Intelligent MPPT Control for Wind Energy Conversion Systems Based on Reinforcement Learning

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Abstract. This article gives the best intellectual strength wind energy variable-speed point detection algorithm systems of transfer focused on improving instruction. Since reinforcing learning (RL) helps the variable-speed wind method to learn by direct contact with the environment. Awareness of factors of wind turbines or wind speed is not concerned. The first proposed MPPT control scheme facilitates a mix of the ANN and the Q-learning method to ensure the optimal coordination between PMSG engine speed and power. The proposed ANN-based RL MPPT control algorithm is supplied with simulation and experimental data.

Keywords: MPPT control algorithm, RL, ANN, wind system

1. Introduction

The last wind power was built extensively decade, and a key alternate source is planned in future to have clean, sustainable, reliable fuel. Wind conversion systems currently provide maximum wind power with variable speed (WECSs) \textsuperscript{[1-2]}. The spinning shaft speed can be regulated at a changing WECS varying speed to monitor the maximum power points (MPPs) for certain wind speed situations to produce the maximum energy only within desired voltage. The advantages are increased performance, higher energy density, lower running costs and an improved defect passage \textsuperscript{[3-6] and grid help}. In comparison, PMSG-based type WECSs with direct drive is more efficient. These benefits make them more appropriate for large-scale and offshore uses. For flagship WECS, an efficient Maximum Power Point Tracking (MPPT) algorithm is important to maximize wind energy effectiveness. The wind turbine model, an ideal speed ratio (ISR) and optimal interaction-based checks \textsuperscript{[7-8]} are some significant MPPT methods, which are usually found in large WECSs. In these are the following: Methods, the features of wind turbines, and the optimization of power versus wind direction, maximum torque or torque versus the generator speed curve, are given by the suppliers \textsuperscript{[9-11]}

However, the precision of these typical wind turbine curves is primarily determined by the WECS operational environment. For instance, in the performance where the blades are gravel, bugs or frost, power could deviate from the usual power curve \textsuperscript{[12-13]}. In the excessive mechanical wear, turbine blade erosion and the associated factors eventually would also lose their pre-establishing accuracy due
to the device ageing effect, which makes wind generation less successful over time. This makes it beneficial to adapt MPPT controls to the WECS's, particularly those in the rugged and less-accessible offshore setting, with a sophisticated online learning algorithm [14-15].

The P&O regulation needs no previous knowledge of the WECS and is independent of the details about wind velocity and the properties of wind turbines. The WECS does not, however, benefit from the experience in the P&O regulation. It then actively scans for the MPP, even the MPP. This slowly triggers the WECS reaction to changes in wind direction.

2. Proposed System

In the RL an agent can rely on the understanding of his own experience, through communicating with the world directly, through actions, states and recompenses, as opposed to the supervised learning, by examples given by an external supervisor. Whenever the handler receives, a reward takes a transportation function between nations. The RL's goal is to map states into acts so that incentives can be maximized.

Most RL theories discuss the final decision-making mechanism in Markov. A final MDP can be represented by a tuple where S is a state variable, and A is the set of acts, the status change probability distribution specifies the likelihood of moving from one location to another, whereby action is taken, and the optimization technique defines the reward following state transition.

The setup of a PMSG-based motor-driven WECS displayed in Figure 1, where the PMSG directly binds the wind turbine. An adjustable speed converter consisting of a System side Converter (MSC) and a Raster-Line Converter converts the power produced by the PMSG via the power grid (GSC). To obtain the full wind power or meet with the wind energy control centre, the MSC monitors the PMSG. The GSC retains the continuous DC connection voltage, and regulates the responsive voltage, power traded by the WECS for the grid.

![Diagram](image_url)

**Figure 1:** Direct-drive PMSG WECS

Mediator will learn about their own experience in the RL by direct interaction with the area via states, reminder and intervention. The agent's objective is to locate a selection of optimal steps to optimise the world's overall incentive. A state determines this ultimate incentive role of meaning or activity value, which calculates how it is good if the agent is in a specific situation or conducts an action given in a specific state, respectively. The approximation of the value function is the foundation of the RL technique. Q-learning is a common model-free RL.
Three major objects, namely state space, space for action and incentive, should be adequately specified to execute the Q-learning method on the Mpp tracking as in Figure 2. The WECS reached then a new argument and the agent was given the rt+1 reward to update the importance of the operation in the former state.

The agent attempts to produce the full amount of energy from the wind. To this end, an operation with a higher valuation with better probability will be selected any time the agent decides to get action. The instructional output is mainly influenced by Q-study algorithm parameters, such as a discount, training rate and temperature. They should then be correctly chosen.

3. Results

Simulation experiments apply the theoretical ANN based MPPT RL control algorithm. The WECS-based RL with the MPPT control system is shown in Figure 3. Figure 4 shows the P&O method where vector control system controls the rotor speed of the PMSG. The energy comparison is achieved, as shown in Figure 5.
Figure 4: Vector control system controls the rotor speed

Figure 5: conventional P&O MPPT method

Figure 6: Comparison of PMSG energy generated

Figure 5 GSM alert with location route, when the alert message is received from the monitoring authority's cell phone, the individual bin is cleaned automatically, and the original value is displayed on the recording device. In other words, 18 cm because all of these data are stored on the Cloud Server, this IoT-based waste and waste management system can be tracked efficiently. The Figure 6 displays the same field.

4. Conclusion
In this paper, the load scheduling and energy consumption based SVM optimization in a power system which integrated with the distributed energy generators and EMS system and control is accomplished using the machine learning-based SVM technique. The results are obtained and optimized for the power system based energy consumption and scheduling is achieved. SVM output by neural networks and genetic programming is higher than that of other relevant studies. SVM's solution is unique and suitable since SVM implies that quadratic programming is confined linearly. The proposed model reduces the energy cost by scheduling end-use-loads.

References
1. Hansen, Iov, Blaabjerg, Hansen, “Review of contemporary wind turbine concepts and their market penetration”, Wind Engineering, 28(3), 247-263, 2004.
2. Hossain and Ali, “Future research directions for the wind turbine generator system. Renewable and Sustainable energy reviews, Vol.49, pp.481-489, 2015.
3. Liu, Z. and Zhang, L., 2020. A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings. Measurement, 149, p.107002.
4. Liserre, Cardenas, Molinas, and Rodriguez, "Overview of multi-MW wind turbines and wind parks", IEEE Transactions on Industrial Electronics, 58(4), 1081-1095, 2011.
5. Anjana, R. (2019, Feb). Fuzzy and PI Based Speed Control of BLDC Motor using Bidirectional Converter for Electric Vehicle Application. Trends in Electrical Engineering, 8(3), 35-45.
6. Mohandas, R., & Krishnamoorthi, K. (2017). MANET security betterment by enhanced multiple key management scheme. Wireless Personal Communications, 94(4), 2173-2188.
7. https://www.wiley.com/en-us/Large+Wind+Turbines%3A+Design+and+Economics-p-9780471494560.
8. Macinnis, A.G. and Walls, F.G., Avago Technologies General IP Singapore Pte Ltd, 2018. Bounded rate near-lossless and lossless image compression. U.S. Patent 9,883,180.
9. Babu, M. S., & Rajasekhar, S. (2016). ANFIS Based UPQC for Power Quality Improvement. International Journal for Modern Trends in Science and Technology, 2(5), 6-10.
10. Gibbons, M. S., Gilbert, C. L., & Deshpande, M. S. (2019). U.S. Patent Application No. 15/801,772.
11. Ceaki, Seritan, Vatu and Mancasi, “Analysis of power quality improvement in smart grids”, 10th international symposium on advanced topics in electrical engineering (ATEE), pp. 797-801, 2017.
12. Dash, S.K. and Ray, P.K., 2018. Power quality improvement utilising PV fed unified power quality conditioner based on UV-PI and PR-R controller. CPSS Transactions on Power Electronics and Applications, 3(3), pp.243-253.
13. Liu, Li, Hu, and Luo, “A transformer integrated filtering system for power quality improvement of industrial DC supply system”, IEEE Transactions on Industrial Electronics, 67(5), pp.3329-3339, 2019.
14. Zhang, Pan, Chen, Han, Zhao and Zhang, “Short-term wind speed prediction model based on GA-ANN improved by VMD. Renewable Energy, 156, Pp.1373-1388, 2020.
15. https://www.researchgate.net/publication/329680977_Literature_Review_of_Wind_Turbines