Analog filter diagnosis using Support Vector Machine

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Abstract

The paper will present the application of artificial neural network of Support Vector Machine (SVM) type to the fault location in analog electrical filter. The recognition of fault is based on the measurements of the accessible terminal voltage and current of the network, transformed according to the proposed procedure. The SVM network is applied as the recognizing system and as the classifier. The numerical results of recognition of faulty elements in electrical filter are presented and discussed in the paper.

1 Introduction

The detection of faults and their location in analog circuits belong to the classical subjects in circuit theory [1-4]. This paper will present the neural approach to this problem. It will be based on the application of Support Vector Machine network.

It is assumed that the general structure of the circuit under investigation is known. The fault of element is considered as the parametric change of its value over the tolerance limit. Only fault of one element at a time is considered. The detection of the faulty element is performed on the basis of the measurements of the terminal signals of the circuit, i.e., the terminal voltages and currents of the circuit, operating in normal and faulty conditions. The measured signals undergo the preprocessing to extract the main features of the process. These features form the input signals to the neural network, performing the recognition which element is faulty.

The neural network is trained on the examples of patterns belonging to the normal operation of the circuit and to the representatives of the typical faults of the particular element. The important advantage of the neural method is its ability to treat the non-ideality of the elements and the tolerance of their values. The method is effective and offers a great speed and acceptable accuracy of fault detection in the large range of parameter changes, if the appropriate measurements and signal preprocessing are applied. In comparison to standard neural networks, like the multilayer perceptron or self-organizing Kohonen network [5,6,7] Support Vector Machine offers much better generalization properties at smaller number of training samples.

2. Principle of fault location in the circuit using neural network

The main idea of application of neural networks to the fault location in electrical circuit is neural processing of the signals measured on the output terminals of the electrical networks in order to discover the faulty element of the circuit. The neural network are trained on the patterns of signals corresponding to the typical examples of different faults and can perform good recognition of the faulty element on the basis of actual measurement made in the network [5,6,7].

Let us assume that there is a sufficient number of independent signal measurements in the circuit, greater than the number of the elements in the analog circuit of known topology and nominal values of its elements. For simplicity we will consider here only single faults. Each faulty element in the circuit can be associated with certain individual pattern of measured signals. The measured signals should be chosen and then preprocessed in such a way that the pattern associated with each fault is unique and different from the other.

The aim of training the neural network is to adapt the weights of neurons in such a way, that they represent the patterns corresponding to each type of fault plus one, associated with the normal operation of the circuit. The signals used to train or test the neural network may be measured at different node points of the circuit (if possible) and at multiple frequencies.

From the practical point of view the most important is the case of measurements at two points of the circuit: one on the input and one of the output side. To increase the number of measured signals the multiple frequencies of the excitation should be applied. The signals measured at these frequencies, transformed appropriately, will form the learning patterns for the neural network. The number of measured frequency points influences the dimension of the input vector **x** to the neural network.

We consider here the parametric faults of the circuit elements. As the faults we have assumed all changes of the nominal values of conductances and capacitances ($G_n \to kG_n, C_n \to kC_n$) with the value of coefficient k varying from zero to one minus tolerance value (the representation of the non-ideal open-circuit of the element) and from 1 plus tolerance to the infinity (the representation of the non-ideal short-circuit of the element). Each fault has been associated with the tolerance of the remaining non-faulty elements changing in the experiments from 0 to 5%.

As a result of such assumption two different kinds of faults for each element will be recognized: one corresponding to the increase of the admittance, called here the short-circuit type, and the second leading to its decrease, of the open-circuit type. At number of circuit elements equal n, the number of resulting fault types is equal $2n$. The neural network should be designed in a way to recognize either appropriate fault or to indicate the normal operating condition of the circuit. It means that the number of recognized classes is equal ($2n+1$).

The most important issue at this step is the choice of the frequency points at the measurements. These frequencies should be chosen in a way to enhance the differences between different states of the circuit and should provide the greatest sensitivity of the measured signals of the circuit to the changes of its elements. To determine these frequencies the most reasonable way seems to be the sensitivity analysis of the circuit. The proper (optimal) frequencies correspond to the points of extremes (maximum or minimum) of each sensitivity curve [7].

To illustrate the procedure of selecting the frequency points consider the low-pass bi-quadratic multi-loop filter structure presented in Fig. 1, designed for the normalized frequency range (0, 0.5). All further experiments have been performed for this normalized low-pass filter of the following nominal values of the elements: G_1=1mho, G_3=0.81mho, G_4=1mho, C_2=2F, C_5=0.41F.

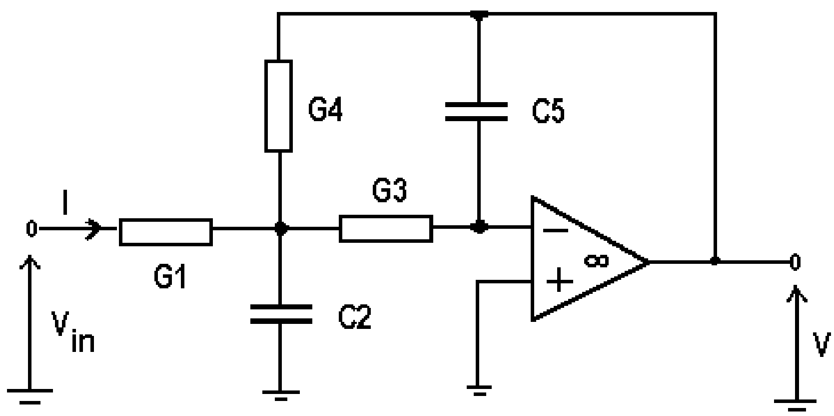
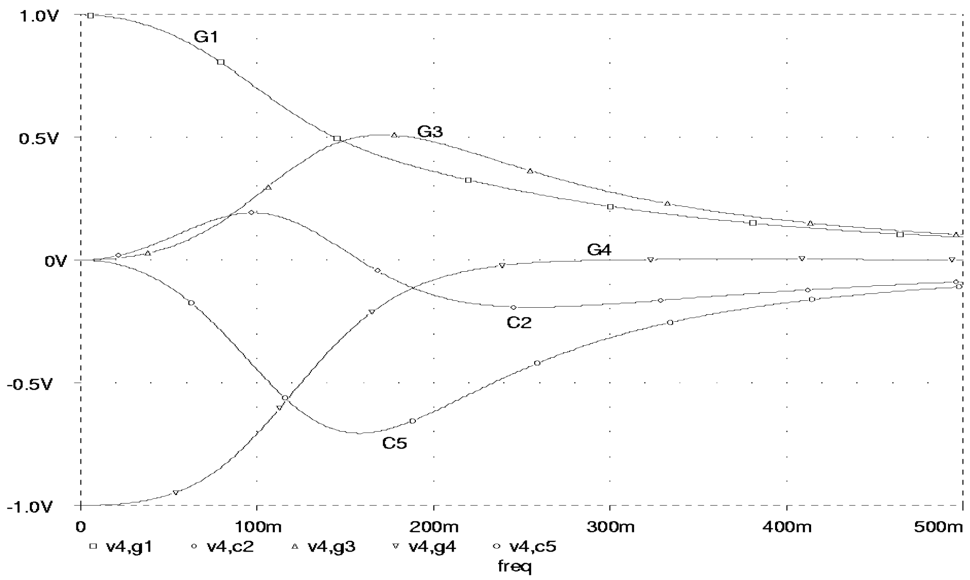
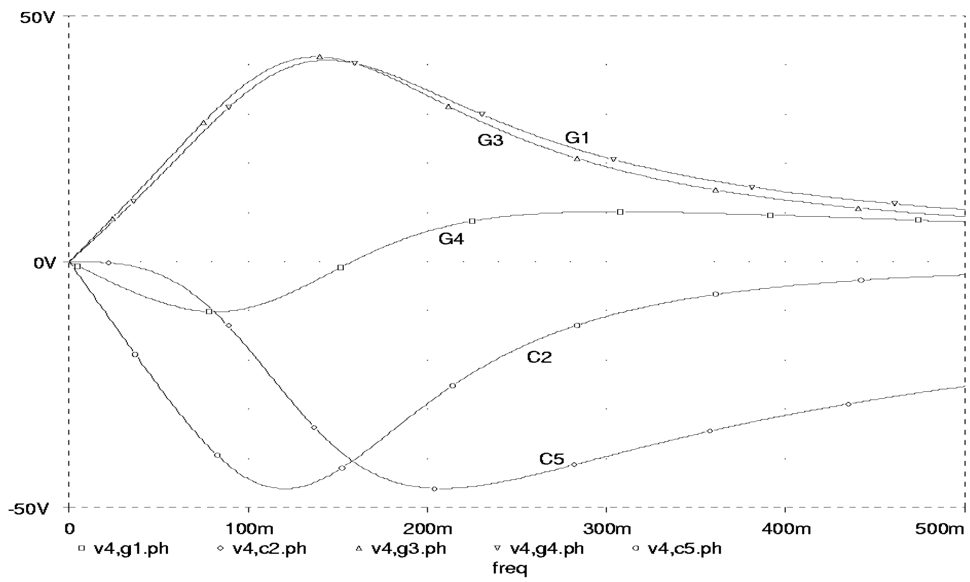


Fig. 1 The structure of the bi-quadratic filter used in the experiments

Fig. 2 presents the exemplary sensitivity curves for the magnitude and phase of the output voltage $V=V_4$, obtained for this filter using PCNAP analyzer-[13]. The letters G_1, G_3 G_4, C_1 and C_2 indicate what sensitivity parameter is actually considered. The points of the maximum or minimum of these curves indicate the frequencies that should be applied at the preparation of the learning data for the neural network used as the recognizing system.



a)



b)

Fig. 2 The sensitivity curves of the bi-quadratic filter: a) the magnitude, b) the phase of the output voltage. The x-axis represents the normalized frequency

The choice of points corresponding to the maximum or minimum of these curves provides the maximum sensitivity of the measured signal to the change of appropriate parameter. This will help in getting the most sensitive system for fault recognition.

To enhance the differences between various faults we take here the learning signals as the magnitude and phase frequency characteristics of the circuit, considering the relative differences between the faulty and non-faulty modes of circuit operation. Applying the general notation x for either output voltage V or input current I (magnitude or phase) we define the relative difference at the frequency f_i, as follows

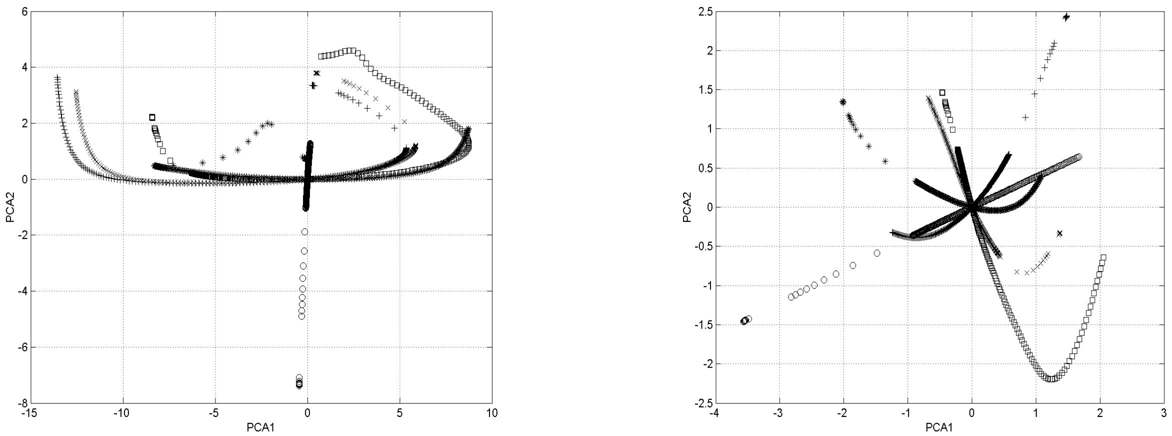
$$x_r(f_i) = \frac{x_f(f_i) - x_n(f_i)}{x_n(f_i)} \tag{1}$$

The subscript f in this expression is related to the faulty state and n for non-faulty (normal) operation of the circuit. The maximum size feature vector $\mathbf{x}$ used in learning is given by

$$\mathbf{x} = [abs(\mathbf{V}_r), \arg(\mathbf{V}_r), abs(\mathbf{I}_r), \arg(\mathbf{I}_r)] \tag{2}$$

where the vectors: $\mathbf{V}_r = [V_r(f_1), V_r(f_2), ..., V_r(f_{m1})]$ and $\mathbf{I}_r = [I_r(f_1), I_r(f_2), ..., I_r(f_{m2})]$ represent relative voltages and currents of the terminals at different frequencies f_i, normalized according to the relation (1), *abs* stands for the magnitude and *arg* for the phase of the corresponding complex value.

The next issue that should be solved is the determination if the measured data well separate different states of the circuit, and hence if they are sufficient for recognition between different fault types. To solve this problem we have applied principal component analysis (PCA) for different representations of the input vector $\mathbf{x}$ containing: a) both magnitudes and phases of the output voltage and input current and b) only chosen representations of the output voltage and input currents. Fig. 3a presents the results of PCA at full feature vector described by (2) and Fig. 3b corresponds to the feature vector $\mathbf{x}$ from which the phase information of the input current has been removed. The x-axis represents the first principal component and y-axis the second largest principal component. The data forming the graphs correspond to different values of elements, changing in experiments from zero to infinity. Point (0,0) on the figures corresponds to the nominal values of all parameters. Each fault type has been associated with different symbol (G1 $\rightarrow$o, G3 $\rightarrow$x, G4 $\rightarrow$+, C2 $\rightarrow$* and C5 $\rightarrow$). All graphs corresponding to the changes of parameter values of different elements cross this particular nominal point.



a) b)

Fig. 3 The results of the principal component analysis of the data corresponding to the voltage and current measurements of the bi-quadratic filter: a) full feature vector containing magnitude and phase information, b) the feature vector deprived of phase information of current

It is seen from these pictures, that full feature vector does not provide the best separation of different states of the circuit. The PCA analyses of different feature representations have confirmed that the best separation of different states of circuit parameters are obtained when we take into account the reduced feature vector defined as follows

$$\mathbf{x} = [abs(\mathbf{V}_r), \arg(\mathbf{V}_r), abs(\mathbf{I}_r)] \tag{3}$$

Fig. 3b corresponds to the PCA distribution, associated with this particular feature representation.

3. The Support Vector Machine network as the classifier

As the neural system used for the recognition and classification of the fault we have chosen the Support Vector Machine (SVM) network. SVM is the solution of the universal feedforward networks, pioneered by Vapnik [8,9,10,11]. It is known as the excellent tool for classification problems of good generalization performance. In distinction to the classical neural approaches, the formulation of SVM learning problem leads the quadratic programming with linear constraints of the global minimum.

Basically, the SVM is a linear machine working in the high dimensional feature space formed by the nonlinear mapping of the N-dimensional input vector **x** into a K-dimensional feature space (K>N) through the use of function $\varphi(\mathbf{x})$. The equation of the hyperplane separating two different classes is given by $\mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) = \sum_{j=0}^{K} w_j\varphi_j(\mathbf{x}) = 0$, where $\boldsymbol{\varphi}(\mathbf{x}) = [\varphi_0(\mathbf{x}), \varphi_1(\mathbf{x}), ..., \varphi_K(\mathbf{x})]^T$ with $\varphi_0(\mathbf{x}) = 1$ and $\mathbf{w}$ – the weight vector of the network $w = [w_0, w_1, ..., w_K]^T$. The learning task of the SVM network working in classification mode is defined as the maximization of the separation margin between two classes (d_i=1 and d_i=-1), which mathematically corresponds to the minimization of the following cost function $\phi(\mathbf{w}, \boldsymbol{\xi})$

$$\min\ \phi(\mathbf{w}, \boldsymbol{\xi}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{p}\xi_i \tag{3}$$

with the following constraints for i= 1, 2,…,p

$$d_i\mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) \geq 1 - \xi_i \tag{4a}$$

$$\xi_i \geq 0 \tag{4b}$$

where C>0 is the user specified constant, $\xi_i \geq 0$ is the non-negative slack variable and p – the number of given learning data pairs ($\mathbf{x}_i$, d_i).

The most distinctive fact about SVM is that the learning task is simplified to the quadratic programming by introducing the so called Lagrange multipliers α_i. All operations in learning and testing modes are done in SVM using so called kernel function, satisfying the Mercer conditions [8]. The kernel is defined as $K(\mathbf{x}, \mathbf{x}_i) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$. The most known kernel functions are radial basis, polynomial, spline or sigmoidal functions [9].

The learning problem of SVM, described by (3) and (4) is transformed to the so called dual problem of maximization of the quadratic function $Q(\boldsymbol{\alpha})$, defined in the way [8,9,10]

$$Q(\boldsymbol{\alpha}) = \sum_{i=1}^{p}\alpha_i - \frac{1}{2}\sum_{i=1}^{p}\sum_{j=1}^{p}\alpha_i\alpha_j d_i d_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{5}$$

with the constraints

$$\sum_{i=1}^{p}\alpha_i d_i = 0 \tag{6a}$$

$$0 \leq \alpha_i \leq C \tag{6b}$$

The solution with respect to the Lagrange multipliers results in the optimal weight vector $\mathbf{w}_o$, as $\mathbf{w}_o = \sum_{i=1}^{N_S} \alpha_{si} d_{si} \boldsymbol{\varphi}(\mathbf{x}_{si})$. In this equation index s points to the set of N_s support vectors, i.e. the learning vectors $\mathbf{x}_{si}=\mathbf{x}_i$, for which the decision function $d_i\left(\sum_{j=1}^{K} w_j \varphi_j(\mathbf{x}_i) + w_0\right) \geq 1 - \xi_i$ ($\xi_i \geq 0$ - the slack variables) is fulfilled with the equality sign. The output signal $y(\mathbf{x})$ of the SVM in the retrieval mode (after learning) is determined as

$$y(\mathbf{x}) = \sum_{i=1}^{N_S} \alpha_{si} d_i K(\mathbf{x}_{si}, \mathbf{x}) + w_o \tag{5}$$

and does not need to know the explicit form of the nonlinear function $\varphi(\mathbf{x})$. Although SVM separates the data only into two classes (one output neuron) the recognition of more classes is straightforward by applying either "one against one" or "one against all" approaches [12].

4. The results of numerical experiments

The numerical experiments have been performed for the bi-quadratic low-pass filter of the structure presented in Fig. 1. The parametric changes of the element admittance values varying in the range extending from the zero to infinity have been considered. The parameter values within the tolerance limit mean normal operation of the circuit. Other values are associated with the faults of either open-circuit or short-circuit type. The principal component analysis discussed in section 2 has shown, that parametric faults in the circuit can be best separated on the basis of the magnitude and phase information of the output voltage and magnitude of the input current feature vector, determined for the set of selected frequencies. These frequencies have been adjusted on the basis of sensitivity analysis of the circuit. The extreme points (maximum or minimum) of the magnitude and phase characteristics have defined the proper frequency points. At 5 circuit elements 17 such frequency points have been selected (4 for the magnitude and 6 for the phase characteristics of the output voltage, and 7 for amplitude characteristics of the input current). Hence the dimension of the input vector **x** to the neural network is equa1 17.

From the principle of operation, the SVM network has only one output neuron, capable of recognizing between two classes. In our case there were 11 classes for recognition: one corresponding to the normal operation of the circuit and another 10 for recognition of either open-circuit or short-circuit type fault of 5 passive RC elements of the filter. To solve this multi-class recognition we have applied the one-against-one strategy [12], resulting in learning 11 independent SVM networks. We have applied the gaussian RBF type of SVM networks. The numbers of hidden neurons of SVM networks as well as their weights are adjusted in the learning process, performed here by applying the Lagrangian SVM (LSVM) algorithm of Mangasarian [11]. We have used 200 learning data pairs corresponding to different faults and normal operation of the circuit, all associated with the tolerance of the non-faulty elements.

After learning phase, all parameters have been frozen and the network tested by using additional 1800 data points. To check the generalization properties of the SVM network in the testing mode, different values of the faulty element parameters have been used, especially those on the limit of the tolerance. Additionally they have been also associated with random variation of the parameters of other non-faulty elements within the tolerance limit.

The first experiments have been made at zero tolerance of elements. Zero tolerance means, that any deviation of the parameter value is regarded as the fault. It is just pure theoretical case, very demanding for the recognition of faults, especially in the region very close to the nominal values of parameters. Only normal operation of the circuit is trivial and its recognition is possible without any mistake. Most errors made by the neural network classifier correspond to the faults placed in a close vicinity of the normal operating conditions of the circuit. The average testing error in this case did not exceed 0.48% .

Inclusion of any tolerance of elements introduces some margin of operation. Any values of elements within tolerance limit are regarded as normal operation of the circuit. The other values of parameters mean faults. Table 1 presents the results of testing the trained neural recognizing system at 1% tolerance. The numbers given in the table denote the statistical average errors of the recognition of proper fault type. The faulty element values have been placed uniformly in the considered faulty range. 300 cases of faults of each element have been tested, from which 120 were of open-circuit, 120 of the short-circuit type and 60 within tolerance limit, regarded here as the normal operation of the circuit. As it is seen the average errors of recognition is of very limited value. The maximum average error for the most difficult case (G_3) did not exceed 5.1% and the mean of all average errors for all considered cases (including faults and normal operation) is equal only 2.19%.

Table 1 The average misclassification rate of the faulty element on the testing data at 1% tolerance of elements (the average percentage errors for each fault type)

Faulty element	Fault of the short-circuit type	Normal operation	Fault of the open-circuit type	Mean error
G_1	1.65%	0	3%	1.55%
G_3	4.1%	0	5.1%	3.07%
G_4	2.4%	0	2.3%	1.56%
C_2	3.3%	0	3%	2.1%
C_5	4.1%	0	4%	2.7%
Mean	3.1%	0	3.48%	2.19%

Increasing further the tolerance of elements deteriorates a bit the operation of the recognizing system in nominal state (the nominal state is associated now with a wide tolerance range, regarded as a normal operation) but the error of recognition of the faulty states has been significantly decreased, especially the faults of the open-circuit type. Table 2 presents the results of testing the trained SVM network on the same data at 5% tolerance of the elements. This time the worst results have been obtained for nominal operation of the filter. However all misclassifications for normal operation have been committed at the tolerance limit (20% of the testing data were placed at exactly tolerance limit). This increase of errors is due to the large changes of the patterns represented by the output voltages and input currents, associated with the normal operation of the circuit. Additionally all tests have been performed for the data fuzzified by the telerance of all non-faulty elements.

Table 2 The average misclassification rate of the faulty element at 5% tolerance (the average percentage errors for each fault type)

Faulty element	Fault of the short-circuit type	Normal operation	Fault of the open-circuit type	Mean error

G_1	0	0	0	0
G_3	1.7%	0	0	0.56%
G_4	0.8%	4.5%	0	1.76%
C_2	1.7%	4.5%	0	2.06%
C_5	2.5%	9%	0	3.83%
Mean	1.34%	3.6%	0	1.64%

However, even in this demanding case the mean of all average errors did not exceed the value of 1.64%.

5 Conclusions

The new approach to the diagnosis of an analog filter, based on the application of Support Vector Machine neural network has been presented. The diagnosis is understood as the recognition of the individual fault of element, where the fault means the change of the value above or below the assumed tolerance of elements. The important feature of the proposed solution is high accuracy and great speed of operation. Once the network has been trained, the recognition of fault is achieved immediately, irrespective of the size of the circuit. Thus the solution is suited for real time applications for fault location. The distinct advantage of the SVM neural network solution is its good generalization properties. Trained on only limited number of representative examples of each fault, the network is able to recognize the non-ideal fault in the wide range of changed parameters and at some tolerance of elements. The accuracy of fault recognition checked on the example of bi-quadratic filter by using SVM is better than those presented recently for similar tasks [5,6,7].

Although the paper has presented only the solution for single faults, it may be automatically extended to multiple faults, simply by increasing the number of neurons in the layer (additional neurons will represent the multiple faults) and the number of training samples associated with these multiple faults.

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