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Research Article

Fault Detection and Location In DC Microgrids by Recurrent Neural Networks and Decision Tree Classifier

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Abstract
Microgrids have played an important role in distribution networks during recent years. DC microgrids are very popular among researchers because of their benefits. However, protection is one of the significant challenges in the way of these microgrids progress. As a result, in this paper, a fault detection and location scheme for DC microgrids is proposed. Due to advances in Artificial Intelligence (AI) and the suitable performance of smart protection methods in AC microgrids, Recurrent Neural Networks (RNNs) are used in the proposed method to locate faults in DC microgrids. In this method, fault detection and location are done by measuring feeders current and main bus voltage. Furthermore, the performance of the proposed method is assessed in grid-connected and the islanded operation modes of the microgrid. The result has confirmed the efficiency of the proposed scheme . In this paper, MATLAB and DIgSILENT are used to design RNNs and DC microgrid simulation respectively.

Keywords: DC Microgrids, Protection, Fault Detection, Fault Location, RNN, Machine Learning, Decision Tree Classifier.

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1. Introduction

Microgrids are proposed for their efficient use of distributed generation (DG) resources [1]. The development of this kind of source results in a decrement in environmental pollution and an increment in microgrid reliability [2,3]. Generally, microgrids are divided into AC and DC types. Due to the similarity between AC microgrids and conventional grids, comprehensive research has been done on AC microgrids. However, these days, DC microgrids have attracted attention due to their benefits including fewer conversion stages and the capability of more power transmission through a specified cable [1]. Due to ignoring skin effect, power loss in DC microgrids is lower than AC microgrids [4, 5]. Despite many advantages of DC microgrids over AC microgrids, the protection of DC microgrids is still one of the main challenges in developing DC microgrids. Furthermore, acceptable standards and strategies for industrial and commercial applications have not been provided in recent years [6]. Currently, most studies on DC microgrids are in the field of topology and microgrid control. As a result, proper attention has not been paid to the protection of DC microgrids yet [1]. Therefore, in this paper, the purpose is to design a suitable protection system for DC microgrid. Due to inaccurate measurements, traditional protection systems are prone to positive and negative errors. A positive error usually results in the system's malfunction, and a negative error causes the system to be unable to detect the error. As a result, equipment may severely be damaged [7, 8].

In DC networks, due to the presence of DC-link capacitors in the output of converters, after the occurrence of a fault, the capacitors are discharged quickly and cause the fault current to reach the maximum value in a short time, which leads into equipment damage. Therefore, fault detection in a short time is one of the requirements for the protection of DC microgrid. In [9], the fault has been detected and located by measuring DC-link voltage, but the proposed protection scheme has not performed properly in multi-branch microgrids. In [10], the proposed protection method is based on distance protection whereby two units of voltage measurement are used at a specified distance from one another, yet the proposed method is susceptible to the impedance of the fault. Also, in [11], wavelet transform (WT) is used to detect a fault, but the proposed method is not able to determine the location of the fault. Traveling wave (TW) based methods have a good performance in fault detection and location; However, the implementing of these methods is an important challenge [12]. Another group of protection methods measure local variables. Three examples of these methods are presented in [13-15], but the common weakness of all these methods is the bulk calculation, while the time of detection and location of fault in microgrid protection, due to the transient current, is critical. Artificial Intelligence (AI) based protection methods have shown exemplary performance in AC microgrids. Nevertheless, these protection methods have not yet been adequately used in DC microgrids. In [16], an Artificial Neural Network (ANN) has been used to detect the fault and its location. However, the microgrid used in this paper is very simple and overfits ANNs when the number of hidden layers increases [17]. In [18], the combination of ANN and WT is used to detect the occurrence of the fault and its location, but the proposed method is not able to identify the exact location of the fault. Also, in [19], the Convolutional Neural Network (CNN) is used to detect faulty equipment like PV arrays or converters, yet this protection scheme is not able to protect lines and loads properly. Therefore, in this paper, a protection scheme is presented in which recurrent neural networks (RNNs) are used to determine the fault location on load feeders with high accuracy. Besides, a decision tree-based classifier (DTC) is used to determine the overall state of the system_ whether it is healthy or defective_ as well as whether the fault is on the main bus or the lines. Besides, for a deeper study , in this paper, a comparison has been run not only between a support vector machine (SVM) and decision tree (DT) algorithm in the field of classification but also, between feed forward neural network (FFNN) and RNN to determine the location of error and its resistance. In this work, DIgSILENT software has been used to design DC microgrid and extract the required data to train neural networks (RNNs,FFNNs) and machine learning algorithms (SVM,DT). Furthermore, MATLAB software has been deployed to implement neural networks and machine learning algorithms and their evaluation. In section II, the studied DC microgrid is described, and in section III the principles of the proposed protection scheme are presented. In section IV, the numerical results of the simulation and the comparison results are presented as well. Finally, in section V the conclusions are presented.

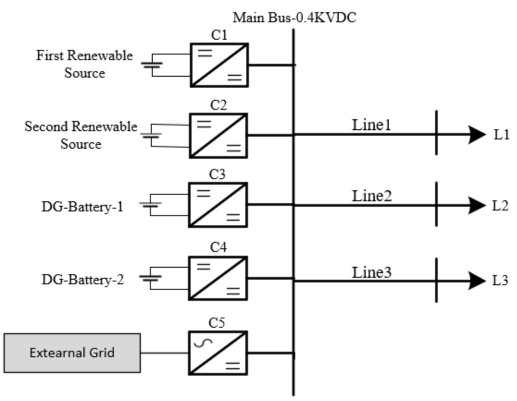

Fig. 1: DC Microgrid diagram

2. The Studied DC Microgrid

The Studied DC Microgrid is modeled in DIgSILENT software, and the results of simulations have been used to evaluate the performance of the proposed protection scheme and to collect the required data for training the neural networks and for machine learning algorithms. Fig. 1 shows a simplified model of the understudy DC microgrid. As it can be seen, the external grid and asynchronous generator, which has been modeled as the first renewable source, are connected to the microgrid through rectifiers. Furthermore, a DC source is used as the second renewable source, which is connected to the microgrid using a chopper. Also, two batteries are used to supply the microgrid in the islanded mode.

As it was mentioned before, DC microgrids can operate both in grid-connected and in islanded modes. In the grid-connected mode, the rectifier is connected to the external grid to control the main bus voltage, and the renewable energy sources converters are controlled by constant power mode. Furthermore, the batteries are charged in this mode. In the islanded mode, since the microgrid is no longer connected to the external grid, the converter of the first battery is responsible for controlling the voltage of the main bus. If the first battery runs out, the converter of the second battery takes over. In this case, the converters related to the renewable energy sources are controlled as constant power mode and inject a constant power into the microgrid. In addition, three load feeders are connected to this microgrid both in grid-connected and in islanded modes. Table 1 presents the specifications of the used converters in this microgrid. Also, in Table 2, the length of the lines is listed. Finally, in Table 3, the power consumption ranges of the loads connected to the microgrid are shown. The nominal voltage of the microgrid is 0.4KVDC.

3. The Proposed Scheme

This section describes the proposed protection scheme. Generally, in DC networks, two types of faults are expected: pole-to-pole (P-P) faults and also pole-to-the ground (P-G) faults [20]. Since in DIgSILENT software, the negative pole of the DC network is connected to the ground, both types of faults are modeled as (P-P) faults. After the fault has occured, the magnitude of fault current varies according to the location and the resistance of the fault. Also, because of fault resistance and faulty line resistance and inductance as well as due to the transient component of fault current, specific voltage appears on the main bus. Since in DC microgrids, the sources are mostly connected to the microgrid by converters such as choppers, and these devices ultimately limit the magnitude of the fault current to the rated current, measuring the current of these sources is suitable for detecting the occurrence of a fault, even though this measurement is not sufficient to determine the location of the fault.

Due to the existence of inverter-based distributed resources (IBDGs) and fault current limitation, in this paper, along with the current of feeders, a main bus voltage is also used to detect and locate the fault. In this scheme, first, DTC determines the general state of the DC microgrid, according to Table 4. If there is a fault on the load feeders, considering microgrid operation mode (grid-connected mode or islanded mode), the RNN determines the location of the fault and its resistance with high accuracy. Since the understudy microgrid can operate both in grid-connected and in islanded modes and since there is a difference in the fault current in these modes, different RNNs are deployed. In the following, the used DTC and RNNs are presented. The flowchart of the protection scheme has been presented in Fig. 2.

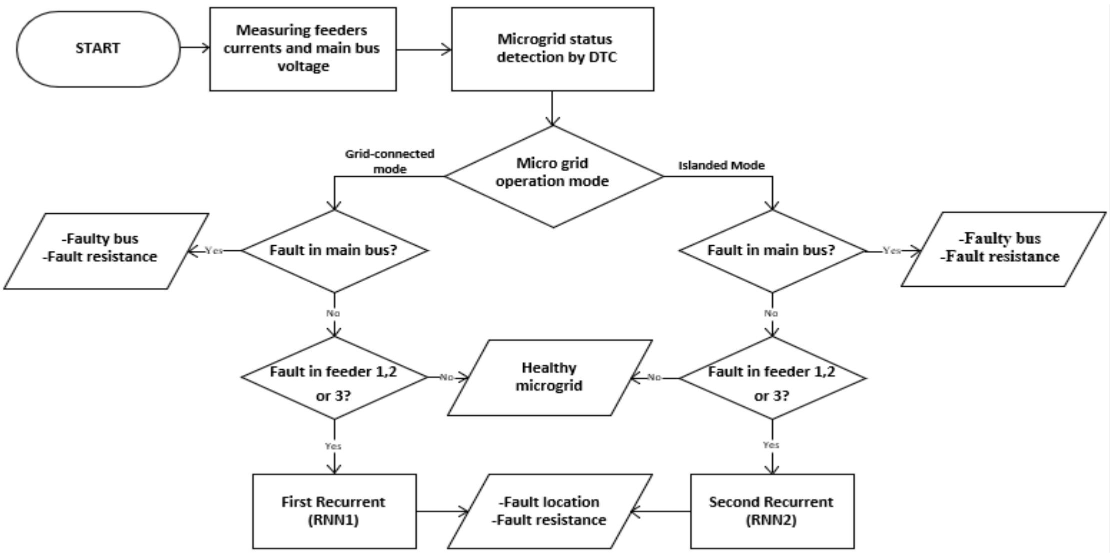

Fig. 2: Schematic Diagram of Proposed Fault detection and Location method

Table 1: Capacity Of Converters In Microgrid

Converter	Capacity (Kw)
C1	500
C2	250
C3	100
C4	100
C5	800

Table 2: Length Of Lines In Microgrid

Line	Length(m)
Line1	150
Line2	480
Line3	600

Table 3: Power Consumption Of Loads In Microgrid

Load	Power(kW)
L1	200-300
L2	150-250
L3	150-200

Table 4: Possiible States For Understudy

State Number	Description
State 1	Healthy Microgrid
State 2	Fault on Feeder 1 - Grid Connected
State 3	Fault on Feeder 2 - Grid Connected
State 4	Fault on Feeder 3 - Grid Connected
State 5	Fault on main Bus
State 6	Fault on Feeder 1 - Islanded
State 7	Fault on Feeder 2 - Islanded
State 8	Fault on Feeder 3 - Islanded

3.1. Decision Tree Classifier (DTC)

Since the understudy DC microgrid can operate both in grid-connected and in islanded modes and since there are three load feeders and a main bus, there are eight modes for the system, which are shown in Table 4. Since fault location is not required for the faults on the main bus like faults on the load feeders, just one mode is considered for the faults on the main bus, and the type of microgrid operation mode (islanded or grid-connected mode) is neglected. It is clear from Table 4 that in this protection scheme a classifier is needed to identify fault occurrence in the microgrid, and in case such a fault occurs, the classifier should be able to identify the fault type based on Table 4. One of the machine learning algorithms is the decision tree (DT) algorithm. This algorithm is one of the powerful machine learning algorithms that can be used both for regression and for classification methods. This algorithm also works well for complex datasets, and since in the proposed scheme, both the load feeders current and main bus voltage are measured continuously, a big dataset should be analyzed. As a result, this algorithm is used to design an appropriate classifier. The DTC determines the understudy microgrid's mode based on Table 4. As it can be seen, there are eight possible modes for microgrid, and in case the fault is detected on the load feeder lines, according to the operation mode of microgrid, an appropriate RNN will determine the location of the fault. In order to compare the performance of DT machine learning algorithm in solving the desired classification problem with other machine learning algorithms, in addition to the DT algorithm, SVM machine learning algorithm has been used as well. To this end, both algorithms have been trained and tested with the same

data and their performance results on the test data have been compared with each other. The results of this comparison are shown in Section IV. In the following, the details of RNNs have been explained.

3.2. Recurrent Neural Network (RNN)

RNNs are a type of ANN that can use time series as an input to predict the future data. For instance, this type of neural networks can be used for automated systems and stock market forecasting [21]. In this type of neural network, the output at any given moment depends on the input at that moment and the output of the previous moment. Fig. 3 shows a simple RNN consisting of only one neuron. Also, the described shape of this neural network is shown in Fig. 4. In this type of neural networks, there are two weight coefficients per neuron, one of which is related to the input x(t) and appears in simple neural networks. The other factor is the output of the moment y (t-1). The output of a recursive neuron is calculated using Equation 1.

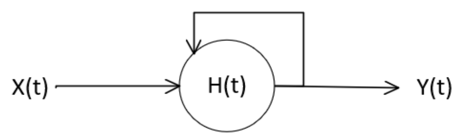

Fig. 3: Single neuron of RNN

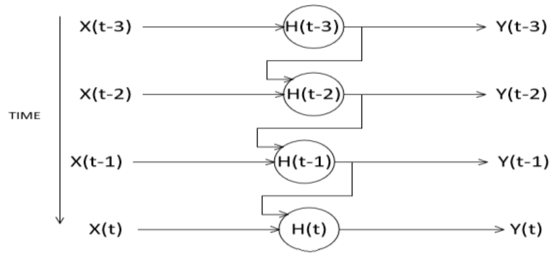

Fig. 4: RNN performance for different time

$$Y(t)=\Phi\,(x(t) * W_x + y(t\text{-}1) * W_y + b) \qquad (1)$$

In (1), parameter *b* represents the bias value, and *Φ* represents the activation function. Since in RNNs, the output at any time depends on the input at the same time and the output of the last time, so it can be concluded that in this type of neural networks, there is a memory. A recursive neuron which is modeled in Fig. 3 is an elementary memory, while there are more powerful types of memory in RNNs. For example, LSTM memory can detect long-term dependencies among input information. In this paper, considering that the current of the load feeders as well as the main bus voltage are time series, soothe RNNs are used to determine the location of the fault at the lines of load feeders with high accuracy. Also, because of the differences between fault current magnitude both in grid-connected and in islanded modes, two different RNNs are provided to achieve a better performance of the proposed scheme, each of these RNNs is related to one of microgrid operation modes. In addition to determining the fault location, the proposed RNNs determine the fault resistance with high accuracy; that means the proposed scheme is not sensitive to fault resistance like the impedance-based methods.Besides, for demonstration of the proper RNNs performance presented in this paper, the results of estimating the fault location and its resistance by the RNNs network are compared with those of FFNNs. In FFNN, there is no feedback loop, and the signal only moves in one direction. The results of this comparison have been shown in Section IV.

Table 5: Non-Fault Microgrid Modes

Load	Power Range (Kw)	Step (Kw)
L1	200-300	25
L2	150-250	25
L3	150-200	25

Table 6: Non-Fault Microgrid Modes

Parameter	Values Range
Feeder	L1, L2, L3
Location (%)	0-2.5-5-…-100
Fault Resistance (Ω)	0-0.2-0.4-…-2
Operation Mode	Grid Connected-Islanded

Table 7: Faulty Bus Modes

Parameter	Values
Fault Resistance (Ω)	0-0.05-0.1…-2

Also, as mentioned above, for better evaluation of the method presented in this paper, an SVM classifier and two FFNNs with the same training and testing data, as the DTC classifier and the RNNs, have been trained and tested.

4. Simulation and Numerical Results

This section shows the results of evaluating the proposed scheme. As mentioned earlier, the RNNs and DTC must firstly be trained using generated data from various state simulations in DIgSILENT software, and then the performance of the proposed protection scheme is to be evaluated. As listed in Table 4, there are generally eight possible modes for the understudy microgrid to gather the needed data for training DTC and RNNs. Different scenarios, consisting of both faulty and non-faulty modes, and different locations for fault must be considered to obtain a comprehensive dataset that covers all possible modes for the understudy microgrid. In the following, Tables 5, 6 and 7 show the scenarios intended to collect the required data for training RNNs and DTC. It can be seen in Tables 5, 6 and 7 that 32 modes have been simulated for healthy microgrid and 2400 modes for the fault on load feeders with different locations and fault resistance. As there have been 40 modes simulated for the fault on the main DC bus with different fault resistance ha. The results were used for training RNNs and DTC. Since the fault at the main bus does not require precise location determination to reduce the volume of data, only the grid-connected mode is considered for the faulty bus. After having collected the required data, this dataset is used in a 4:1 ratio for training and testing RNNs and DTC respectively. In the following, the test results of RNNs and DTC are presented.

4.1. Decision Tree Classifier Evaluation

The confusion matrix, which is the result of applying this classifier to the test data, was used to evaluate the efficiency of the proposed DTC. Fig. 5 shows the results of the application of DTC on the test data as it can be seen, the performance accuracy is about 99%, which means a robust performance for the determination of the microgrid mode using DTC. It should be noted that when a fault occurs at the lines, since DTC first determines the faulty line and, then, the location of the fault in the line, the proposed protection scheme will work well even in those microgrids that consist of multiple branches. However, many methods such as impedance-based methods cannot detect and determine the location of faults at multi-branches buses.

4.2. Recurrent Neural Network Evaluation

As mentioned before, if a fault is detected at the load feeders, according to the operating mode of the microgrid (grid-connected or islanded mode), appropriate RNN will be used to determine the fault location and its resistance. In This section, some fault cases on load feeders are considered to assess the efficiency of RNNs. Since there are many fault cases for the line feeders, the sample cases are selected randomly. Details of these cases are listed in Table 8. Also, the results of this evaluation both for fault location and for fault resistance determination are shown in the Table 8. Through the examination of the results of Table 8 and also those results in MATLAB software, it is understood that the error both of RNNs in detecting the fault location and of its resistance is less than 3%. Therefore, the results confirm the proper performance of the proposed protection scheme.

Fig. 5: Confusion matrix related to DTC

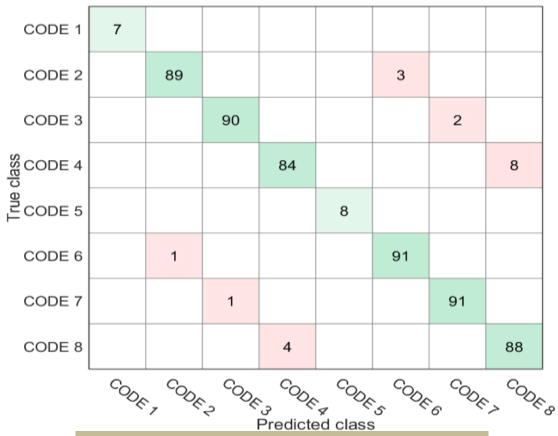

Fig. 6: Confusion matrix related to DTC

4.3. Comparison Results

Fig. 6 shows the confusing matrix resulted from the application of the trained SVM classifier on the test data. As it can be seen, the accuracy of this classifier is about 96%, which is less than the accuracy of the DT classifier. The DT algorithm solves the classification problem using decision rules which are created in the training phase, while the SVM algorithm solves the problem by classifying the data into different classes, which may result in the lower accuracy of the SVM algorithm in solving the desired classification problem. In addition, Table 8 shows the results of estimating the location of the fault on the lines and its resistance using FFNNs. As it is clear, the accuracy of these networks is less than that of RNNs, one reason of which is the lack of recursive feedback in FFNNs.

5. Conclusion

In this paper, a protection scheme is proposed for DC microgrid, which can detect and determine fault location with different fault resistance. Due to the advances in artificial intelligence science, the proposed scheme is based on DT algorithm and RNN. Since in DC microgrids, the sources are generally connected to the microgrid through converters, their short-circuit current is limited to the rated current. As a result, in the proposed method, the current of the load feeders and that of the main bus voltage have been used to detect the occurrence of the fault, its location, and resistance. In this scheme, after measuring the current of the load feeders as well as the main bus voltage, DTC determines the mode of the microgrid according to Table 4. If the fault is detected on load feeders, by using two RNNs, one of which is related to the grid-connected mode and another to the islanded one, the fault location and its resistance will be determined with high accuracy. Also, the proper performance of proposed DTC and also RNNs are shown in Fig. 5 and Table 8 respectively. The proposed scheme can protect the DC microgrid both in grid-connected and in islanded modes. In addition, an SVM classifier and two FFNNs with the same data, as the DTC anRNNs, have been trained and tested, the results of which are shown in Fig. 6 and Table 8 respectively. It was concluded that in terms of classification, the accuracy of SVM classifier is less than DTC, and in terms of determining the fault location and resistance the accuracy of FFNNs is less than RNNs. Furthermore, since the microgrid status and the location of the fault are determined first by DTC, this scheme works well in microgrids with multi-branches buses. In this paper, DIgSILENT software has been used to simulate the studied microgrid. MATLAB software has also been used to train and test the neural networks and the machine learning algorithms.

Table 8: Result Of (Rnns) In Determining Fault Locatio And Resistance

Feeder	Location (%)					Resistnce (Ω)					Mode of Operation
	RealValue	RNN		FFNN		Real Value	RNN		FFNN		
		Estimated Value	Error	Estimated Value	Error		Estimated Value	Error	Estimated Value	Error	
1	87.5	88.97	1.68	68..27	21.97	1.2	1.19	0.84	1.19	0.84	Grid-Connected
2	12.5	12.93	3.44	10.44	16.48	0.8	0.79	1.25	0.78	2.5	
3	42.5	43.21	1.67	46.68	9.83	0.2	0.2	0	0.22	10	
4	52.5	52.41	0.17	53.02	0.99	0.4	0.39	2.5	0.38	5	Islanded
5	0	0.39	__	7.11	__	0.4	0.39	2.5	0.37	7.5	
6	37.5	36.94	1.49	34.02	9.28	1.8	1.79	0.55	1.83	1.6	

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