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Fault location on transmission lines using complex-domain neural networks

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ABSTRACT

Fault location is a critical task when a severe disturbance is caused by insulation failure on a transmission line. In order to avoid further economical and social costs because of load interruptions, the fault diagnosis has to be concluded as soon as possible. Intelligent systems have been successful in dealing with fault diagnosis problems. This paper proposes the application of complex-domain neural networks for mapping the relationship between electrical signals and fault locations on transmission lines. Complex-domain neural networks allow voltage/current representation without arbitrarily decoupling amplitude and phase. Furthermore, several voltage and current representation schemes, based on electromagnetic transient and steady-state information, are analyzed in this paper. For comparison purpose, these input representations are also tested with real-domain neural networks. The tests consider realistic operating/fault conditions and assume that fault classification has already been handled.

1. Introduction

Transmission lines are among the power system components with the highest fault incidence rate, mainly because of weather influence. In order to speed up normal operation restoration after fault clearing by protection devices, it is important to determine the fault location as soon as possible. In long transmission lines, visual inspection can be very time consuming, delaying the faulted line maintenance. On the other hand, the accuracy of automatic fault location depends on the quality of data acquisition and processing. A common case that makes fault location harder, usually related to interconnections, is when on-line fault recordings are available at one terminal only. In such cases, fault location based on the solution of electric equations can lead to large errors, because of the missing information from the other terminal.

Literature on transmission line fault location can be grouped based on the frequency range under analysis and on the use of information from one or both line terminals. Some proposals for fault location apply frequency domain analysis at the fundamental frequency, using pre and post-fault voltage and current phasors [1–3]. Other research projects have focused on the high frequency content of voltages and currents [4]. When measurements from both terminals are taken into account, although line parameters can be neglected, communication reliability is a major issue [5,6].

The application of wavelet transforms to decompose the fault signals has shown great promise [7,8]. In [9], the combination of multiresolution and modal analyses of traveling waves has been proposed. Neural Networks (NNs) have been extensively applied to power systems, from load profiling to security assessment [10,11]. As NN models can cope with uncertainties on power system parameters, they have been successful in dealing with fault diagnosis [12,13]. Pre and post-fault phasors at one line terminal have been used in [14] as inputs to NNs for fault location and impedance estimation. Lately, support vector machines have shown promising results for fault location [15], too.

The identification of the faulted component(s) in a power system is usually solved via an expert system approach [16]. Although expert systems can also be applied for transmission line fault classification, promising results have been obtained using wavelet transform and NNs [17]. However, the present work assumes that the system faulted section corresponds to the line of interest and that the fault type has already been identified, regardless of the solution technique.

All previously proposed NN based methods for fault diagnosis have represented voltage and current signals via real-valued variables. Amplitudes and corresponding phases have been coded using different variables. Because of that, dependencies between these pairs of variables have to be re-established by the neural model. Therefore, when complex-valued variables are involved, a real-domain NN imposes an unnecessary extra burden to its training, which usually degrades the model accuracy. Complex-domain NNs have been developed [18,19] to avoid splitting the real and imaginary parts of complex-valued variables. They fit well for modelling physical phenomena that inherently exist in the complex domain.

This work investigates the application of complex-domain NNs to the fault location problem on transmission lines. This paper also

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contributes on exploring many possibilities to define an appropriate input space for the fault location model. The paper shows how location can be improved if the combination of signal processing and model selection also considers the appropriate domain for the input variables. The performances of different NN models have been compared, i.e., complex-domain versus real-domain NNs, considering several input space representations.

The paper is divided as follows. Section 2 describes the electric network modelling and the simulation process for building datasets with a large variety of faults. Section 3 presents the basic concepts related to complex-domain NNs. Section 4 shows how the datasets are processed via Fourier or wavelet transform. It also presents the NN models that have been developed in this work. The tests described in Section 5 consider hundreds of different operating and fault conditions, including a mixture of fault impedances, inception angles, line loadings, equivalent system impedances, soil resistivity, and fault locations. Finally, Section 6 concludes the paper with directions for future research.

2. Electric network modelling and simulation

Several factors can be influential for the correct fault classification and location on transmission lines, such as: mutual effect of zero sequence components, uncertainty on parameters of the line (mostly on the zero sequence), absence of transposition, type of compensation (series or shunt), pre-fault unbalanced power flow, etc. With the proposed black-box approach for fault location, it is not possible to develop a model based on field measurements, only. In fact, even when the history of faults related to a certain line has been fully recorded, it is still far from covering the necessary diversity of possible fault situations for estimating such a model. Therefore, in order to produce representative patterns, it is necessary to calculate currents and voltages under several fault conditions, using a realistic system modelling. The test cases presented here are based on actual data from a 440 kV transmission line in the southeast of Brazil (see Fig. 1 and Appendix A).

The transmission line has been represented using a cascade connection of untransposed lines, with the individual circuits being transposed as on a real transmission line. Each untransposed transmission line has been represented by a frequency dependent model with a constant transformation matrix [20]. The reason why the actual transposition is taken into account is twofold. First, it allows the simulated system to be closer to reality. Second, tests indicate that an ideally transposed transmission line has a lower harmonic content, i.e., higher damping. The transmission line is implemented in ATP (Alternative Transient Program) using the JMarti model.

The actual voltage used for fault location analysis is bandwidth limited because of the frequency response of the Capacitive Voltage Transformer (CVT). The CVT can be understood as a band-pass filter with the highest gain at the pre-fault fundamental frequency. Therefore, even though one may have high frequencies (e.g., above some kHz) at the high voltage side of the CVT whenever a fault occurs, the secondary CVT voltage (V_{in}, Fig. 1) contains the fundamental component and some heavily damped high order harmonics, only. In order to avoid such a problem, one may use an optical transducer, despite its high cost. However, the great majority of power systems are equipped with conventional CVTs.

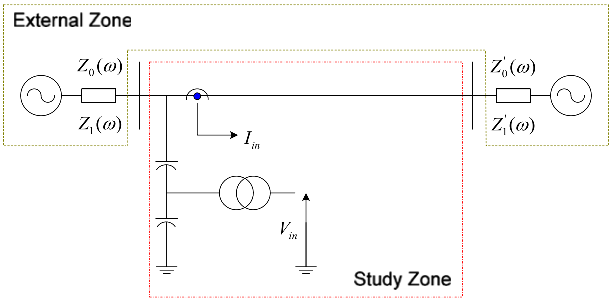

Fig. 1. Network diagram with internal and external zones' components.

In this work, a rational model of order nine, based on *Vector Fitting* (VF), has been used for representing the CVT. VF is a pole relocating routine, first developed in [21] and later in [22]. It is based on a pole-residue identification of an auxiliary function. Essentially, VF is a robust reformulation of the Sanathanan–Koerner iteration. It uses rational basis functions (partial fractions) instead of polynomials, and pole relocation instead of weighting. VF allows high order functions and wide frequency bands.

The current transformer is assumed as an optical based current transducer, therefore being able to reproduce all the harmonic content of the fault currents. Nevertheless, a conventional current transducer could be used for data acquisition, as the Total Harmonic Distortion (THD) of fault currents is usually lower than fault voltages' THD. The external zone in Fig. 1 is modelled as a frequency dependent network equivalent on the positive and zero sequences, i.e., $Z_0(\omega)$, $Z_1(\omega)$, $Z_0'(\omega)$, and $Z_1'(\omega)$.

Steady-state analysis and transient simulations with ATP have been performed to build two datasets of fault signals. The first one corresponds to pre and post-fault steady-state values, while the second represents transient voltage/current signals. The dataset based on electromagnetic transients provides a richer content. However, it does not necessarily produce the most effective information from the fault location model point of view. Temporal waveforms describing voltage and current transients are hard to be coded as useful variables for fault location. On the other hand, information based on a steady-state assumption is easy to be represented. However, valuable features from the power system transient behaviour can be lost. In fact, it is hard to predict beforehand, i.e., at the training set specification stage, which type of analytical study would be the most effective for estimating a fault location model. Afterwards, as described in Section 4, the two datasets of fault signals are processed using Fourier or wavelet transform.

3. Complex-domain neural networks

Useful information for fault location can be conveniently coded using complex-valued variables. Voltage and current measurements find in the complex domain an appropriate space for data representation. Complex-domain NNs are simple extensions of standard feedforward real-domain NNs. In the place of real input/output variables, complex-domain NNs have complex-valued input/output variables. Their interconnection weights (and biases) are also complex numbers and, consequently, the activation function has its domain and counter-domain defined on the complex axis.

Analysis of the two basic algebraic operations performed by a NN is an easy way to understand the differences in information processing between real and complex domain NNs. As summation of complex values adds their real and imaginary parts in separate steps, it does not show any difference in information processing. However, with multiplication, results are totally different. Multiplication of two complex numbers results in an amplitude equal to the product of the original amplitudes, and in a phase equal to the summation of the original phases. Obviously, such a result is not achieved when complex-valued input variables and corresponding connection weights are separated into their real and imaginary parts.