in Fig. 2. It is not possible to track the MPP perfectly, but the controller moves the operating point very close to the peak power.

3.3 Neural Networks based MPPT-Algorithms

Artificial Neural Network (ANN) models, also called Neural Networks (NN), take their inspiration from the basic framework of the brain [16]. ANN consists of many nodes and connecting synapses. Nodes operate in parallel and communicate with each other through connecting synapses[17]. A NN consists of three layers:

- input,

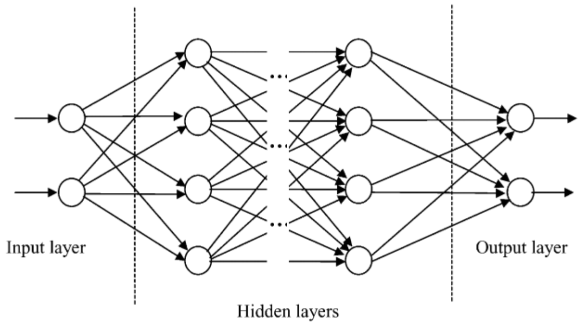

Fig. 4: Structure of a neural network [18]

- hidden,
- and output layers.

The layers are connected with nodes. The number of nodes in each layer varies dependent of the used model. The architecture of a NN is shown in Fig. 4

The input variables can be:

- pitch angle,
- terminal voltage,
- output torque,
- wind speed,
- rotor speed,

etc. or any combination of the variables [3]. The output is generally a reference signal:

- reference power,
- rotor speed,
- reference torque,

etc. that is used to drive the power electronic circuit of the wind turbine close to the MP [3]. There are numerous approaches using NN to determine the MPP [19–21].

4 Critical analysis and comparison

Although the OT algorithm is widely used in WECS, it requires the information of air density and turbine mechanical parameters, which vary in different systems. Moreover, the OT curve, which is mainly obtained via experimental tests, will change when the system ages [12, 22–24]. This will also affect the MPPT efficiency [3].

The HCS algorithm is the simplest MPPT algorithm that does not require any prior knowledge of the system or any additional sensor except the measurement

https://doi.org/10.25974/ren_rev_2021_05

of the power which is subjected to maximization. That is the reason why the HCS algorithm can be used in any renewable energy system that exhibits a unique power maximum. Although these features should make HCS the top choice for MPPT in any renewable energy conversion system but in reality it is only feasible in the slow varying systems. For instance it is quite feasible for the PV energy systems where the sun's irradiance changes over the period of several minutes but not for the WECS where the wind may change quite fast in the matter of seconds.[25] However, the method deviates to trace the peak power point under sudden wind gusts. In order to overcome this drawback, there are many improved HCS methods presented in literature [3, 13, 14, 26].

ANN based control [27], [20] can be quite effective and robust only after it is sufficiently trained for all kinds of operating conditions. This is quite a tough requirement and requires a long offline training. Therefore, this MPPT control can be quite efficient when trained [3] for long time but this long offline training makes ANN quite unattractive for the real time practical applications. The ANN for its training requires wind velocity sensor additionally with the generator speed sensor which is again not a good feature.

4.1 Comparison and assets of the described algorithms

In other papers the presented methods have already been analyzed and compared. Nevertheless the authors used different criteria to compare the methods. Based on the above description and literature [3, 28, 29] comparing the different MPPT methods, Tab. 1 was compiled.

Tab. 1: Comparison of characteristics of the described MPPT algorithms

	HCS	Modified HCS	OTC	ANN-based
Complexity	Simple	Medium	Simple	High
Wind turbine characteristics	No	Yes	Yes	No
Convergence speed	Slow	Medium	Fast	Medium
Prior training/ knowledge	No	No	Yes	Yes
Perfomance under varying wind	Medium	Good	Medium	Very good
Wind speed measurement	No	No	No	No (dependent on the used NN)
Rotor speed measurment	Yes	Yes	Yes	Yes

5 Conclusion

Due to the increasing penetration of wind turbine power, it is necessary to get the maximum power from the wind. In some cases, the implementation of mechanical sensors is unfavorable, due to the reasons mentioned above. In this case, MPPT methods without mechanical sensors are the preferred technique. Due to their simplicity, HCS and OTC are promising methods to determine the MPP. Especially improved HCS methods have generated a great deal of interest lately because they overcome the drawbacks of the conventional HCS method by increasing the efficiency and accelerate the process of determining the MPP. ANN-based methods are of interest because of their good performance under varying wind speed. The main problem encountered when using ANN-based methods is the need of a long offline training. This problem has not been solved so far. Once the the long training time can be reduced, ANN-based methods can become the best choice for sensorless MPPT systems. Finally, it must be noted that none of the presented methods should be the preferred choice in any case. The assets and drawbacks are different and need to be considered before using the described systems in practical applications. This paper servers as a reference, to decide which sensorless MPPT system might be the most feasible for the given application. For instance, in areas with many sudden wind changes, the ANN-based algorithm should be the preferred choice. While the HCS algorithm could be considered a feasible method in areas with less varying wind speed due to the simplicity and the fact that no prior training is required for this algorithm.

References

[1] J.-D. Pittleoud (2019). [Online; accessed 28-December-2020]. URL: https://library.wwindea.org/global-statistics/.

[2] W. Qiao. "Intelligent mechanical sensorless MPPT control for wind energy systems". *2012 IEEE Power and Energy Society General Meeting*. IEEE. 2012, pp. 1–8.

[3] D. Kumar and K. Chatterjee. "A review of conventional and advanced MPPT algorithms for wind energy systems". *Renewable and Sustainable Energy Reviews* 55 (2016), pp. 957 –970. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2015.11.013. URL: http://www.sciencedirect.com/science/article/pii/S1364032115012654.

[4] Hui Li, K. L. Shi, and P. G. McLaren. "Neural-network-based sensorless maximum wind energy capture with compensated power coefficient". *IEEE Transactions on Industry Applications* 41.6 (2005), pp. 1548–1556. DOI: 10.1109/TIA.2005.858282.

[5] M. Karrari, W. Rosehart, and O. P. Malik. "Comprehensive control strategy for a variable speed cage machine wind generation unit". *IEEE Transactions on Energy Conversion* 20.2 (2005), pp. 415–423. DOI: 10.1109/TEC.2005.845525.

[6] M. Grimble and M. Johnson. “Optimal Control of Wind Energy Systems” (2008).

[7] Z. Chen, J. M. Guerrero, and F. Blaabjerg. “A review of the state of the art of power electronics for wind turbines”. *IEEE Transactions on power electronics* 24.8 (2009), pp. 1859–1875.

[8] L. L. Freris and L. Freris. *Wind energy conversion systems*. Vol. 31. Prentice Hall New York, 1990.

[9] A. Abdelkafi and L. Krichen. “New strategy of pitch angle control for energy management of a wind farm”. *Energy* 36.3 (2011), pp. 1470–1479.

[10] P. Nema, R. Nema, and S. Rangnekar. “A current and future state of art development of hybrid energy system using wind and PV-solar: A review”. *Renewable and Sustainable Energy Reviews* 13.8 (2009), pp. 2096–2103.

[11] M Nasiri, J Milimonfared, and S. Fathi. “Modeling, analysis and comparison of TSR and OTC methods for MPPT and power smoothing in permanent magnet synchronous generator-based wind turbines”. *Energy Conversion and Management* 86 (2014), pp. 892–900.

[12] S. Ganjefar, A. A. Ghassemi, and M. M. Ahmadi. “Improving efficiency of two-type maximum power point tracking methods of tip-speed ratio and optimum torque in wind turbine system using a quantum neural network”. *Energy* 67 (2014), pp. 444–453.

[13] M. A. Abdullah, A. Yatim, C. W. Tan, and R. Saidur. “A review of maximum power point tracking algorithms for wind energy systems”. *Renewable and sustainable energy reviews* 16.5 (2012), pp. 3220–3227.

[14] S. M. R. Kazmi, H. Goto, H.-J. Guo, and O. Ichinokura. “A novel algorithm for fast and efficient speed-sensorless maximum power point tracking in wind energy conversion systems”. *IEEE Transactions on Industrial Electronics* 58.1 (2010), pp. 29–36.

[15] A. C.-C. Hua and B. C.-H. Cheng. “Design and implementation of power converters for wind energy conversion system”. *The 2010 International Power Electronics Conference-ECCE ASIA-*. IEEE. 2010, pp. 323–328.

[16] E. Alpaydin. *Introduction to machine learning*. MIT press, 2020.

[17] Y. S. Murat and H. Ceylan. “Use of artificial neural networks for transport energy demand modeling”. *Energy policy* 34.17 (2006), pp. 3165–3172.

[18] S. A. Kalogirou. “Artificial neural networks in renewable energy systems applications: a review”. *Renewable and sustainable energy reviews* 5.4 (2001), pp. 373–401.

[19] M. Pucci and M. Cirrincione. “Neural MPPT control of wind generators with induction machines without speed sensors”. *IEEE Transactions on Industrial Electronics* 58.1 (2010), pp. 37–47.

[20] J. Thongam, P Bouchard, R Beguenane, and I Fofana. “Neural network based wind speed sensorless MPPT controller for variable speed wind energy conversion systems”. *2010 IEEE Electrical Power & Energy Conference*. IEEE. 2010, pp. 1–6.

[21] L. Shanzhi, W. Haoping, T. Yang, and A. Aitouche. “A RBF neural network based MPPT method for variable speed wind turbine system”. *IFAC-PapersOnLine* 48.21 (2015), pp. 244–250.

[22] S. Morimoto, H. Nakayama, M. Sanada, and Y. Takeda. “Sensorless output maximization control for variable-speed wind generation system using IPMSG”. *IEEE Transactions on Industry Applications* 41.1 (2005), pp. 60–67. DOI: 10.1109/TIA.2004.841159.

[23] M. Shirazi, A. H. Viki, and O. Babayi. “A comparative study of maximum power extraction strategies in PMSG wind turbine system”. *2009 IEEE Electrical Power Energy Conference (EPEC)*. 2009, pp. 1–6. DOI: 10.1109/EPEC.2009.5420931.

[24] H. Camblong, I. M. de Alegria, M. Rodriguez, and G. Abad. “Experimental evaluation of wind turbines maximum power point tracking controllers”. *Energy Conversion and Management* 47.18 (2006), pp. 2846 –2858. ISSN: 0196-8904. DOI: https://doi.org/10.1016/j.enconman.2006.03.033. URL: http://www.sciencedirect.com/science/article/pii/S0196890406001245.

[25] S. M. R. Kazmi, H. Goto, H. Guo, and O. Ichinokura. “Review and critical analysis of the research papers published till date on maximum power point tracking in wind energy conversion system”. *2010 IEEE Energy Conversion Congress and Exposition*. 2010, pp. 4075–4082. DOI: 10.1109/ECCE.2010.5617747.

[26] B. Meghni, D. Dib, A. T. Azar, and A. Saadoun. “Effective supervisory controller to extend optimal energy management in hybrid wind turbine under energy and reliability constraints”. *International Journal of Dynamics and Control* 6.1 (2018), pp. 369–383.

[27] H. Li, K. Shi, and P. McLaren. “Neural-network-based sensorless maximum wind energy capture with compensated power coefficient”. *IEEE transactions on industry applications* 41.6 (2005), pp. 1548–1556.

[28] M. Cheng and Y. Zhu. "The state of the art of wind energy conversion systems and technologies: A review". *Energy Conversion and Management* 88 (2014), pp. 332–347.

[29] H. Abouobaida **et al.**. "New MPPT control for wind conversion system based PMSG and a comparaison to conventionals approachs". *2017 14th International Multi-Conference on Systems, Signals & Devices (SSD)*. IEEE. 2017, pp. 38–43.

https://doi.org/10.25974/ren_rev_2021_05