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Artificial Neural Network for High-Impedance-Fault Detection in DC Microgrids

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***Abstract*—In this paper, we present a novel method for detecting high-impedance faults (HIFs) in DC microgrids. HIFs are more difficult to detect than other types of faults because their voltage and current values are not significantly different from those under normal operating conditions. We propose a recurrent neural network (RNN)-based method that can detect events from the temporal behaviour of a current signal, including HIFs and load changes. The method proves to be accurate, distinguishing between HIFs and other waveforms with a high score above 95% on accuracy and F1-score metrics.**

***Index Terms*—DC microgrid, fault detection, recurrent neural network, high-impedance fault**

I. Introduction

The concept of microgrids was introduced in response to an increasing integration of distributed energy resources (DERs) into the power system [1]. DERs are grouped with the local loads to form entities that can operate in a grid-connected or an islanded mode. In the grid-connected mode, bidirectional power exchange is possible to either compensate the difference between the DER generation and the load or to send excess energy to the grid. In the island mode, the microgrid operates independently of the grid, increasing the reliability of the power supply when grid failures occur [2].

Proper microgrid operation requires meeting certain technical challenges, including the development of a suitable protection system that allows a microgrid to operate safely [3]. A microgrid operates in different modes (grid-connected or islanded), and each of these modes includes a variety of operating conditions due to the inclusion of DERs, loads and storage systems, which affect the protection requirements differently. In addition, there are renewable energy sources (RES) that are usually connected through an electronic converter and therefore have an unconventional fault response.

As for the type of fault, there are low-impedance faults (LIF) that cause high currents destructive for electrical equipment. These types of faults are relatively easy to detect using conventional protection methods such as the overcurrent protection, as their fault response is quite different from other transients occurring in the system. However, for the high-impedance faults (HIF) the conventional protection methods are insufficient [4]. The magnitude of HIF current is much lower and less destructive than that of a LIF. However, it is impossible to set clean thresholds for conventional protection because other transients, such as load changes, could trigger them. Therefore, there is a need for an efficient fault detection of HIFs.

Although microgrids can be quite diverse, they generally contain DERs, energy storage and controllable or noncontrollable loads. Photovoltaics (PVs) are one of the most popular RES and are often used together with battery energy storage system [5]. In addition, there is an increasing number of DC loads such as electric vehicle charging stations, user electronics, etc. In order to avoid unnecessary power conversions, these DC devices may be combined into DC microgrids, which offer various advantages as compared to their AC counterparts. These include higher efficiency, no power quality issues and less complex control as there is no reactive power flow and no frequency control [6]. To further improve the safety of DC microgrids, this work focuses on fault detection of HIFs in DC microgrids.

II. Related Work and Contribution

Detection of HIF is challenging due to the low current that conventional protection cannot detect. Differential protection is able to detect HIF because it uses a difference in currents at the ends of a line and reacts when a difference is detected. Therefore, the differential protection is immune to the value of the fault resistance. This protection strategy has been implemented for the protection of DC microgrids in [12], but even if it proves effective, it has certain drawbacks. It protects only one element of a microgrid and relies heavily on communication, which is prone to interference and failure. In addition, the communication link makes it more expensive to implement because it has to be fast to synchronise the data.

Different authors have proposed various approaches to HIF detection. In [7], the incremental resistance measured at the output of a converter is used as a HIF indicator. However, only a single converter and its load are observed. In [8], a signal

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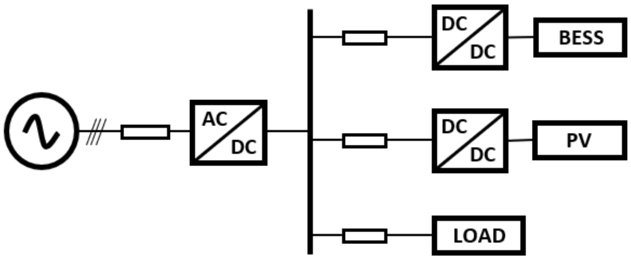

Fig. 1. Block diagram of the microgrid.

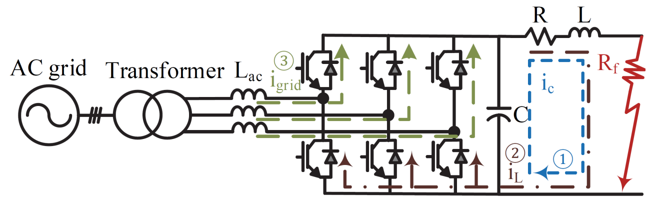

Fig. 2. VSC stages during a short-circuit fault [4].

processing method is also used for this task. The discrete wavelet transform is used to prepare the current signal for multi-resolution analysis, and a k-nearest neighbours classifier is used to distinguish faulty and non-faulty states.

The increasing popularity of neural networks (NNs) for classification tasks led to the implementation of a Group Method of Data Handling (GMDH) neural network for HIF detection in [9]. The input to GMDH NN is the power signal obtained by multiplying the voltage and current signals, and the output is a signal prediction. The difference between the signal prediction and the actual signal is then used for fault detection, and NN has proven to be a reliable classifier. However, there is a type of NNs called recurrent neural networks that are able to extract knowledge from the sequential data and use it to classify events based on their waveforms. This concept is highly convenient for detection of HIFs due to their characteristic waveform that distinguishes them from other transients. RNN have already been used for the detection of low-impedance faults (LIF) in microgrids, where it has proven to be highly accurate [10]. In [11], it was used for arc fault detection in electric vehicle charging stations and also showed high accuracy. Therefore, the RNN is considered a suitable candidate for HIF detection.

The contribution of this work is to develop a HIF fault detection method for DC microgrids based on the RNN as an intelligent classifier.

III. System Description

The microgrid simulation model was created in Matlab Simulink software package in accordance with the DC microgrid testbed presented in [13], where all information about the model is available. This RES-based radial microgrid includes a PV and a battery energy storage along with a DC load. The connection to the AC grid is via a bidirectional inverter. The original model of the microgrid includes a flow battery, but in this work it is replaced by a lithium-ion battery with similar characteristics. The inverter controls the power exchange between the microgrid and the utility grid, while the DC bus voltage is controlled by a DC-DC boost converter. The battery is connected via the bidirectional DC-DC converter and is in current control mode. The DC load is modelled as a constant impedance load. Block diagram of the microgrid is shown in Fig. 1.

IV. Faults in DC Microgrids

The main difference in protection of AC and DC systems arises from different fault responses. In both systems, fast rising currents of high magnitude occur, but the DC current has no natural zero crossing. This places high demands on the speed of fault detection, because the fault current must be prevented from reaching high values. On the other hand, HIFs have a specific repetitive pattern that distinguishes them from other transients that occur in microgrids, but require an efficient solution for their detection.

A. Low-Impedance Faults

LIFs occur when a pole of the microgrid is short-circuited to another pole or to earth by low impedance, resulting in a voltage drop to zero. Since the microgrid considered in this study contains power converters, a voltage source converter (VSC) fault analysis is presented. VSC fault response consists of three stages. The first stage is the capacitor discharge stage, where the capacitor releases the energy through the cable until its voltage reaches zero (blue path in Fig. 2). In this stage, the fault current reaches its peak value, which is much higher than the nominal VSC current. In the second stage, the fault current commutes to the freewheeling diodes (brown path). The current is still significantly higher than the rated current and there is a possibility that the diodes will be damaged if the protection does not operate in the first stage. In the third stage (green path), the AC grid starts to contribute to the fault and VSC behaves like an uncontrolled full-bridge rectifier, after which a steady state is reached. The DC-DC converters go through the same fault stages in case of short-circuit faults. The fault response of the boost converter includes all these stages, while the buck converter only goes through the first two stages. A detailed analysis of the behaviour of the converters during faults can be found in [4].

B. High-Impedance Faults

As described in the previous section, the detection of LIFs is relatively simple, as the fault response is quite different from the normal operating conditions of microgrids. On the other hand, a HIF fault occurs when a pole comes in contact with earth or another pole through a high impedance. This contact cannot be detected by conventional overcurrent protection, but can have serious consequences such as fire or injury [14].

HIFs are characterised by nonlinear behaviour of the fault current, which resembles a repetitive reignition current. According to [15], the HIF waveform consists of three parts:

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buildup, shoulder, and nonlinearity. In the buildup stage, the current rises to its maximum amplitude, followed by the shoulder stage. In the last, nonlinear stage, the nonlinear behaviour of the HIF becomes apparent. To following is proposed to model the HIF behaviour [15]:

$$i_{j+1} = i_j - \frac{R \cdot i_j + k/i_j^{1.2} + 35 - V_{DC}\sin(\omega t)}{R - 1.2k/i_j^{2.2}} \tag{1}$$

$$2n\pi + pi/3 < \omega t < 2n\pi + 2pi/3, n \in \mathbb{N}_0 \tag{2}$$

where k is the arc constant, i is the HIF fault current, V_{DC} nominal voltage, and R equivalent fault resistance. The equivalent fault resistance can be extracted from (1):

$$R = \frac{1.2k \cdot i_{j+1}/i_j^{2.2} - 1.2k/i_j^{2.2} - k/i_j^{1.2} - 35 + V_{DC}\sin(\omega t)}{i_{j+1}} \tag{3}$$

V. Fault Detection Method

The aim of fault detection is to uncover adverse system conditions that could be dangerous to people and equipment. This process is performed by monitoring the current and voltage values that change when transients occur in system. If the change is significant, i.e. if the values exceed thresholds applicable to normal operation, the protection system isolates the faulty section. The problem, however, is that HIFs do not usually exceed these thresholds, so a different approach is required for their detection. In general, fault detection is a classification task, as it converts input states into a discrete decision on whether a fault is present or not. Neural networks are particularly good at solving this type of task. Moreover, neural networks are considered universal approximators and are able to approximate any function if they have input and target values. In other words, the function that maps the inputs to the decision can not only be approximated by the NN, but it can also be made more complex than just having a fixed threshold value. Thus, the NN can be trained to detect HIFs that cannot be detected by conventional protection, which improves the ability to detect faults in microgrids.

A. Recurrent Neural Networks

There are different types of neural networks suitable for specific purposes, but they all go back to the standard Feed Forward Neural Network (FFNN). The architecture of the FFNN consists of an input layer, one or more hidden layers, and an output layer. When the FFNN is used for classification, the output layer is followed by the *softmax* layer. The formulation can be expressed in vector form:

$$\mathbf{h}_1^{(t)} = \sigma(\mathbf{U}_1\,\mathbf{x}^{(t)} + \mathbf{b}_1) \tag{4}$$

where $\mathbf{x}^{(t)}$ is the input vector, $\mathbf{h}_1^{(t)}$ is the output of the first transformation, and σ is arbitrary nonlinear function. The most commonly used nonlinear functions are sigmoid, tanh, and rectified linear unit. The matrix $\mathbf{U}_1$ and the bias vector $\mathbf{b}_1$ transform the input into its representation. The hidden layers can be stacked so that the output of the first hidden layer is the input to the second hidden layer, and so on. Expressed in vector form:

$$\mathbf{h}_k^{(t)} = \sigma(\mathbf{U}_k\,\mathbf{h}_{k-1}^{(t)} + \mathbf{b}_k) \tag{5}$$

The output layer takes the output of the last hidden layer and outputs the vector that has dimensionality equal to number of classes.

$$\mathbf{o}^{(t)} = \mathbf{U}_n\,\mathbf{h}_n^{(t)} + \mathbf{b}_n \tag{6}$$

where $\mathbf{h}_n^{(t)}$ is the last hidden layer, and $\mathbf{o}^{(t)}$ is the output layer. The output layer is followed by the *softmax* layer, which transforms an output into the probability distribution. The output of this layer can be interpreted as the probability of the input sample belonging to the classes. These probabilities are determined by the equation:

$$\hat{\mathbf{y}}^{(t)} = \frac{\exp o_i^{(t)}}{\sum_{i=1}^{K}\exp o_i^{(t)}}. \tag{7}$$

where exp is a standard exponential function, $o_i^{(t)}$ is an element of the output vector $\mathbf{o}^{(t)}$, K is a number of classes and $\hat{\mathbf{y}}^{(t)}$ is a vector containing probabilities, of which the class with the highest probability is taken as the one to which the input belongs.

The recurrent neural network is an extension of the FFNN that is able to take into account previously seen inputs when classifying the current input. In other words, it extracts knowledge from the sequence and uses it to improve its classification ability. This behaviour is achieved by adding an additional, recurrent layer to the standard FFNN. The past states of the hidden layer are taken into account when generating an output of the hidden layer at this time step. This is shown in the following equation for the first recurrent layer:

$$\mathbf{h}^{(t)} = \sigma(\mathbf{U}_1\,\mathbf{x}^{(t)} + \mathbf{W}_1\,\mathbf{h}_1^{(t-1)} + \mathbf{b}_1) \tag{8}$$

where $\mathbf{h}_1^{(t-1)}$ is the past state of the hidden layer. The recurrent layers can also be stacked so that the output of one recurrent layer is the input to the following one. This is shown in Fig. 3, where on the left side can be seen a recurrent connection with a hidden layer. On the right side is unfolded representation of the architecture. The output is generated at each time step and depends on the current input, but also on a previous hidden state that takes into account a previous input.

The training procedure aimed at minimising the loss function is the same for both FFNN and RNN. The loss function is defined as:

$$L(\mathbf{x}^{(t)}, \mathbf{y}_{oh}^{(t)}, \boldsymbol{\theta}) = -\sum_{k=1}^{K}\mathbf{y}_{oh,k}^{(t)}\ln\hat{\mathbf{y}}_k^{(t)}. \tag{9}$$

where $\mathbf{y}_{oh}^{(t)}$ is the one-hot representation of the label $y^{(t)}$, and $\hat{\mathbf{y}}^{(t)}$ is the output of the model obtained from (7). The parameter θ represents all trainable parameters of the NN, including the matrices $\mathbf{U}_k$ and the bias vectors $\mathbf{b}_k$, $k \in [0, n]$ where n is the number of layers. These parameters are found in the training phase, where the gradient descent algorithm is used to minimise the loss function.

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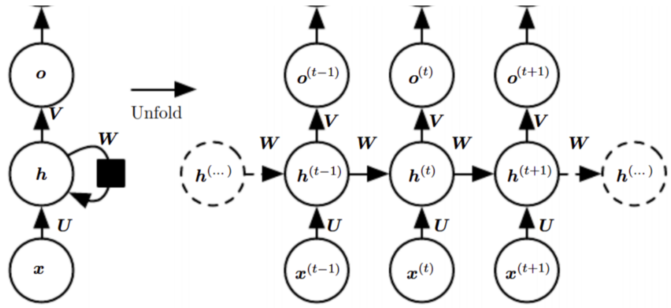

Fig. 3. Recurrent neural network with recurrent connections between hidden layers [16].

B. Dataset

The training of the RNN is performed on a dataset that contains different events that must be distinguished. In this case, the dataset consists of events that characterize the behaviour of the microgrid in the normal operating state and in the faulty state. For example, the normal operating state is a load or generation change, while a fault state is LIF or HIF. The task of the classifier, in this case the RNN, is to distinguish between these events by learning specific patterns for each of the events. As the RNN is used, each event in the dataset is stored as a sequence. Therefore, the dataset contains normal operating conditions without the transients, the load change events, and the HIFs.

The behaviour of the HIF, as described in section IV-B, depends on several parameters: initial current level, fault resistance, DC voltage, and frequency of oscillations. Since the microgrids DC voltage is constant, the other parameters are changed to produce different characteristics of the HIF. These are shown in Fig. 4. The fault occurs after the 30th sample in the sequence, where the current rises sharply and continues its nonlinear operation. The figure also shows two different oscillatory behaviours depending on the frequency of the fault. Fault locations are set at all laterals of a microgrid and measurements are taken at each. The number of measurements per event is given in Table I.

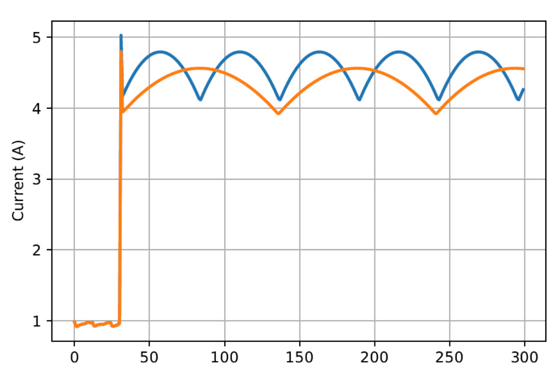

Fig. 4. High impedance faults of different characteristics.

TABLE I
NUMBER OF SEQUENCES PER EVENT.

Event	Number of sequences
Normal operation	100
Load change	100
HIF	200

C. Fault Detection with RNN

An overview of the method is provided in Fig. 5. The current measurement of the lateral is taken by the RNN classifier which determines the event based on the signal waveform. The classifier is trained on the training dataset, obtained by randomly selecting 80% of the data from the original dataset. The remaining unused samples from the original dataset are used for validation. The validation dataset thus contains samples that the classifier did not see during training, which is important to properly determine the performance of the classifier.

The classifiers architecture chosen is as follows: the fully connected later is followed by the six recurrent layers, which are followed by the fully connected layer and *softmax* function. The number of nodes per layer is set to 400.

VI. RESULTS

As elaborated in the previous section, the RNN is trained on the dataset containing normal operating states of the microgrid and HIFs. The performance of the RNN is measured using two score metrics, accuracy and F1-score, on a validation dataset. Accuracy is typically used score metrics when for machine learning models, while F1-score is intended for situations where the dataset is unbalanced and thus represents a more conservative score. The results are shown in the Table II. The scores achieved are high, with the F1-score being slightly lower than the accuracy score.

This high score shows that the RNN classifier correctly detected the waveform patterns of the HIFs and distinguished them from the other waveforms. The static operation of the microgrid, where no transients occur, is relatively easy for the classifier to learn because it is an almost flat line with additional noise. The load change is transient, but after the initial change in current level, static operation is reached again. In contrast, the behaviour of the HIF is not static after it has occurred. The current continues to oscillate and RNN has

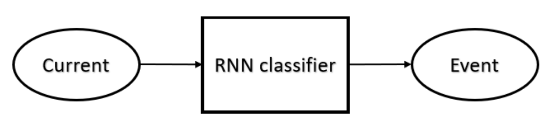

Fig. 5. Overview of the method.

TABLE II
CLASSIFICATION SCORES.

Accuracy	F1-score
98.79 %	95.52 %

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captured the characteristics of this behaviour that allow detection. In addition, the RNN classifier is shown to detect HIFs with different impedances and nonlinear behaviour, which is important for practical implementation as failure to account for a variable fault response will lead to ineffectiveness of the protection. The RNN offers the possibility to extract enough knowledge from the data so that this is not a difficulty.

The fault detection time depends on the waveform of the signal, since the recurrent neural network is used. In this case, the RNN recognizes a spike and subsequent nonlinearity. However, it correctly classifies the HIF after the first lobe has occurred because the initial response is very similar to the load change. The width of the lobe is determined by the frequency of the nonlinear oscillation. The widest lobe used in this study, which is the worst case for fault detection time, lasts 40 ms. However, this time can also be as short as 10 ms. Comparing the fault detection time with that in [9], it is longer, but the waveforms used are different from those in this study, which affects the detection time.

VII. Conclusion

Detecting HIFs is a difficult task for conventional protection because of the low current. However, the characteristic waveform of a HIF can be used for its detection. Therefore, this paper presents a RNN-based method for fault detection. The RNN is a type of NN that is able to capture a temporal behaviour of the signal or detect certain patterns in the signal waveform, which makes it an ideal candidate for HIF detection. The proposed method uses a current signal as input and produces a prediction of the event that occurred. The method scored high, above 95%, on both accuracy and F1-score metrics.

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