USING OF THE ARTIFICIAL NEURAL NETWORKS TO THE LOCALIYATION OF THE EARTH FAULTS IN RADIAL NETWORKS

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ABSTRACT

At present, digital protections using the admittance principle are able to identify quite reliably a single phase-to-ground connection and to determine the affected feeder. Still, the location of the fault presents a task yet to be solved. The main problem of a fault location consists is a low value of the fault current during a single phase-to-ground fault in compensated networks This paper describes a published neural network approach [1], [2] for transient based earth fault location applied to the part of real compensated 22kV network.

INTRODUCTION

A connection between a phase conductor and the ground in MV networks is called earth fault. Since the fault current in this case does not depend on the point of the fault, but only on the total capacity (size) of a network, earth fault location keeps being a problem for MV network operators. This paper describes a published neural network approach [1], [2] for transient based earth fault location in 22kV applied to the part of real compensated network.

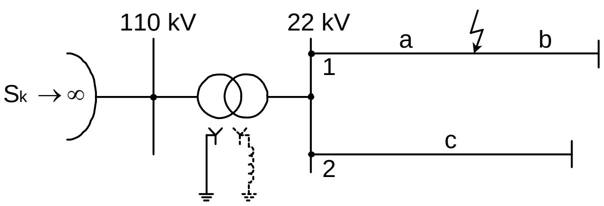

Fig. 1. Elementary diagram of the method

EARTH FAULT DISTANCE ESTIMATION

This paper presents an application of the Artificial Neural Network (ANN) which uses the harmonic components of the neutral voltage transients for earth fault distance computation. The benefit of this method is that only one measurement per primary transformer is needed. The results are compared to other ANNs trained by phase current and voltage samples. To make different solution comparable, a similar signal preprocessing was applied to all the cases considered. The signal preprocessing, which covers the extraction of the dominating transient component from the other signal parts, is discussed. Special focus is also given to the scaling and adaptation of the input data, aiming for high correlation in the training information and enabling one single ANN to estimate fault distances in power distribution networks of different sizes.

The key issue in signal pre-processing is to extract the charge transient, used for earth fault distance computation, from the other parts of measured signals. The signal pre-processing is made in the following steps:

1. Removal of the fundamental frequency component.
2. Spectrum analysis for estimating the charge transient frequency.
3. Low-pass filtering in order to remove the higher frequency components.

For fundamental frequency removal a straightforward technique is used. The filter removes, in addition to the fundamental frequency, also its steady state harmonic components. Theoretically the transients are affected al well, but since in real power system circumstances there always is some attenuation present, this effect is very small and can be ignored. The spectrum analysis is performed by Fourier algorithm, which covers only a 20 ms window, starting from the beginning of the transient. The highest amplitude spectrum component is assumed to be the one corresponding to the charge transient frequency.

The cut-off frequency of the low-pass filter is set 400 Hz higher than the estimated charge frequency. A second order Bessel filter is applied. The attractive feature of this filter is that it has a flat transition band. However, because of the recursive nature, the transient effects of the filter itself are difficult to control. To mitigate this problem, the measured signals are processed in reversed order. In the harmonic based approach the neutral voltage components of 216,66 Hz is used.

As [1] describes the Artificial Neural Network (ANN) seems to be a very attractive tool for the ground fault distance estimation problem, since it does no require the explicit formulation of the solution algorithm, but is able to implicitly utilize various dependencies in the training data. Analyzing the charge transient can be regarded as the evaluation of special characteristics (frequency, amplitude and damping) with respect to the information content of the fault distance. It is therefore a task of pattern recognition, which corresponds to the abilities of the ANN. In this work an ANN structure known as the Multilayer Perceptron was used. It consists of the input vector, one hidden layer and the output layer (Fig.2).

A data window of 20 ms starting from the beginning of the transient determined the input data. The resulting number of harmonic components used as input values was 35. The harmonic amplitudes were scaled to the range of 1 to due their maximum. It has been proved that, in general, one hidden layer is sufficient for representing any given input-output transformation. Using more than one hidden layer is necessary if the pattern recognition task seems to be quite sophisticated and if there is a large number of input neurons. In this work the ANN consisted of only one hidden layer. The number of the hidden neurons was varied in the range from 15 to 25. The fault distance was given by the activation of one single output neuron. Because the maximum activation of a neuron is 1, the output parameters were scaled to the maximum values the occurred.

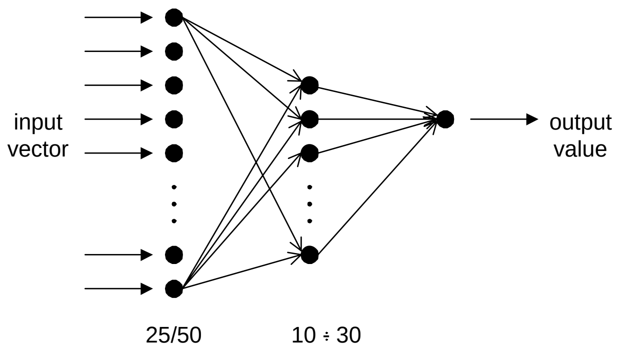

Fig. 2. Structure of Multilayer Perceptron

The Backpropagation method with the Lavemberg-Marquart training algorithm provides a fast and stable training process and sufficient error decrease for the ANN. The training process was done several times each with different initial values. This is because the error minimum depends on the random initial values of the weights and biases. The lowest training error that could be achieved was used for assessing the performance of the ANN. Training was done in the offline training mode. This means all training patterns must be put through the ANN before the networks parameters (the weights) are changed in one single step. Doing so, the order of the training patterns has no importance to the weight changes and the learning success. For implementation, training and verification of the ANN, the software Matlab 7 and its ANN toolbox were applied.

For training and testing of the ANN a large data set of neutral voltage samples is necessary. The affecting parameters must be varied within an appropriate range to provide the ANN with all the important features. Earth faults were simulated by the common simulation tool ATP/EMTP. The basic 22kV overhead lines were modeled using the Line Constants ATP/EMTP Program taking into account the real geometrical and electrical values.

Table 1. Comparison of different ANN methods and symmetrical components algorithm

Network size (km)	Fault distance (km)	Fault Resistance (Ω)	ANN input			Conventional algorithm Error (km)
			Voltage Error (km)	Voltage/current Error (km)	Uo spectrum Error (km)	
200	10	0	2,5	1,1	1,4	2,4
350	10	0	2,1	0,7	0,2	2,0
200	30	0	2,7	0,9	0,2	0,3
350	30	0	2,4	1,2	0,3	2,6
200	10	30	3,1	1,1	2,2	1,6
350	10	30	2,7	0,6	4,3	1,9
200	30	30	1,9	0,8	2,3	1,1
350	30	30	2,1	2,3	1,8	0,9

CONCLUSION

In networks with an isolated or compensated neutral, for fault distance estimation is not possible using the fundamental frequency signals. That is why transient based techniques have been applied. In high impedance earthed networks, the charge transient, which is due to the voltage rise of the two sound phases, is the most useful component for fault location purposes. Neural network approach is an alternative to the more conventional solutions for ground fault distance estimation, since it does not require the explicit formulation of the solution algorithm. It is able to implicitly utilise various dependencies in the training data. The ANN type Multilayer Perceptron with one hidden layer and trained with Backpropagation method was used. The performance of the ANN was comparable to that of the symmetrical component algorithms [4], [6]. Regarding only the earth faults with very low fault resistance the ANN with voltage and current input vector gave the better results. The error was about 3% and 5% for conventional algorithms. Symmetrical components algorithms worked better with higher fault resistances. The performance of earth fault location is restricted by the attenuation of the transients. The highest fault resistance that allowed for fault location was 50 Ω.

Acknowledgments

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