Towards a Power System Fault Classification System: A Rough Neurocomputing Approach

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Abstract
A rough neurocomputing approach to classifying power system faults is presented in this paper. Preprocessing fault data entails discretization of power system fault data obtained from the Transcan Recording System at Manitoba Hydro. An approach to discretizing power system fault data is briefly described in this article. After preprocessing, rough set methods are used to prepare fault decision tables and generate fault classification rules. Each condition vector contain values of attributes for a new power system fault becomes input to mixture of rough set-based expert networks, where each the processing performed by each "expert" is tailored to a particular fault type. A collection of rough expert networks are connected to what is known as gating network that selects the output of competing expert networks (the winner) as the output of the network. That is, the gating network implements derived fault classification rules and selects the expert network with the best classification (i.e., highest probability of correctly classified fault). The architecture of such a network is extensible inasmuch as a new rough expert network can be added to accommodate the discovery of a new type of power system fault. The basic architecture of a new fault neural classification system is presented. The contribution of this paper is an overview of the basic building blocks in a rough set-based power system fault classification system.

1. Introduction

This paper presents an overview of a framework for a rough set-based power system fault classification system. This work is part of an ongoing effort to classify power system faults using rough set methods [10]-[12], new optimization methods [13], and rough neurocomputing [2]-[3], [8]-[9]. This is part of an ongoing research project begun several years ago for Manitoba Hydro. The goal of this research has been to design an automated power system fault classification system that could be used in place of existing manual classification methods. This paper includes a brief description of discretization as part of preprocessing fault data, and a brief presentation of a committee of experts gating rough neural computing approach used in classifying faults. The study of discretization of power system fault data is part of growing research on discretization methods [14]-[15]. The basic features of the rough neural computing architecture described in this article are reported in more detail in [3], [8].

This paper is organized as follows. An overview of an electrical fault classification system is given in Section 2. A preprocessing methodology for power system fault data is presented in Section 3.

2. Electrical Fault Classification System

The complete structure of the power fault classification system is shown in Fig. 1. By pressing the view button in (1) in Fig. 1, a sample Transcan fault file can be viewed (see (2)), and processed by the Fault Detection and Identification (FDI) module (parts (3) to (9) in Fig. 1). Parts (3) to (7) in Fig. 1 represent preprocessing on inputs to what are known as rough experts in a rough neural network (parts (8) and (9) in Fig. 1). We know that 3 *AC* phase voltages, namely the *A*-phase, *B*-phase and *C*-phase, have fixed phase difference between each other which is 120°. By studying the data file, we can find that one period of *AC* phase voltage is represented by 96 sampled data. So if we shift *B*-phase by 32 points and *C*-phase by 64

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points then the shifted *B* phase and *C* phase voltage will be exactly as same as *A* phase voltage if no error occurred. Then we can determine if the *AC* voltages have distortion by computing the error signal using (10).

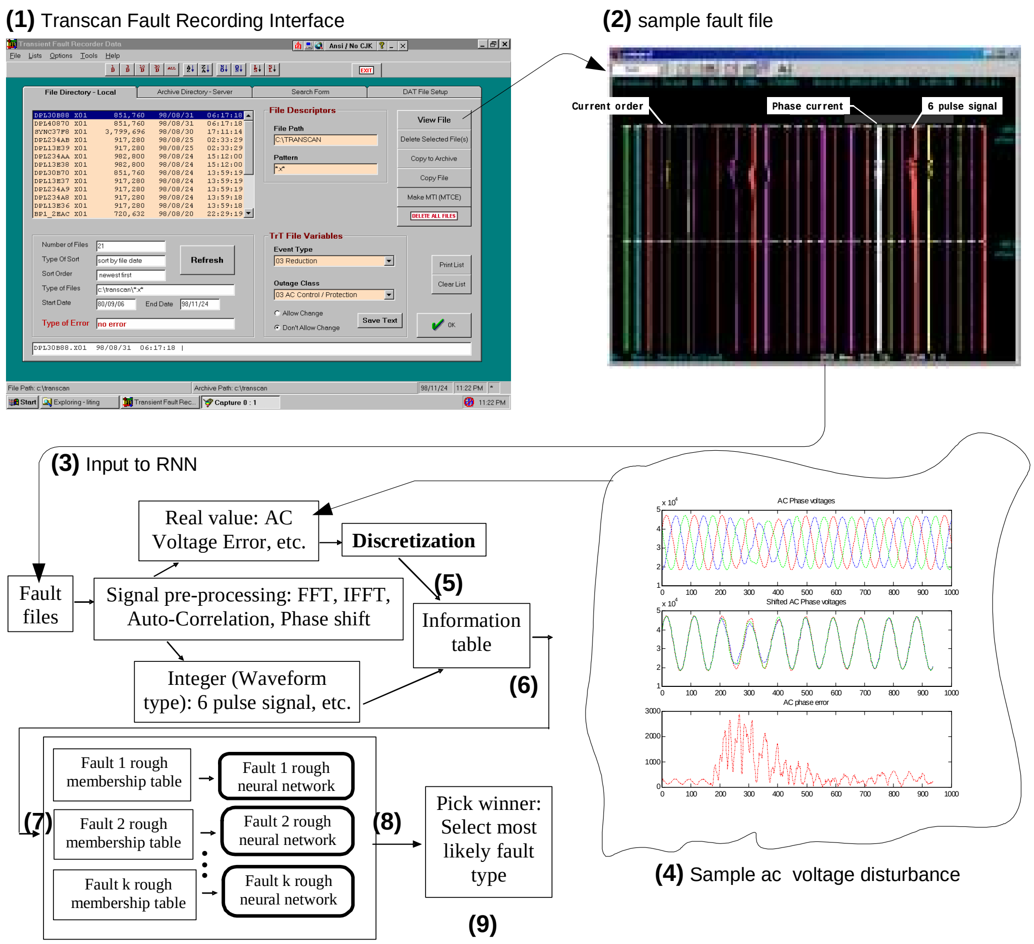

Fig. 1 Basic Structure of Fault Classification System

The 3rd of 3 plots in (4) gives a sample error plot using (10).

$$\text{error} = \frac{|\text{Aphase-Bphase}_{\text{shifted}}| + |\text{Bphase}_{\text{shifted}}\text{-Cphase}_{\text{shifted}}| + |\text{Cphase}_{\text{shifted}}\text{-Aphase}|}{3} \quad (10)$$

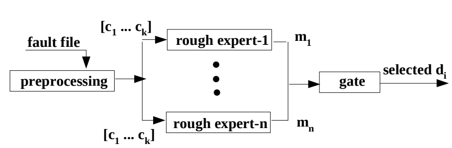

Fig. 2 RNN

Each rough expert in (8) in Fig. 1 is a rough neural network (RNN). There is rough expert for each fault type (see [13] for details). Input to each expert is a condition vector derived during preprocessing. The gate block in Fig. 2 selects a fault decision based on an evaluation of the outputs $m_1, \ldots, m_n$ from the "rough" experts. This model is analogous to one found in [1]. A model for RNNs is given in [9].

3. Preprocessing Methodology

In fault type classification for high voltage power systems, an information table ((6) in Fig. 1) is set up to represent the features of 26 signals in different fault conditions. Each row of this information table provides a condition vector to used to calibrate a rough expert neural network ((8) in Fig. 1). In this information table, some feature signals such as the error of *AC* phase voltage, the ratio of phase current and current order etc., are discretized into three sets: low, medium and high. Two parameters, *c* for the center and *s* for the span, are defined to represent each set. For an *AC* error input, $x_{li,}$ discretization is carried out using (11) .

$$\{\exp(-\frac{(x_{li}-c_1)^2}{s_1^{\ 2}}),\ \exp(-\frac{(x_{li}-c_2)^2}{s_2^{\ 2}}),\ \exp(-\frac{(x_{li}-c_3)^2}{s_3^{\ 2}})\} \quad (11)$$

where, x_{li} is for the i^{th} value in the l^{th} type of fault. c_1, c_2, c_3 are the centers of the low, medium, and high sets respectively. s_1, s_2, s_3 are the spans for low, medium, and high sets, respectively. The *AC* error falls inside the range (360, 7000). A sample ac error discretization is shown in Fig. 3. The partition criteria force the data points which belong to the same type of fault to fall into the same set and force the data points which belong to the different type of fault fall into a different set.

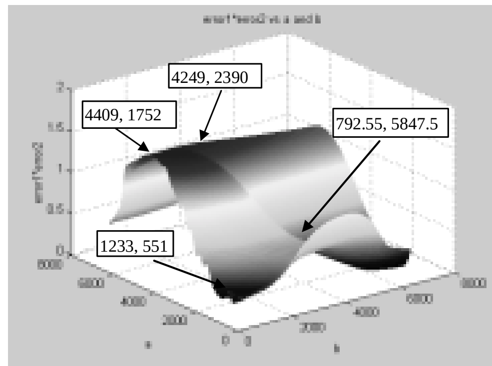

Fig. 3 Sample *ac* Error Discretization

In other words, we discern memberships close enough for the points in the same type of faults combined with the condition of the most discernible memberships for the points in different types of faults. The position of two partition line *a* and *b* has the relation with c_i and s_i in (12)-(14).

Low: $c_1 = a/2$; $s_1 = a/2$, **Medium**: $c_2 = a+b/2$; $s_2 = b/2$, **High**: $c_3 = (7000+a+b)/2$; $s_3 = (7000-a-b)/2$ (12-14)

Constraints *a* and *b* in (12)-(14) are defined as follows: $a > 360$; $b > 360$; $a + b < 6640$. The plot in Fig. 3 is obtained using $f(a, b)$ = DOS/DOD where

$$\text{DOS} = \sum_{l=1}^{11}\sum_{\substack{i=1\\j=1\\i\neq j}}^{N(l)}\sum_{r=1}^{3}[\exp(-\frac{(x_{li}-c_r)^2}{s_r^{\ 2}})-\exp(-\frac{(x_{lj}-c_r)^2}{s_r^{\ 2}})]^2, \quad \text{DOD} = \sum_{l=1}^{10}\sum_{i=1}^{N(l)}\sum_{k=l+1}^{11}\sum_{j=1}^{N(k)}\sum_{r=1}^{3}[\exp(-\frac{(x_{li}-c_r)^2}{s_r^{\ 2}})-\exp(-\frac{(x_{kj}-c_r)^2}{s_r^{\ 2}})]^2$$

A more detailed explanation of preprocessing of power system fault data is given in [13].

4. Concluding Remarks

The features of a complete rough set-based power system fault classification system have been briefly presented in this article. Preprocessing of fault files obtained from the Transcan Recording System at Manitoba Hydro has been carried out with a form of discretization of sample signal values that makes it possible to isolate global minima and maxima. Discretization is important because it makes it possible to distinguish features of different faults more easily. Discretization of the 3-phase *AC* error in power system faults has been briefly described. A complete presentation of the discretization method is outside the scope of this article. This article presents for the first time the complete architecture of a power system fault classification system, both its approach to preprocessing as well as its approach to rough neural computing to provide a basis for predicting power system faults. Future work will consider the application of rough measures in discriminating between faults and entail the design of a parallel processing architecture for the fault classification system.

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