

Fault detection and classification in wind turbine by using artificial neural network

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ABSTRACT

Wind turbine is one of the present renewable energy sources that has become the most popular. The operational and maintenance cost is continuously increasing, especially for wind generator. Early fault detection is very important to optimise the operational and maintenance cost. The goal of this project is to study fault detection and classification for a wind turbine (WT) by using artificial neural network (ANN). In this project, a single phase fault was placed at 9 MW doubly-fed induction generator (DFIG) WT in MATLAB Simulink. The WT was tested under different conditions, i.e., normal condition, fault at Phase A, Phase B and Phase C. The simulation results were used as inputs in the ANN model for training. Then, a new set of data was taken under different conditions as inputs for ANN fault classifier. The target outputs of ANN fault classifier were set as '0' or '1', based on the fault condition. Results obtained showed that the ANN fault classifier outputs had followed the target outputs. In conclusion, the WT fault detection and classification method by using ANN were successfully developed.

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1. INTRODUCTION

Renewable energy sources, especially wind energy is presently the most popular technology as there were more than 282.48 GW installed capacity at the end of 2012 [1-4]. There is a need for an early fault detection in this increasingly popular technology, since the early fault detection in WT can help to reduce the cost for effective maintenance and operation [1, 5-12].

In literature, there are several publications on fault detection investigation in WTs. In [13], condition monitoring and fault detection in WT based on DFIG by using fuzzy logic were presented. It was focused on faulty short circuit. In [5], fault detection in WT was focused on neural network. The fault detection was based on current signature analysis. Fault detection in WT by using artificial neural network (ANN) based on SCADA data analysis was proposed in [1]. In [7], condition monitoring for WT generator by using temperature trend analysis was developed. The unbalance voltage fault of doubly fed asynchronous generator WT was studied in [14]. Meanwhile in [15-18], faults diagnosis by using a-priori knowledge-based ANFIS for WT was proposed.

The research was focused only on fault detection and not on fault classification. Moreover, most research developed fault detection by using an artificial intelligent approach like fuzzy and ANN, based on current as the input. An artificial intelligence (AI) method like fuzzy is very complicated due to the required rule to develop the fuzzy system.

AI means the ability of a machine to perform similar functions that characterise the human thought [19]. AI becomes the most popular method for fault detection due to many advantages as compared to the

conventional fault diagnostic approaches [13]. ANN is one of the AI methods and it is a type of network because it sees the nodes as ‘artificial neurons’ [19-22]. There are two types of ANN, which are feedforward and feedback ANN. The feedforward ANN does not contain any connection between input and output, while the feedback ANN contains connection between input and output. In static purpose the feedforward ANN is usually used and in dynamic purpose the feedback ANN is used [24]. ANN structures consist of input layer, hidden layer and output layer, as shown in Figure 1.

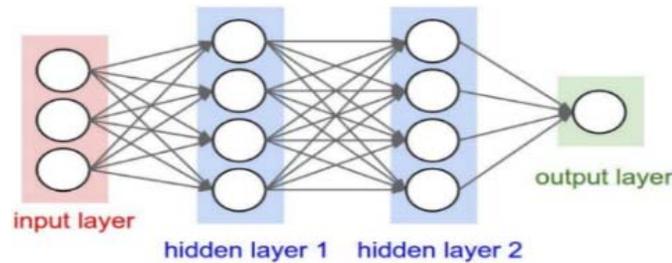


Figure 1. ANN structure

In this project, fault detection and classification for WT was developed by using ANN model in MATLAB, based on three phase currents, DC voltage, and induction generator speed as the model input. A 9 MW WT that use a detailed DFIG model was simulated with normal and fault conditions. A single phase fault was inserted into the WT model for fault at Phase A, Phase B, and Phase C. The simulation results of three phase currents, DC voltage, induction generator speed, active power, and reactive power were obtained. Then, the ANN model was developed. The ANN was used to study the dynamic of WT system from the input and output pattern collected from the dataset. The modelled ANN input consisted of five inputs, which were three phase current, DC voltage and induction generator speed. Meanwhile, the output for training process of modelled ANN consisted of one output which was active power or reactive power. Two ANN models were developed, which were for active and reactive power models. Then, the output responses from ANN training process model were compared to the target output to evaluate the ANN training model performance. The comparison was made by calculating the root means square error (RMSE) value. When RMSE values were satisfactory for training, a few data were taken for the ANN fault classifier. The ANN fault classifier target output was set as ‘0’ or ‘1’, based on fault condition. The ANN fault classifier was developed with different data from all conditions to see the performance. The ANN fault classifier model was validated with a new set of data from different conditions and fault resistances.

2. METHODOLOGY

A 9 MW wind farm that use a detailed model of a Doubly-Fed Induction Generator (DFIG) driven by a wind turbine is shown in Figure 2. First, the WT was simulated under normal condition to get the simulation result of three phase currents, I_{abc} (pu); DC voltage, V_{dc} (V); induction generator speed, ω_r (pu); active power, P (pu); and reactive power, Q (pu). Later, a three phase fault was inserted between line B575 and DFIG wind turbine. The faults were simulated for fault at Phase A, Phase B, and Phase C.

The simulation results for normal and fault conditions of WT model were used to develop the ANN model. The ANN model was developed to detect the types of fault. The ANN model used back propagation as it was more efficient in producing the target values as output values [24]. Moreover, back propagation does not require the exact form of analytical function on which the model should be built [1]. Two ANN models were developed in models, which were ANN training model and ANN fault classifier model.

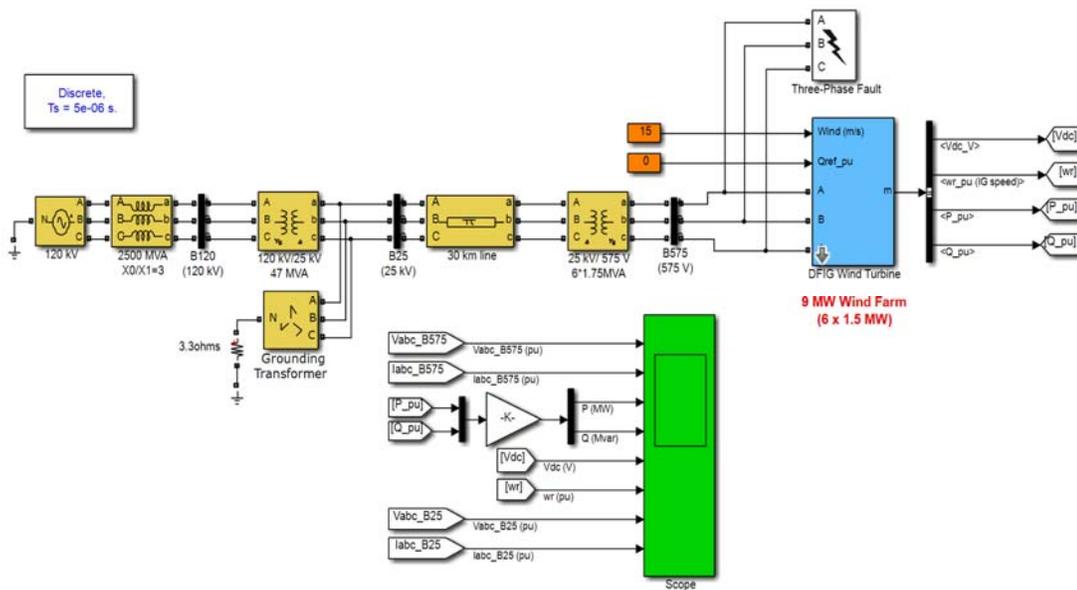


Figure 2. A 9 MW wind farm with three phase fault [25]

2.1. ANN training model

The ANN training model was developed by using MATLAB. This model had multi-input. The inputs for ANN training model were three phase currents, I_{abc} (pu); DC voltage, V_{dc} (V); and induction generator speed, ω_r (pu). The output for ANN training model was active power, P. Then, the ANN model was repeated for reactive power, Q, as an output. The ANN training model was developed for four conditions, which were normal, fault at Phase A, Phase B, and Phase C. Figure 3 shows the ANN training model. The ANN training model consisted of 5 inputs and 1 output. The hidden layer was set to 40 and the output layer was set to 1.

The performance of ANN training model was evaluated by comparing the target and the ANN model output by using RMSE value. The training processes were repeated until the RMSE values were satisfactory. The training processes were done to get the best ANN structure and select the input of ANN fault classifier.

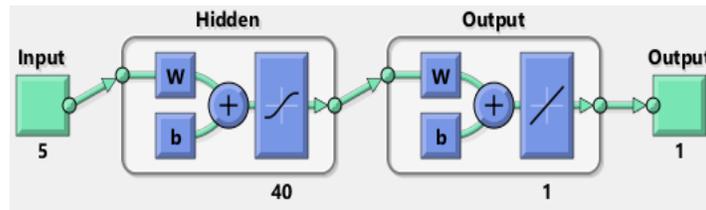


Figure 3. ANN training model

2.2. ANN fault classifier model

Later, a few data were taken for ANN fault detection for WT. Figure 4 shows the ANN fault classifier model. The structure of ANN fault classifier was selected as 5 inputs, 40 hidden layers, 3 output layers and 3 outputs.

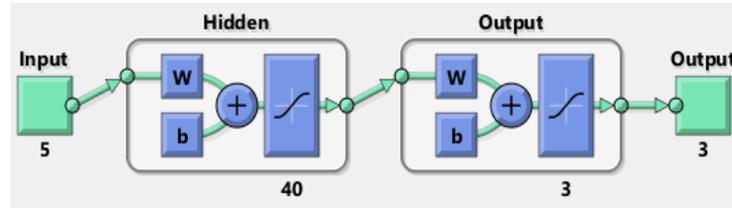


Figure 4. ANN fault classifier model

The inputs of ANN fault classifier were three phase currents, I_{abc} (pu); DC voltage, V_{dc} (V); and induction generator speed, ω_r (pu). Meanwhile, the outputs for ANN fault classifier were represented as X, Y, and Z. The value of each output was set as ‘0’ or ‘1’, based on fault condition. Table 1 shows the target output for ANN fault classifier model. It consisted of four conditions, i.e., normal, fault at phase A, Phase B, and Phase C.

The ANN fault classifier was validated with three different fault resistance values, i.e., 0.001Ω, 0.01Ω and 0.1Ω. The performance of ANN faults classifier model was evaluated by comparing the target output of ANN faults classifier model by using different data for all conditions.

Table 1. Target output for ANN fault classifier

Condition	X	Y	Z
Normal	0	0	0
Fault at Phase A	1	0	0
Fault at Phase B	0	1	0
Fault at Phase C	0	0	1

3. RESULTS

3.1. Result for ANN training model

Figure 5 shows the training result for reactive power, Q (pu) for fault at Phase A and Figure 6 shows the training result for active power, P (pu) for fault at Phase B. The solid line represented the target output, while the dashed line represented the ANN model output. The ANN model outputs in Figure 5 captured the target output well. The graph of ANN model in Figure 6 was oscillated but the RMSE value was still low.

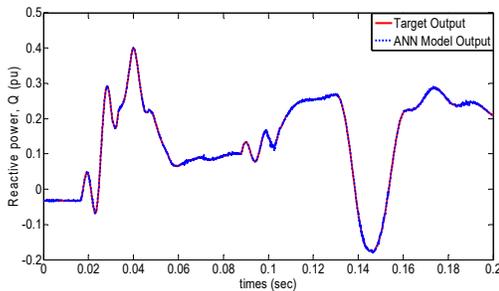


Figure 5. Reactive power, Q for fault at phase A

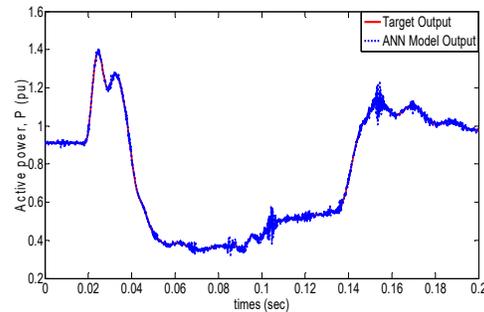


Figure 6. Active power, P for fault at phase B

Table 2 shows the result of RMSE value of ANN model for training purpose with different fault conditions for active and reactive power. All the RMSE values were low. The highest RMSE value was for active power for normal condition, which was 0.0226. The lowest value of RMSE was for reactive power for fault at Phase C which was 0.0014.

Table 2. RMSE value for ANN training model

Condition	RMSE	
	Active power, P	Reactive power, Q
Normal	0.0226	0.0082
Fault at phase A	0.0041	0.0016
Fault at phase B	0.0108	0.0039
Fault at phase C	0.0047	0.0014

3.2. Results for ANN fault classifier model

After the training process was satisfactory, the ANN fault classifier was developed. The ANN fault classifier was tested and validated with different fault resistance values. Table 3 shows the results of ANN fault classifier for all conditions with different fault resistances. The results showed that ANN fault classifier followed the target output.

Table 3. Results of validation for ANN fault classifier model

CONDITION	Fault Resistance (ohm)	TARGET			ANN OUTPUT		
		X	Y	Z	X	Y	Z
Normal	none	0	0	0	8.07E-04	2.03E-04	0.0003
	0.001	1	0	0	0.9997	2.68E-04	1.54E-04
	0.01	1	0	0	1.0000	2.08E-06	9.62E-06
Fault at phase A	0.1	1	0	0	1.0000	4.43E-04	2.47E-04
	0.001	0	1	0	0.0002	0.9997	1.34E-04
	0.01	0	1	0	4.56E-14	1.0000	0.00E+00
Fault at phase B	0.1	0	1	0	3.36E-04	0.9996	5.30E-06
	0.001	0	0	1	4.02E-07	1.21E-04	0.9997
	0.01	0	0	1	1.19E-10	3.29E-13	1.0000
Fault at phase C	0.1	0	0	1	5.72E-04	2.84E-04	0.9988

4. DISCUSSION

The aim of this research is to develop a fault detection and classifier model for WT by using ANN. The results obtained for training process showed that the ANN training model output followed the target outputs excellently, except for normal condition. Although the ANN model for training process in normal condition was oscillated but the RMSE was still low. The performance of training process can be seen by calculating the RMSE values. The nearest RMSE value to zero value was the highest model performance. Therefore, the training process performances depended on the RMSE. From the results obtained, all the RMSE values for training were near to zero. After the ANN training model process was successfully developed, the ANN fault classifier was developed by using the same input and structure. The ANN fault classifier was tested and validated under different fault resistances and conditions. The results obtained from ANN fault classifier showed that ANN fault classifier followed the target output exactly for different data under all conditions. Thus, the ANN model for fault detection was proven to have a good performance.

5. CONCLUSION

In conclusion, the ANN model was less complicated as it did not require the exact form of analytical function on which the model should be built to develop the model. Moreover, the developed ANN model had shown good efficiency, based on the output and target values of ANN fault classifier model were exactly the same. In conclusion, the fault detection and classification method of WT by using ANN were successfully developed.

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