Diagnosis and localization of fault for a neutral point clamped inverter in wind energy conversion system using artificial neural network technique

Introduction. To attain high efficiency and reliability in the field of clean energy conversion, power electronics play a significant role in a wide range of applications. More effort is being made to increase the dependability of power electronics systems. Purpose. In order to avoid any undesirable effects or disturbances that negatively affect the continuity of service in the field of energy production, this research provides a fault detection technique for insulated-gate bipolar transistor open-circuit faults in a three-level diode-clamped inverter of a wind energy conversion system predicated on a doubly-fed induction generator. The novelty of the suggested work ensures the regulation of power exchanged between the system and the grid without faults. Advanced intelligence approaches based on a multilayer artificial neural network are used to discover and locate this type of defect; the database is based on the module and phase angle of three-phase stator currents of induction generators. The proposed methods are designed for the detection of one or two open-circuit faults in the power switches of the side converter of a doubly-fed induction generator in a wind energy conversion system. Methods. In the proposed detection method, only the three-phase stator current module and phase angle are used to identify the faulty switch. The primary goal of this fault diagnosis system is to effectively detect and locate failures in one or even more neutral point clamped inverter switches. Practical value. The performance of the controllers is evaluated under different operating conditions of the power system, and the reliability, feasibility, and effectiveness of the proposed fault detection have been verified under various open-switch fault conditions. The diagnostic approach is also robust to transient conditions posed by changes in load and speed. The proposed diagnostic technique’s performance and effectiveness are both proven by simulation in the SimPower /Simulink® MATLAB environment. References 31, tables 2, figures 7.

Key words: artificial neural network, insulated-gate bipolar transistors, fault diagnosis technique, neutral point clamped inverter, wind energy conversion system.

Introduction. The latest global reports on the state of wind energy in the world show that this energy has become an important investment sector in major industrialized countries. This is due to various factors such as the significant drop in production costs and the development of the field of power electronics that has solved many problems regarding the quality of the energy produced and the possibility of integrating this energy into the grid [1].

The wind turbines are equipped with a double fed induction generator (DFIG) to produce electricity at variable speeds. It is connected to a multi-level inverter of neutral point clamped (NPC) structure, to improve the performance of this system. During operation, NPC inverter faces various constraints that can cause certain faults which is why production lines must be equipped with efficient fault detection and diagnostic systems, because any failure even the most trivial, can lead to multiple mandatory damages. The causes of IGBT failure in NPC inverters can be classified into three categories: control faults, transient operating regimes, in particular those concerning terminal voltages, thermal overloads, and environmental conditions of use [2]. The environmental conditions leading to IGBT failure are mainly extreme ambient temperatures, humidity, natural ionizing radiation, and mechanical vibration [3, 4]. Less frequently, contamination and dust are also sources of IGBT malfunction.

A simple switch-open or circuit-open defect usually results in the whole or partial loss of operation of one of the IGBTs constituting the static converter it occurs due to a gate failure or a break in a connecting wire in the transistor, this break can be caused by thermal cycling or a short circuit fault [5]. An open circuit (OC) fault is one of the most prevalent faults of the IGBT in NPC inverter, it is necessary to examine and fault diagnosis in the arm of the inverter and detect it [6-8].

Recently, several methods for detecting faults in power transformers have been developed to correspond to
the diversity of problems encountered [9-17]. Park’s vector-based methods [18-22] unfortunately require complex pattern recognition algorithms. Voltage-based methods require the use of additional sensors [23, 24]; The proposed diagnostic approach [25] is based on analyzing the inverter’s output pole voltages and output currents. In [26] utilized a diagnostic procedure based on the phase current’s instantaneous frequency after analyzing it with the Hilbert transform. In [27, 28] an artificial neural network (ANN) based multiple open-switch fault diagnostic approach was proposed. Using the DC components and total harmonic distortion (THD) of the stator currents, the 21 fault modes of multiple open-switch faults were localized. In this article, we focus on sophisticated intelligent techniques based on ANN to identify and detect these faults. We are interested in intermittent faults of the open circuit type of IGBT in the rotor side converter (RSC) to diagnose and locate them, to avoid degradation of the performance in the wind energy conversion system (WECS).

**Topology of a three-level diode-clamped inverter and fault detection method. Topology of an inverter.** Figure 1 depicts the NPC inverter topology [29, 30]. The DC-link supply was shared by each phase of the inverter, as indicated in Fig. 1. The common point of the series capacitors is connected to the center of each phase. The inverter is powering a three-phase load with an AC. According to the DC-bus voltage, the output has 3 levels: (−Vdc), 0, and (+Vdc).

The working principle is shown in Table 1. The converter should offer complementarities between both the couples of switches (S₁₁, S₄) and (S₁₂, S₃) in obtaining to get the appropriate 3-level voltages, where i denote the indication of phase (i = A, B, C), and Vio is the phase-to-fictive midway point value.

<table>
<thead>
<tr>
<th>Switching states</th>
<th>NPC inverter i-phase</th>
<th>Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>1 1 0 0</td>
<td>+Vdc/2</td>
</tr>
<tr>
<td>O</td>
<td>0 1 0 1</td>
<td>0</td>
</tr>
<tr>
<td>P</td>
<td>0 0 1 1</td>
<td>−Vdc/2</td>
</tr>
</tbody>
</table>

Table 1 depicts i-phase switching in Fig. 1 with switching stages and output voltage levels.

To simplify the intricacy of the structure of a 3-level inverter, each pair (transistor – diode) semiconductor is marked by a single bidirectional switch S, and can be seen that, the structure is symmetric. Figure 2 illustrated the structure of a single leg, with an open circuit fault in S₃₁.

The OC fault is influences by raising the oscillations of the power signals and the deformity at the level of the stator-phase current with the increase of their amplitudes. In order to avoid these faults, which negatively affect the work of the power conversion system, we must put in place mechanisms to monitor and detect these faults in order to avoid any disaster that may arise. Among the detection techniques, we have presented in this work a technique based on the neural network, which has shown us a satisfactory performance.

**Fault detection method.** Diagnosis by neural networks (NN) is a computational model whose design is very schematically inspired by the functioning of real human neurons, so the principle is inspired by biological neurons, to identify faults in a system, the diagnosis carried out by NN must have an adequate number of examples of good functioning and defects to be able to learn them. During the training phase, the features are provided to the input network, and the output network receives the required diagnosis [31].

Firstly, we apply a Fourier analysis technique to the stator current properties presented in Fig. 3 in this model. After the neuron network processes, the data, the system monitors the phase angle and amplitude of the 3-phase stator currents (Iₛabc), which will be the inputs to the NN; the semi-faulty driver is recognized and identified by the network. The selected features of each fault, which are specified in the tabular form of samples to be investigated, are used to extract features.
Simulation of system studies. In this work, for power conditioning in the WECS applications, various topologies of power converters have been suggested (Fig. 4). The multilevel converters, particularly the NPC topology, are widely utilized in the creation of high voltage and high power, wind power plants because of their benefits, which include the optimum waveform of the output voltage and a reduction in overall harmonic distortion.

We simulate the wind energy conversion chain (WECC) based on a DFIG on SimPower/Simulink® MATLAB environment, as shown in Fig. 5. In which the multilevel inverter of NPC structure is controlled with indirect vector control of active and reactive powers.

Structure of ANN. The process of creating and validating NNs is separated into 3 stages.

Inputs of the network. An ANN’s inputs are the two features of a 3-phase stator current ($I_{abc}$), resulting in a total of 2 inputs to this network.

Outputs of the network. When a fault is detected, the network displays a binary code. Any output relating to a component’s failure. In our work, we have the following:
- the total outputs of the network are 12;
- Table 2 lists the numerous problems in the inverter’s components, along with their related codes.

The system was able to assess circuit faults using a NN to obtain fault codes for OC switches. The system was tested using two inputs, the first representing the amplitude of stator current and the second representing the phase angle.

Tests of ANN. The NN achieved higher learning performance to discover the fault position in the circuit after numerous tests; Fig. 6,a,b,c shows the training performance, regression, and error histogram of the study. To achieve and assess the NN learning and training performance, we use the mean quadratic error (MQE).

The ANN in our case reached a value of $1.9656 \times 10^{-20}$. The goal error has been reached after just 470 of the 1000 epochs of the training parameter, and the regression figure shows an acceptable regression ($R$ equal to 1) among both network outputs and network targets.

Error Histogram with 20 Bins

Fig. 6. $a$ – Training performance plot for the classifier; $b$ – NN-training regression and $c$ – error histogram

Fig. 4. Structure of the wind power conversion chain based on DFIG with NPC structure of RSC

Fig. 5. Model Simulink of WECS and fault diagnosis using neural network

Electrical Engineering & Electromechanics, 2022, no. 5
Checking the performance of the neural network. We did tests for numerous sorts of operations, and the results are displayed in Fig. 7. Once the ANN was established and our learning had attained an acceptable level, we made tests for various types of operations.

<table>
<thead>
<tr>
<th>Faulty switch</th>
<th>Training data</th>
<th>Output code of neural network</th>
<th>Faulty switch</th>
<th>Training data</th>
<th>Output code of neural network</th>
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<tr>
<td>Normal</td>
<td>22.26</td>
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<td>Sc1</td>
<td>45.52</td>
<td>–1.21</td>
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<tr>
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<td>–0.3975</td>
<td>Sc2</td>
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<tr>
<td>Sa2</td>
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<td>1.233</td>
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<td>2.59</td>
<td>Sc4</td>
<td>47.93</td>
<td>0.3295</td>
</tr>
<tr>
<td>Sa4</td>
<td>45.78</td>
<td>–0.2721</td>
<td>Sa1 &amp; Sa2</td>
<td>49.54</td>
<td>–1.683</td>
</tr>
<tr>
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Conflict of interest. The authors declare that they have no conflicts of interest.

REFERENCES


