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MACHINE LEARNING BASED ALGORITHMS FOR WIND TURBINES WITH DFIG CONTROL

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Abstract. Survey is aimed to simulate fault conditions on wind turbine equipped with double-fed induction generator (DFIG) and to analyze the behavior of WT's control system. Mathematical model of WT with DFIG was created in Matlab Simulink. That model has a variety of input parameters and their adjustment represents a complicated optimization task. Authors propose the solution of that task with the machine learning methods, known as Reinforcement Learning. Reinforcement learning allows to interact with the environment, and can learn the set of input parameters, which produces the desired behavior of the system.

Keywords: DFIG, Wind Turbines, RSC, GSC, Machine Learning, Reinforcement Learning, Crowbar, Neural Networks.

Introduction

According to world wind power development reports [1], over the past 10 years, there has been an exponential increase in the commissioned capacities of wind power plants, and an increase in the capacity of commissioned wind farms and unit capacities of wind turbines.

The requirements for ensuring stable operation in power systems are met by the two most popular types of wind turbines - wind turbines with a variable speed with a synchronous generator, and wind turbines with a variable speed with an double-fed induction generator (DFIG).

In the design of wind turbines with DFIG, the power converter is located in the rotor circuit, and should be designed only for 30% of the nominal power of the wind turbine. This reduces the cost of the wind turbine, and allows the use of wind turbines with large unit capacities, however, has its drawbacks. The first is a more complex control system than in the case of a synchronous generator. Nevertheless, at the moment, many approaches to the management of wind turbines with DFIG [2, 3] have been studied. Another disadvantage is the limited ability of a wind turbine to operate in emergency mode, since complex wind turbine protection systems are required.

This article describes an approach using machine learning to identify the best control strategy for wind turbines with DFIG in emergency conditions.

1. Control system of a doubly-fed induction generator

DFIG is basically an induction geneartor with a phase rotor with slip rings on the rotor, where the stator is directly connected to the network, and the rotor is through an oncoming partial power converter. Dual power means that the voltage on the stator is determined by the network and the voltage on the rotor also depends on the network and is transmitted through the power converter. The
Converter consists of two typical voltage converters (rotor side converter — RSC and grid side converter GSC) and a DC bus [4].

Fig. 1 shows a general wind turbine control system with DFIG and variable speed. Two wind turbine control levels with different speed of operation are used: wind turbine control level, and generator control level. At the generator control level, power converters are electrically controlled. At this level, two controllers are a controller for controlling the GSC and a controller for controlling the RSC.

![Diagram of wind turbine control system with DFIG](image_url)

**Fig. 1. The block diagram of the control of wind turbines with DFIG**

2. The algorithm for dynamic adjustment the PI coefficients of the controllers and the parameters of the protection system

To solve the problem of ensuring the stable operation of wind turbines with DFIG in various emergency conditions, it is necessary to develop an algorithm for dynamically adjusting the parameters of the simulink model. Changing individual gain of PI controllers or electrical parameters and the response time of the protection system leads to a change in the operating mode of a wind turbine [3].

The simulink model receives an input voltage profile. By setting this profile, emergency modes can be simulated by reducing voltage. Regardless of the voltage profile, the settings for the active and reactive power and the current wind speed are applied to the wind turbine control system. The combination of these conditions can create particularly difficult emergency conditions for wind turbines, which can lead to its shutdown.

PI controllers of a wind turbine control system understand us:
- PI controllers for RSC $i_d$ and $i_q$ currents, responsible for regulating the reactive and active power transmitted through the stator, respectively;
- PI controllers for GSC $i_d$ and $i_q$ currents, which are responsible for regulating the voltage of the DC bus and the reactive power transmitted through the GSC.
After starting the simulation, the simulink model provides real-time output parameters that immediately go to the machine learning algorithm [5].

The task of the machine learning algorithm is to select the input parameters coming from the simulink model in order to obtain the most stable state of the wind turbine model [6]. This is achieved by constantly fine-tuning the settings. The steady state of the model is determined from the output parameters of the simulink model generator. When developing a machine learning algorithm, the task is to determine the function at the input of which the parameters of the generator are received, and at the output of which is an aggregated value that allows judging the effectiveness of the selected parameters. The general structural diagram of the interaction of the simulink model and the machine learning algorithm is shown in Fig. 2.

![Fig. 2. Block diagram of the interaction of the wind turbine model and machine learning algorithm](image)

**Conclusion**

At present, machine learning algorithms, and in particular neural networks, are a serious tool for solving complex problems, which are based on many time-varying parameters with non-linear dependencies. Neural networks of even simple architecture have the ability to approximate nonlinear functions, with increasing complexity of the function, the architecture of neural networks becomes more complicated, which in turn leads to an increase in the computation time, the so-called training time of neural networks.

The task posed in the study can be solved using neural networks, since there are a dozen parameters with unknown dependencies that are difficult to select using traditional methods. The task is also complicated by the fact that the parameters of the regime strongly depend on the initial conditions, and can vary greatly from the calculated theoretical values. To interact with a dynamically changing environment, it is necessary to use machine learning algorithms that can change the hyperparameters of the neural network depending on the changing environment. An example of such algorithms is a group of reinforcement learning algorithms that can be applied to a given task.
References


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