Fault Detection System with Noninvasive Magnetic Passive Sensor and Support Vectors Machine

Alexandre Miguel de Carvalho[1], Francisco Xavier Sevegnani[2], and Carlos A. França Sartori[2,3]
[1]Primeira Opção Engenharia Elétrica LTDA, 13044-610 Campinas, SP, Brazil, carvalho@poengenharia.com.br
[2]Centro das Ciências Exatas CCET/PUC/SP, 05508-900 São Paulo, SP, Brazil
[3]Escola Politécnica da USP LMAG/PEA/EPUSP, 05508-900 São Paulo, SP, Brazil, sartori@pea.usp.br

Abstract — A robust fault detection system is presented in this work. This methodology show how magnetic passive sensor and pattern classification system like Support Vector Machines can classify magnetic signals for fault diagnoses.

I. Introduction

Noninvasive measurement techniques in electrical power systems to detect fault are quite new [1], [2]. In previous work, where a new approach suitable for fault detection and classification by analyzing the related magnetic signature was presented [1]. In this paper, fault detection and type classification is presented using support vector machines for diagnoses purposes.

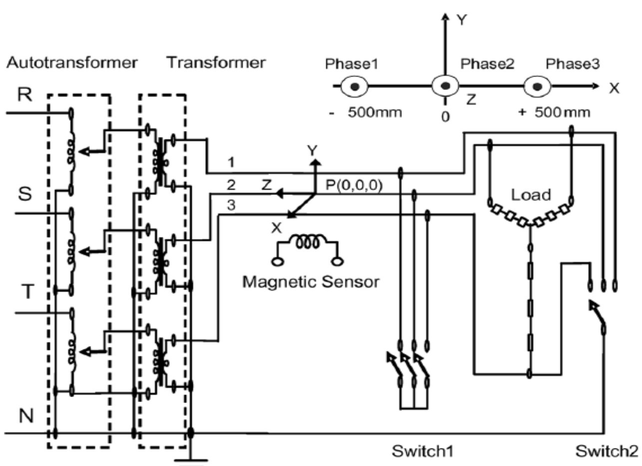

Fig. 1. Diagram of the experimental setup. Resistive Load.

II. Support Vector Machines

Support Vector Machines (SVM) is a pattern classification technique [3],[5],[6] with supervised learning algorithm. It can solve linear and non-linear classification problems. In Fig. 2, there is support vector machines architecture were, $K(x,x_m)$ is the inner-product kernel, y is output and X is a input vector. For training support vector machines, designer must define kernel function and kernel parameters, and penalty parameter C [3], [5], [6]. In this work, Radial-basis function kernel was used (equation 1).

$$K(x_i,x_j) = e^{-\gamma\|x_i-x_j\|^2}, \gamma > 0 \qquad (1)$$

C and γ parameters are determined in the training process.

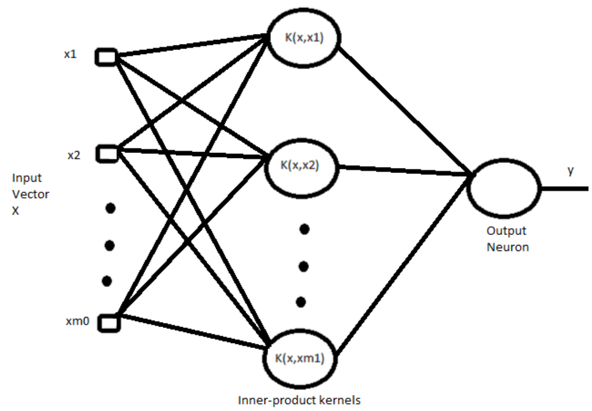

Fig. 2. Support Vector Machines Architecture.

III. Methodology

Methodology implemented here has three steps: first of all, like described in [1], experimental data acquisition is performed. Fault type, fault current and magnetic flux density are acquired. Fig. 1 shows the experiment schematic plant. Waveforms of magnetic flux density generated by short-circuits were acquired by a unidirectional magnetic sensor. These sensors were located close to the lines in a variety of distances h1 (distance between line and Magnetic Sensors) and d2 (distance between Magnetic Sensor 3 and Magnetic Sensor 4). Fig. 3 shows Magnetic Sensors configuration. Sample frequency used was 10kHz and 2000 samples were stored. Total measurements in this experiment: 220. That results in 440 training vectors.

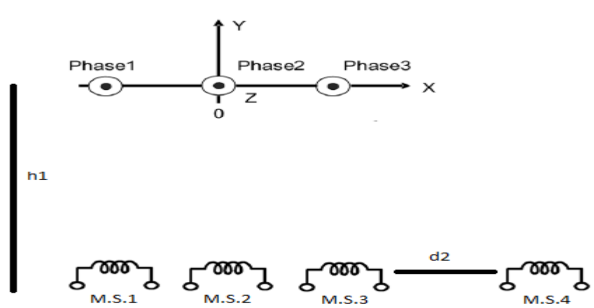

Fig. 3. Diagram of magnetic sensor position.

Second step consists in data processing that is manipulation and organization of them. In this step, it is defined how data can be organized for classification system. Classes of classification are defined and training vectors are prepared to use with support vectors machines training processes. In this work, faults codification are (NO

FAULT = 0, F3N = 1, F2N = 2, F1N = 3, F2F3 = 4, F2F3N = 5, F1F3N = 6, F1F2 = 7, F1F3 = 8, F1F2N = 9, F1F2F3 = 10), where FxFxN is phase to phase neutral. Training vectors were built using waveforms of magnetic flux density stored in step one. For example, the result of 8 built vectors for experiment F2F3N(phase to phase - neutral) short-circuit with h1=95cm and d2=100cm and M.S.1, M.S.2, M.S.3 and M.S.4 are described in table I.

TABLE I
Details showing how to built 8 training vectors for experiment F2F3N fault.

Vector	Sensor	class F2F3N								
Number	M.S.1	5	a1	a2	a3	a4	a5	...	a2000	2000 elements
	M.S.2	5	b1	b2	b3	b4	b5	...	b2000	2000 elements
	M.S.3	5	c1	c2	c3	c4	c5		c2000	2000 elements
	M.S.4	5	d1	d2	d3	d4	d5	...	d2000	2000 elements
			Final Vectors							
V1	M.S.1	5	a1	a3	a5	a7	a9	...	a1999	1000 elements
V2	M.S.1	5	a2	a4	a6	a8	a10	...	a2000	1000 elements
V3	M.S.2	5	b1	b3	b5	b7	b9	...	b1999	1000 elements
V4	M.S.2	5	b2	b4	b6	b8	b10	...	b2000	1000 elements
V5	M.S.3	5	c1	c3	c5	c7	c9	...	c1999	1000 elements
V6	M.S.3	5	c2	c4	c6	c8	c10	...	c2000	1000 elements
V7	M.S.4	5	d1	d3	d5	d7	d9	...	d1999	1000 elements
V8	M.S.4	5	d2	d4	d6	d8	d10	...	d2000	1000 elements

Each main vector with 2000 elements was built with direct measurement of magnetic sensor induction voltage. Each magnetic sensor terminals were connected in a oscilloscope to store samples in a short-circuit event. For purpose of training support vector machines, this main vectors was divided in two training vectors like described in table I. That operation permits improve vector quantities without lost important samples data.

The third step consists in defining support vector machine kernel and parameters in the training processes.

IV. Application and Results

The main goal here is to build a fault classification system. In this work, classification machine is capable to identify faults type like described in step two of section III with 93,3% average accuracy shown in table II.

Each training vector have a label or class codified. So, there are a pair, vector X with 1000 samples and a class linked with that vector. This structure enable supervised training of a support vector machine for classification purpose. The cross validation process [3],[4],[5],[6] was used. With 440 training vectors, 40 vectors was selected to test only and 400 vectors to training and cross validation. Table II shows accuracy for 40 vectors submitted to classification machine.

Each training and cross validation vector sets and test vectors are defined randomly. In this work, 25 classification experiments was built. Support vector machines parameters results is on table II (C and γ).

One vector test represents, for example, a new fault detected and classified for the system classification and detection here presented.

TABLE II
Accuracy and parameters in 25 SVM training process.

Training	C	γ	Accuracy %
1	128	0.03125	95
2	512	0.0078125	100
3	2048	0.001953125	80
4	32768	0.0001220703125	90
5	32768	0.0001220703125	90
6	512	0.0078125	92,5
7	2048	0.001953125	92,5
8	512	0.0078125	90
9	32768	0.00048828125	100
10	128	0.03125	100
11	128	0.03125	97,5
12	2048	0.001953125	97,5
13	8192	0.00048828125	95
14	512	0.0078125	95
15	8192	0.00048828125	82,5
16	2048	0.001953125	87,5
17	32768	0.00048828125	97,5
18	2048	0.001953125	95
19	32768	3.0517578125e-05	97,5
20	8192	0.00048828125	97,5
21	32768	0.0001220703125	92,5
22	512	0.0078125	87,5
23	8192	0.00048828125	95
24	32768	0.0001220703125	92,5
25	128	0.03125	92,5
		average accuracy	**93,3**

V. Conclusions and Future Work

For improve accuracy, other kernels must be tested and, if does not results in accuracy improvement, more measurements experiments must be done.

Future works will use wavelet transform in magnetic signal and SVM to identify fault distance, fault direction, fault intensity and others important parameters.

VI. References

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