Analog Circuits Fault Diagnosis Using ISM Technique and a GA-SVM Classifier Approach

Sabah Kouachi, Nacerdine Bourouba, Kamel Mebarkia and Imad Laidani

Abstract— **This present work aims to contribute to the solution of the problems encountered in electronic circuits fault diagnosis. One of these troubleshoots faced is the lack of effective features that help to optimize fault classifier and hence improve circuit fault detection and identification. Thus, our feature extraction approach is based on the CUT's transfer function. This is deduced from the Matlab identification system IS model (ISM), namely the OE model belonging to the ARMA model's family. These features are the transfer function polynomial coefficients playing a crucial role in the fault free and faulty circuits construction models and feeding the classifier for the fault diagnosis purpose. The faults we are dealing with are of single parametric type. This is done from PSPICE time domain analysis on the CUT output response under theses circuit conditions and followed by extracting the IS model (ISM) orders (p,q) polynomials. The coefficient values of the latter were considered as efficient comparison elements between faulty and healthy circuit responses. As a result, the OE model has achieved 100% fault coverage and its construction reached high accuracy level exceeding 98% for faulty circuits. This accuracy level ambition us to use its coefficients as input features for our Hybrid proposal fault classifier. This is built with GA and SVM algorithms combination targeting both data reduction and fault classification accuracy respectively. The results achieved are conclusive since the classifier accuracy level reached 100% and a 70% of feature data volume reduction was scored.**

Index Terms—**analog circuit, genetic algorithm (GA), OE model, parametric faults, support vector machine (SVM).**

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I. Introduction

In recent years, several new emerging scientific and technological fields have become very important in our daily life, such as telecommunications, multimedia, biomedical applications etc. These areas have experienced better performance resulting from large-scale insertion of electronic systems whose application required the use of significant and complex analog and mixed integrated circuits. Because of the

complex and fast development of electronic science and technology, high-performance electronic systems are not immune to imperfections and failures that occur within them. In this case fault diagnosis and testing as fundamental tasks in preventive maintenance play a vital role in the product reliability and promoting industrial development [1]-[2]. The presence of different types of analog circuit faults in electronic equipment makes their diagnosis very intricate. This conducted the analog circuit fault diagnosis to be an important research topic [3]-[4]. Mostly, the diagnosis process has been carried out with two common simulation techniques whose one of them is done before test (SBT) and the other is carried out after the test process (SAT) [5]. The SAT technique solves faulty circuit equations by a computation procedure once circuit parameter data are set from measurements. On the contrary, the SBT one, on which our work is based, aims to construct fault dictionary with signal information that comes from circuit simulation run under different selected faults and thus serving as a test and diagnosis tool for faulty circuits [6]. The important activities the researchers undertake for more efficient diagnosis process are a high fault coverage score and best fault identification and isolation. These can be achieved if and only if some key-elements of the process are well selected such as good stimuli (input signals), better features, an efficient feature extraction approach and optimization and classification algorithms. As a result, this will undoubtedly lead us to an improvement in diagnostic accuracy. To execute this diagnosis task, a complete fault simulation must be performed by examining various parameters of faulty circuits. Afterwards; important criteria are established in purpose of better fault identification and localization of involved classifiers. The analog circuit faults are broadly classifying into catastrophic and parametric faults. We should precise that the faults being concerned in this paper work are of parametric type because of to their severe effect in analog circuits [7]-[8]. They manifest as a deviation value of the component nominal one and causing a circuit to a malfunctioning state but escaping to the test process. In contrary to the catastrophic faults that are well covered in most of research works, the parametric faults are paying more attention from researchers because of trouble some's encountered in a test process [9]-[11]. This is said because of the question emerging from the stimulus choice difficulty for ensuring the fault effect propagation towards the cir-

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cuit accessible point. Another issue as important as the previous one to overcome, is the burdensome encountered when looking for features that allow both the detection of these faults and their isolation from each other. Even the efficiency and the data volume reduction achievement the classifier process should provide, they constitute a challenge for researchers to face [12].

Many feature extraction optimization and classification methods have been proposed to overcome such fences. For this purpose, an attempt to use SVM aims to better classify faults while serving Firefly algorithm (FA) and Particle Swarm Optimization (PSO) as an optimization algorithm by reducing feature data sets to their best ones only. The features used as input classifier have been extracted from the circuit frequency response function [13]. From another fault diagnosis working angle [14], a fault classification approach was built on a fusion of two methods based on ANN and FIS targeting both feature reduction and classifier optimization. The parameters used were of temporal and frequency natures and in number of six which, undergone to this approach, they were reduced to almost 50% while ensuring a very convincing accuracy estimated to over 99%. The Fractional Fourier Transform (FRFT) approach has been conducted for another research work to extract fault detection features in the optimal fractional order domain and that correspond to the statistical parameters such as range, mean, standard deviation, skewness, kurtosis, entropy, median, the third central moment and centroid. Due to the data set that require the involvement of high feature dimension the efficiency of the SVM classifier has been affected disapprovingly. This has urged to reducing the candidate feature dimensionality. Thus, the optimal features have obtained by Kernel Principal Component Analysis (KPCA) and helping the SVM accuracy improvement [15]. In reference [16], the extraction of circuit parameters as features classifier are performed from analog circuit time responses. This has been achieved by the Deep Belief Network (DBN) approach. Their optimization is justified from the learning rates of this approach derived by Quantum behaved Particle Swarm Optimization (QPSO) method and classification faulty components is based on a SVM approach. According to Ruslan Dautov and all [17], wavelet transform to extract coefficients serving as classifier features. Here, two types of classifiers founded on K-Nearest neighbour's method (K-NN) and association data mining algorithm were implicated to improve accuracy and to rise the classifier fault coverage. Throughout these research works, the main attention focused on looking for a best fault classification technique that allow adequate fault analysis and detects the most frequent analogue circuit faults.

In this present work the faults detection approach is carried out on single parametric faults according to the reasons mentioned above and the fault effect is examined by using the circuit transfer function parameters. In fact, these represent the features that built the identification system models (ISM) based on ARMA, ARX and OE approaches. The last one was selected as the best one according to its accurate model results we attained in comparison with experimental outcome. The idea was inspired from several research works based on the use of the models of identification system approach [18], in order to widen the fault diagnosis analysis and to seek a better fault detection. The features representing the input data to be trained by our proposal classifier approach are the polynomial coefficients of the OE model transfer function derived as output data generated by a MATLAB sub-program. Those data exploited by this modelling approach are fed from the CUTs simulation results performed in PSPICE environment. The modelling process has concerned both fault free and faulty circuits in order to build a bank of data for fault classification purpose. This data collection is organized in a data matrix from features and classes. The fault classifier being selected in our project is based on SVM learning machine tool that has shown in several research works versatility and accuracy in fault diagnosis process and achieved a best classifying performance when associated with optimizing algorithms such as a gray wolf optimization (GWO), the slap swarm algorithm and so ones [7], [8], [19].This encouraged us to attempt to train the SVM classifier using kernel polynomial functions of different degrees with the genetic algorithm (GA) approach to optimize the features for better fault classification accuracy.. This hybrid method combination is intending to improve classifier accuracy and eliminate data features that cause redundancy and lead to performance drop. This GA-SVM approach used for feature data training resulted to both selecting the best features with reduced number and achieving better classifier accuracy.

This paper is organized with the remained sections as follows: Section II presents a brief theoretical study of the, genetic algorithm (GA), the output error (OE), and support vector machine (SVM) methods on which our proposal approach is based on. The Section III gives a brief description of the CUTs (Sallen–Key band pass filter and Four Opamp-biquad high pass filter) and followed by the proposal classifier approach review. The Section IV concerns the fault optimization and classification improvement by the GA-SVM combination approach and a comparison with other research works is also included. Finally, a conclusion is drawn in Section V to demonstrate the efficiency of the proposed work.

II. Description of Methods Used in Approach

A. Extraction method of feature extraction

The spectral estimation can be carried out by different spectral analysis methods. Among these methods, the parametric techniques constitute a very interesting class based on several types of models like ARMA, ARX and OE. The signal best modeled by a spectral density with poles and zeros can be presented by the following model theory:

1) The modeling process based on ARMA is a way to understand and to predict values of series data in time domain. It is composed of two elements such as the autoregressive model (AR) element and the moving average (MA) element. The AR-MA is also known as ARMA (p,q), where p and q are the autoregressive (AR) and the moving average (MA) elements orders respectively.

These modelling approaches are expressed in z-variable since the input and output signals are sampled in a time domain and subsequently processed by Z-Transform algorithm implemented in the Matlab software.

MA models are zero-only model, as shown in equation (1):

$$H(z) = \frac{b_0+b_1z^{-1}+b_2z^{-2}+....+b_qz^{-q}}{1} \quad (1)$$

Where q is the model order and are the model parameters.

The AR model is shown in equation (2):

$$H(z) = \frac{1}{1+a_1z^{-1}+a_2z^{-2}+...+a_pz^{-p}} \quad (2)$$

Where p is the model order and a_1, a_2.... a_p are the model parameters. Afterwards, by assuming that the output signal at any time is predicted from the linear combinations use of past p outputs and q inputs, then at time step n, we have:

$$y(t) = \sum_{k=1}^{p} a_k y(n-k) + \sum_{k=0}^{q} b_k x(n-\kappa) \quad (3)$$

Though, these models are depending on time domain samples, they possess very important spectral properties. The transfer function of an ARMA model has the form [20]-[21]:

$$H(z) = \frac{b_0+b_1z^{-1}+b_2z^{-2}+....+b_qz^{-q}}{1+a_1z^{-1}+a_2z^{-2}+....+a_pz^{-p}} \quad (4)$$

where the polynomial denominator has order p and coefficients $\mathbf{a_1}$, $\mathbf{a_2}$, **...,** $\mathbf{a_p}$ and the polynomial numerator has order q and coefficients $\mathbf{b_1}$, $\mathbf{b_2}$, **..., bq**. In the ARMA model the output signal y(t) is given by:

$$y(t) = [B(z^1)/A(z^1)]u(k) + [C(z^1)/A(z^1)]e(t) \quad (5)$$

2) ARX described by AR, is an Auto-regressive model that illustrates the associated noise to a signal X which is an exogenous input and is also called a Controlled Autoregressive model [22]. The relationship sets between the input and the output of the circuit characterizing the ARX model is given by a linear differential equation as Equation (6):

$$y(t) + a_1y(t-1) + a_2y(t-2)+...+a_py(t-p) = b_1u(t) + b_2u(t-1)+...+b_qu(t-q+1) + e(t) \quad (6)$$

The output of this model structure is given by:

$$y(t) = u(t)\left[\frac{B(z^{-1})}{A(z^{-1})}\right] + e(t)\left[\frac{1}{A(z^{-1})}\right] \quad (7)$$

where the dynamic noise model is 1/A and [B(q-1)/A (q-1)] extracts the input-output model. The u(t) and e(t) are the model's input and noise signals respectively.

3) The OE method deals with minimizing an objective function to facilitate the control of industrial system samples. The technique is based on the discrete-time OE model system identification and is frequently used in many researches works in recent years [23]. This is involved in many systems and the resulting model is characterizing a pure white noise, though the noise is independent of the inputs and the output. This let us to possibly conceptualize that the noise arrives at the end of the system (near the output). The output error (OE) model structure is defined by the equation (8) [24]:

$$y(t) = u(t)\left[\frac{A(z^{-1})}{B(z^{-1})}\right] + e(t) \quad (8)$$

where *u*(*t*) and *y(t)* are the input and the output signal sequences, and zero mean white noise *e*(*t*). The $A(z^{-1})$ and $B(z^{-1})$ are the polynomials in the unit backward shift operator z^{-1}. Meanwhile, the polynomial denominator is defined by the order q and coefficients $\mathbf{b_1}$,$\mathbf{b_2}$,**...bq** and the polynomial numerator has an order p and coefficients $\mathbf{a_1}$,$\mathbf{a_2}$,**...**$\mathbf{a_p}$,as shown in equations (9) and (10):

$$A(z^{-1}) = a_1z^{-1} + a_2z^{-2}+....+a_pz^{-p} \quad (9)$$

$$B(z^{-1}) = 1 + b_1z^{-1} + b_2z^{-2}+....+b_pz^{-p} \quad (10)$$

In this paper we transform the output signal to these coefficients ($\mathbf{a_1}$,$\mathbf{a_2}$,**...**$\mathbf{a_p}$ and $\mathbf{b_1}$,$\mathbf{b_2}$,**...bq**) by using the precedent structure in MATLAB subprogram applied, however these coefficients are defined as features extracted for the model of concern.

B. Optimization Genetic Algorithms (GA) method

First of all, the genetic algorithm is proposed by Holland in 1960s. This algorithm based on a Darwin natural selection and natural genetics concept is an evolutionary theory that uses different and general techniques searching for the survival fittest. Its use has been widespread and touched several domains of application. It has been considered as an efficient tool for optimization purposes. In fact, the genetic algorithms (GA) are different from more normal methods in many ways [25]-[27].

As a random-based classical evolutionary algorithm (EA), the GA consists of searching solutions effectively from random changes applied to current solutions having as a target, a generation of new and desired ones to substitute them [28].

To use a such algorithm, one should observe the GA essential criterion that constitute the principle of genetics and evolution using different operators, such as efficient encoding, selection, crossover and mutation. The most crucial starting point of the GA algorithm is the population choice requirement for a reasonable solution and encoded with an appropriate encodings scheme. This process aims from its operating rules to generate populations from which the best individual characterized with the highest fitness value (FV) will have the great chance to construct the new generation population. The point we should stress in is the low FV that will serve to discard the individuals that go far from the best solutions the optimization process requires. Hereafter, the algorithm genetic following step concerns the fitness value calculation which is very necessary to estimate the proposed solution through the best offspring that will replace the parents selected for their production [29].

Algorithm terminology is described by different process operations, among which there are:

1 - gene (decision variable): individual element of the chromosome, encoded in a bit string whose value is either 1 or 0 indicating the acceptance or the refusal state of the gene.

2 - Chromosome: is a set of parameters (genes) whose number characterize the chromosome length and define a proposed solution to the problem that the genetic algorithm is trying to solve.

3 - A population: chromosome set.

4 - Fitness function: is a function, which takes a candidate solution to the problem as simulation guide towards optimal design solutions [30]. The value we get across the fitness function calculation, namely the fitness value (FV), is very beneficial to the population in need of optimization since, it is an indicator of individuals to be discarded.

The best essence of this genetic algorithm is a creation of successive generations aiming to achieve optimal solutions that depend strongly on chromosomes qualified as best ones from the fitness value calculated by the SVM classifier.

C. Classification support vector machine (SVM) method

As a statistical learning algorithm, the SVM was introduced by Vapnik in 1960s to solve some problems related to either training time lasting, non-convergence with training samples dimension and additionally to problems related to over-learning to the structure model. Thanks to the developing of the computer science field, researchers have been led in this field by the help of computer tools to give a boost to the emergence of techniques for the SVM and to make them more practice. This great attention has made SVM as a machine-learning concept to be a precise tool for solving problems related to various application fields in engineering [31].

The SVM is an approach of classification and recognition of classes where the data points occupy regions whose borders delimiting each other are unknown. Moreover, the problem that arises is the existence of a data point whose position is not known. The involvement of classification algorithms must be able to predict the location of this point in one of these regions. Indeed, the SVM provides the solution to this classification problem since it has methods to establish the boundaries between two or more categories / classes of data that are either linearly separable or not. Here, the SVM operate with a modelling process in accordance to the way the data is distributed. Two SVM types are set to perform a data processing:

First, a linear SVM classifier deals with data to be trained defined as finite dimensional vector and where data points can be separate linearly by many hyperplanes. Only, the best hyperplane known as an optimal one to keep is the one that can observe the condition of exhibiting a maximal distance with the closet points of either class /category A or B of data points (see Fig. 1).

To give an illustration of the SVM process we use a simple binary classification case of a certain number of samples belonging to two different groups. If these data are linearly separable, this classification is expressed according to the relationship:

$$y_i = f(x_i) = w_0^T . x_i + b_0 \geq 1 \tag{11}$$

With $x_i \in R^n$, i=1 to n and $y_i \in \{-1, +1\}$;

If the equation (11) equal to zero is satisfied, **$||w||^2/2$** is minimized, the hyper plane is said to be optimal. We remind that **$2/||w||$ is** called the classification interval. The points lying on the hyperplanes H1 and H2 are called super vectors. The margin that separates these hyperplanes characterizes the performance and suitability of the SVM classifier (see Fig. 1).

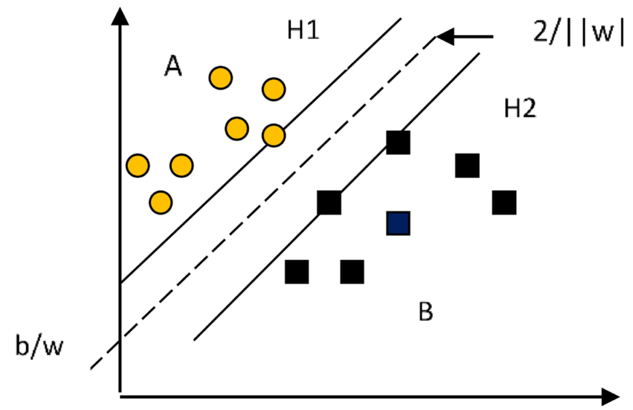


Fig. 1. SVM classification surface.

In general, if optimization problem is raised due to some constraints in finding optimal hyperplanes parameters, a Lagrangian function is introduced [32]. This leads to the solution in the way as the following equation illustrates:

$$y_i = f(x_i) = \sum_{j=1}^{N} \hat{a}_j t_j k(x_i, x_j) + b \tag{12}$$

The optimal parameters being valuable for a set of N support vectors (SVs)will have expression as follow:

$$w_0 = \sum a_i t_i x_i \text{ and } b_0 = \frac{1}{N_s} \sum_i (t_i - \sum_j a_j t_j k(x_i , x_j))$$

The stability of the solution with such b_0 value provides an average over all SVs that expressed as:

$y_{mean} = sign(\sum a_i t_i k(x_i, x_j) + b_0)$, $k(x_i, x_j)$, is the kernel function used mostly with data linearly separable and it is expressed as: $k(x_i, x_j) = x_i^T . x_j$;

At last, the other SVM type is the non-linear one. It deals with data that in reality are linearly inseparable in their finite space. A Mapping process is performed to overcome this situation by transforming this data space into a much higher dimensional one. Thereafter, adapted non-linear hyperplanes can be built by using trick Kernel functions considered as powered functions and we confine our study to the most important ones such as radial basis function (RBF) and polynomial kernel functions with varying degrees and whose expressions are respectively as follow:

1 - RBF $k(x_i, x_j) = e^{(-||x_i - x_j||^2/2\sigma^2)}$;

2 - Polynomial function $k(x_i, x_j) = ((x_i . x_j) + b)^d$, where d is the polynomial degree;

Despite the most suitable kernel function is the RBF, the last one (**polynomial function**) is chosen in our work with six degrees (d=1 to 6). These are examined in order to fetch what accuracy ability the non-linear classification will achieve and the result as discussed later is very amazing.

III. Presentation of Circuit Under Test and Feature extraction

In this section we want to give a presentation of the circuits subjected to the feature extraction approach that will be used to feed the fault classifier. An illustration in a block diagram form is given in Fig.2 showing the different scenarios followed in this approach in two different software environments:

1- PSPICE Environment:

a- Description of CUTs in fault free and faulty simulation in time domain.

b - Collection of sampled input and output signal data of the faulty and fault free circuit

c- Arrangement of this data in a matrix for each CUT operating condition and for each circuit.

2- Matlab Environment:

a - Choice of the SI (Identification System) model for calculating the Transfer Function (TF) of the circuit under study in fault free condition:

- Application of the ARMA, ARX and OE approaches and evaluation of the coefficients and orders of the polynomials

- Evaluation of the accuracy of the model according to the coefficients (ai, bi) and the order (p, q) and selection of the best accuracy and the best fit model.

b - Use of the best model approach for different circuits under different faults:

- Evaluation of the accuracy and the coefficients and orders of the TF polynomials for each fault case

- Selection of the model that gives the best accuracy and best fit and identification of its polynomial coefficients of each fault case.

c - Grouping of all polynomial coefficients (ai bi) in matrix form to be oriented as feature data to fault classification process.

A. *Circuit Under Test*

In this section, we consider an example of two circuits namely a Sallen–Key band-pass filter and Four opamp biquad high pass filter. These circuits have been investigated in several research works [12], [13], [15], [33], and are selected in the present work as a typical models to perform the validation of our proposed approach. Their configurations are illustrated in the Figs. 3 and 4, They are run under the PSPICE simulator which allows us to obtain input and output signals as samples in the time domain. These serve as data to feed the SI modelling process in order to extract the coefficients and orders of the optimal polynomials of the CUT transfer function (TF) using models estimated as described previously. Besides, this process has been applied to these filtering circuits operating under faulty conditions which in our work, are confined to single faults only. The input signal was a mono-pulse signal with the amplitude of 5V and a pulse width **10 µs**. A transient signal analysis is carried out under the aforementioned simulator in order to obtain time domain responses. The CUT's output responses are simulated for both fault-free and faulty cases (see Tables. I and II). Two parametric fault types are of concern and dealing with -50% and +50% component deviation values from nominal ones. Each of these faults are simulated with the Sallen–Key band-pass filter and the Four opamp biquad high pass filter component lists (R1-R5, C1, C2*) and (*R1-R10*, C1, C2)* respectively.

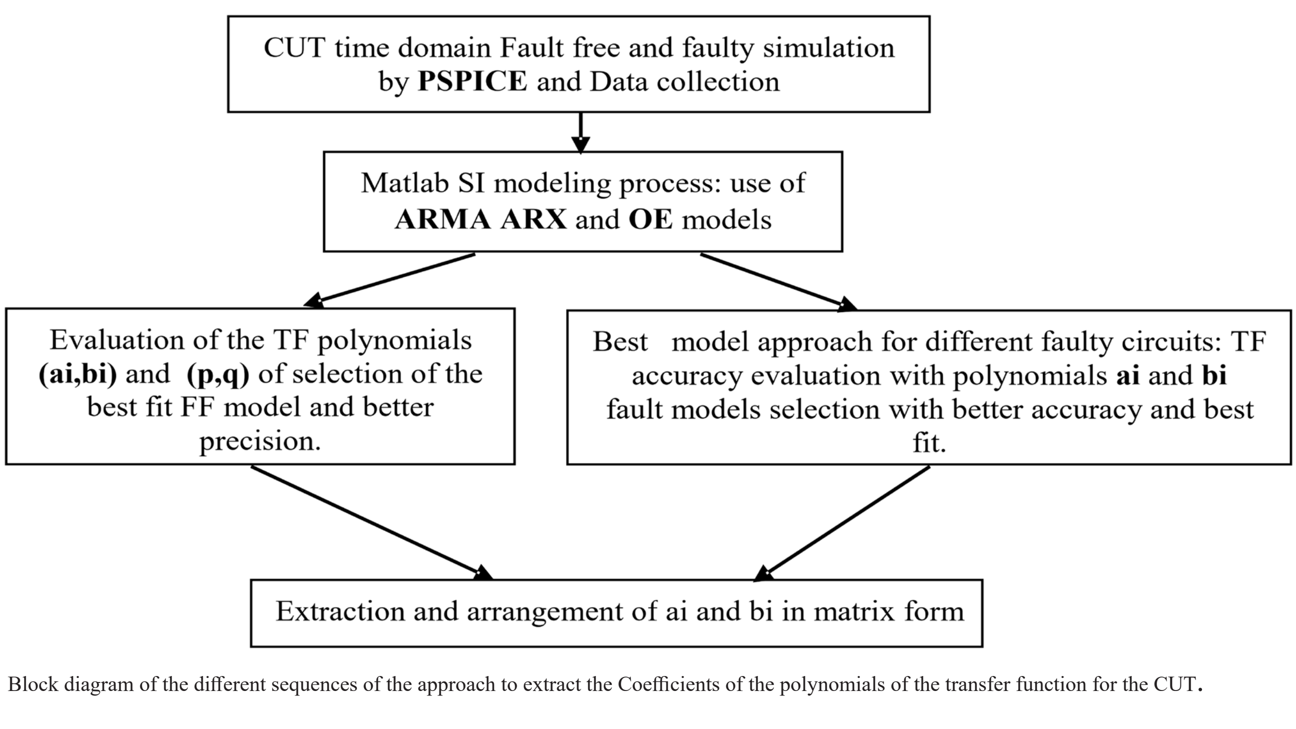


Fig. 2. Block diagram of the different sequences of the approach to extract the Coefficients of the polynomials of the transfer function for the CUT.

B. Results of the experiment circuits

The Parametric faults refer to the degradation parameters of the electronic components at a certain extent. In fact, these are deviation values from nominal ones, called out of tolerance range values as well, and they can be accredited to a large number of components parameters theoretically.

The work carried out in this paper is based on the detection of parametric faults of a Sallen-key band-pass filter and of a Four opamp biquad high pass filter (see Fig. 3 and 4), by extracting the polynomial coefficients and orders from the transfer function of the circuits. This is achieved from the input and output response signals process based on the estimation of the Output-Error model of the identification system. This task is

expended to cover both sane and faulty circuits, whose we assuming that the components are 50% higher or lower than their nominal values [34], as shown in Tables I and II.

1) Fault free circuit signal response analysis and feature extraction

● *First case study circuit*

To ease the understanding of the circuit OE model achievement, were strict our study to the simple filtering circuit known as Sallen-key band pass filter. Before developing the circuit test, one should ensure the good circuit functionality by checking out its nominal specifications such as operating voltage range, frequency bandwidth, lower, upper cut off frequencies

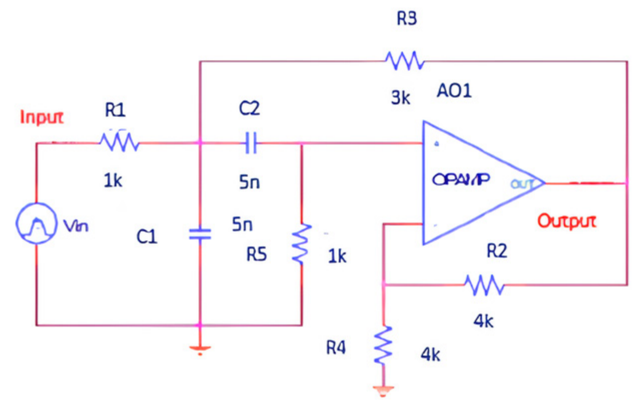


Fig. 3. Sallen–Key band-pass filter configuration.

and so. Thereafter, investigation is set about looking for traces of anomalies, which appear on the circuit function when faulty circuit conditions are concerned. Previous to this, it is necessary to establish a reference signature from electrical parameters of the healthy circuit. At this examination level, one can compare and identify the faulty circuit and then locate and even isolate the faults that occur in it. From the fault free output response signal of this C.U.T run under a one pulse signal test vector, we imported their related data from PSPICE and re-plotted them by MATLAB as seen in Figs. 5(a) and 5(b). From these sketched curves, one can clearly confirm the presence of the high limit frequencies of the signal spectrum. Moreover, one can notice

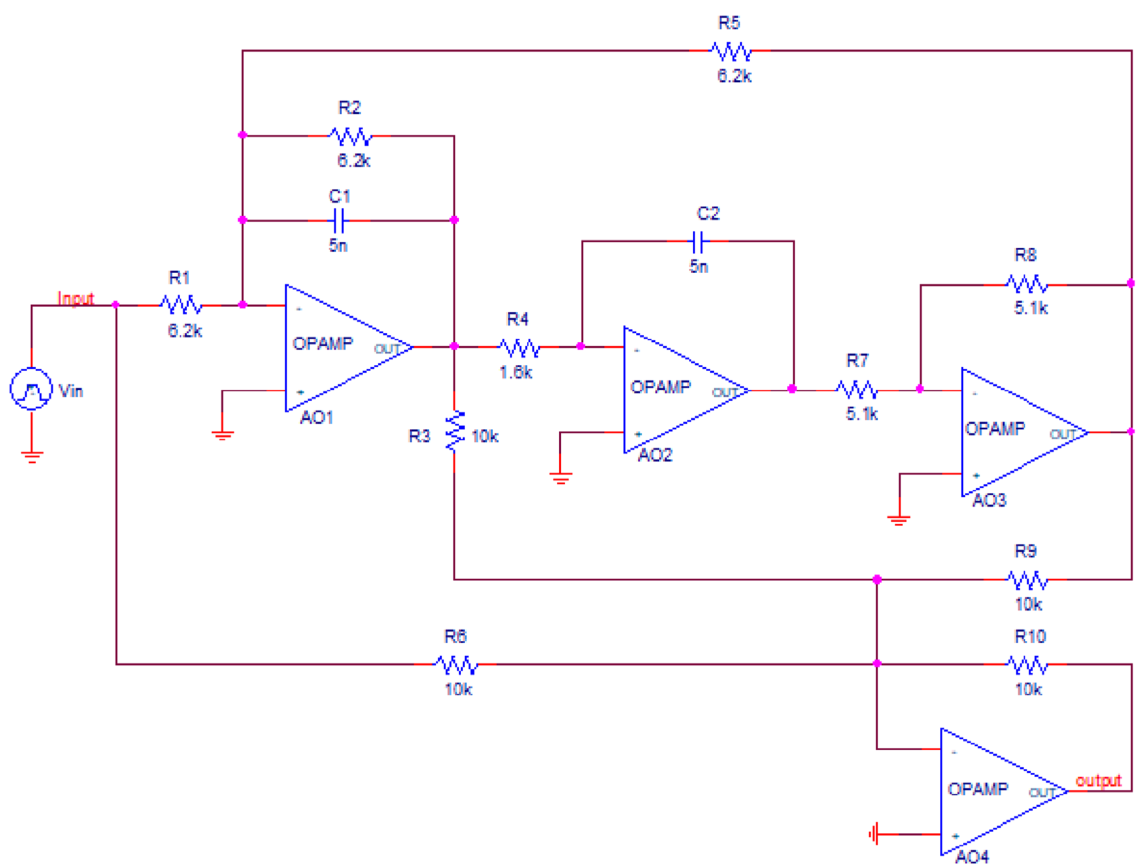
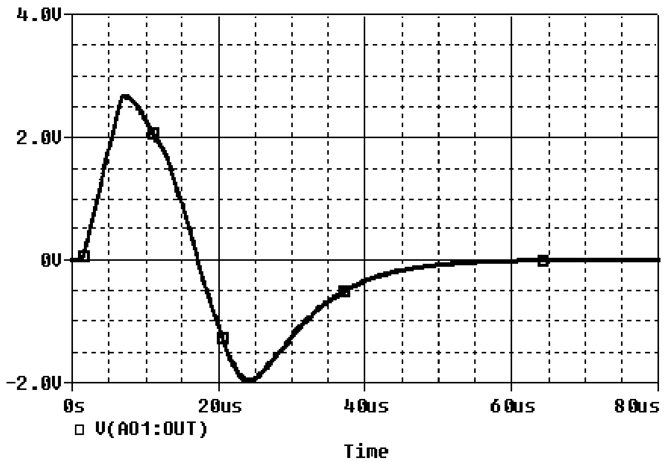


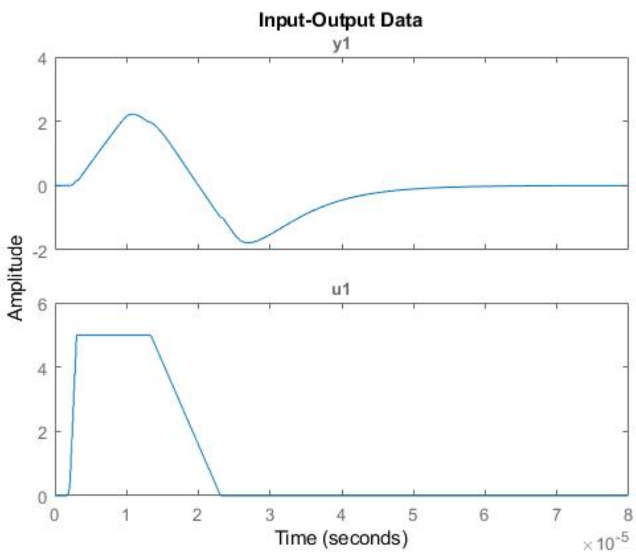
Fig. 4. Four opamp biquad high pass filter configuration.

the output signal form and the level of the signal attenuated up to 2.22V (Fig. 5a).

The two signals characteristics (u1 and y1) depicted in Fig. 5b constitute efficient key parameters to the development of the circuit reference signature. This is accomplished by a very appropriate signal processing under MATLAB software during the linear circuit model building process according to the mathematical approach OE, where the white noise e(t) is chosen as negligible element in our study's case. The characteristics identification of this band-pass filter is carried out according to the difference between the orders polynomials (p,q) and between the number and values of the polynomial coefficients a_p, b_q of the three aforementioned models. One may pay attention to the fact that for each model, different sets of coefficients values and orders as well are provided with regard to the model accuracy level required. From this purpose of which is to choose the optimal accuracy in both fault free and faulty circuit conditions but preserving the essence of a best fault coverage. The signals shown in Fig. 5, are the PSICE output signal of the circuit and the signal resulting from the estimated model. As far as this model result is concerned, it is noted down that the polynomials orders (p,q) of the OE model has shown a best smoothing and a high accuracy (98.17%) with polynomial orders (p,q) equal to (8,9) according to the data drawn on the right side-box of the Fig. 6.



(a)



(b)

Fig. 5. (a): Fault Free Output signal by PSPICE, (b): Fault Free Input-Output signals by MATLAB for a sallen-key band pass filter.

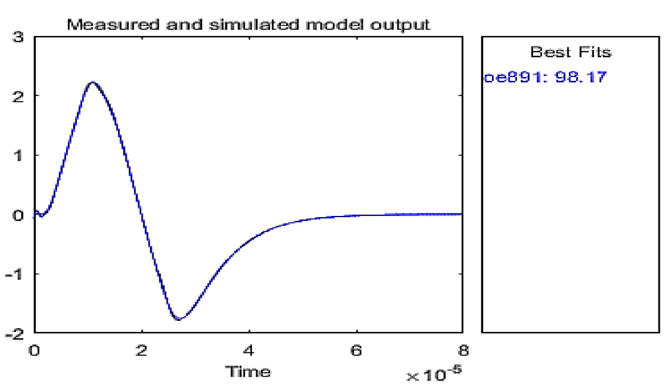


Fig. 6. Plot of measured and estimated orders of OE model output-F0- for a sallen-key band pass filter.

This is an accuracy model option we respected for all circuit faulty conditions and on which will stand the efficiency and credibility of the proposed fault classifier.

In this given data box untitled "Best fit" figure, one can notice the model OE information included numerical values whose three of them refer to the p, q polynomial orders and noise neutrality e equal to 1. The fourth one deals with the accuracy level value corresponding to the curve best fit. These informing notes appear with resulting OE models for all circuit operating conditions. From the analysis of the model result data, it is cumbersome to report the required model data. Thus, we have confined this study to the best and the worst model accuracy levels whose results are sum up in Table III. This indicates the minimum and the maximum values of accuracy level (Amin, Amax) achieved being achieved by the OE model polynomial orders couples $(p, q)_{Amin}$ and $(p, q)_{Amax}$ respectively, for the orders model. Concerning the rest of the polynomial orders couples (p, q), their accuracy ratios are ranged between these boundary levels and they have been discarded due to their worthless contribution to an accurate model construction. As a matter of fact, the results from the scope of this recapitulated study that the OE model is favorably selected for this purpose, As reported in Table III the best maximum average accuracy (98.17%) is scored with this Model and which is far better than those of ARMA and ARX.

- *Second case study circuit*

The Four Opamp Biquad filtering circuit is subjected to modeling process using these three approaches in order to reach out the most precise model used later for the classification of faults in a precise and credible way. By applying the input mono-pulse signal used in the first circuit case, the response of the second CUT by PSICE was that given in Fig. 7.

In order to obtain an accurate circuit model, the processing of the two input and output signals as PSPICE data, is carried out by these three approaches (OE, ARX AND ARMA) implemented in the MATLAB environment. According to the results

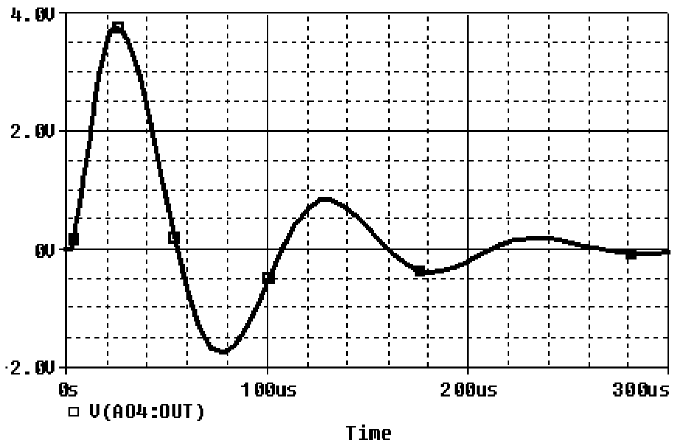


Fig. 7. Fault Free Output signal by PSPICE for a Four Opamp Biquad filter.

collected, the OE model was remarkable once again showing a better fitting displaying a higher precision than those of the other models as illustrated in Table IV. This latter displays both the minimum and maximum accuracy values and their corresponding polynomial orders.

2) Parametric Fault effect on circuit signal response

● *First case study circuit*

The faulty circuit simulation is accomplished in the same way as that of a healthy circuit is done. The impulse response of the CUT was recorded for all possible parametric fault scenarios and are judged necessary in our fault diagnosis work.

Two parametric faults that correspond to +50% and -50% deviations from the component nominal value are simulated for all circuit components (R1, R2, R3, R4, R5, C1, C2). Due to the data that require the fault analysis, we confine the study of the component fault such as a resistor R1-50% (F2). In terms of polynomial orders and coefficients values changes, these parameters have been computed from the implemented OE approach. The objective being fixed is to fetch for both the best orders and coefficients of the transfer function polynomial that contribute so much to a best model accuracy level on one hand, and to select the most convenient orders that will be conducted to set a fault analysis for the selected parametric fault.

TABLE I
Nominal and Parametric Fault Values for a Sallen-Key Band Pass Filter.

Fault ID	Element	Nominal value	Fault type	Faulty value
F0	-	-	FF	-
F1	R1	1kΩ	R1+50%	1.5kΩ
F2	R1	1kΩ	R1-50%	0.5kΩ
F3	R2	4kΩ	R2+50%	6kΩ
F4	R2	4kΩ	R2-50%	2kΩ
F5	R3	3kΩ	R3+50%	4.5kΩ
F6	R3	3kΩ	R3-50%	1.5kΩ
F7	R4	4kΩ	R4+50%	6kΩ
F8	R4	4kΩ	R4-50%	2kΩ
F9	R5	1kΩ	R5+50%	1.5kΩ
F10	R5	1kΩ	R5-50%	0.5kΩ
F11	C1	5nf	C1+50%	7.5nf
F12	C1	5nf	C1-50%	2.5nf
F13	C2	5nf	C2+50%	7.5nf
F14	C2	5nf	C2-50%	2.5nf

TABLE II
Nominal and parametric fault values for Four Opamp Biquad High Pass Filter

Fault ID	Element	Nominal value	Fault type	Faulty value
F0	-	-	FF	-
F1	R1	6.2kΩ	R1+50%	9.3kΩ
F2	R1	6.2kΩ	R1-50%	3.1kΩ
F3	R2	6.2kΩ	R2+50%	9.3kΩ
F4	R2	6.2kΩ	R2-50%	3.1kΩ
F5	R3	10kΩ	R3+50%	15kΩ
F6	R3	10kΩ	R3-50%	5kΩ
F7	R4	1.6kΩ	R4+50%	2.4kΩ
F8	R4	1.6kΩ	R4-50%	0.8kΩ
F9	R5	6.2kΩ	R5+50%	9.3kΩ
F10	R5	6.2kΩ	R5-50%	3.1kΩ
F11	R6	10 kΩ	R6+50%	15 kΩ
F12	R6	10 kΩ	R6-50%	5 kΩ
F13	R7	5.1 kΩ	R7+50%	7.65 kΩ
F14	R7	5.1 kΩ	R7-50%	2.55 kΩ
F15	R8	5.1 kΩ	R8+50%	7.65 kΩ
F16	R8	5.1 kΩ	R8-50%	2.55 kΩ
F17	R9	10 kΩ	R9+50%	15 kΩ
F18	R9	10 kΩ	R9-50%	5 kΩ
F19	R10	10 kΩ	R10+50%	15 kΩ
F20	R10	10 kΩ	R10-50%	5 kΩ
F21	C1	5nf	C1+50%	7.5nf
F22	C1	5nf	C1-50%	2.5nf
F23	C2	5nf	C2+50%	7.5nf
F24	C2	5nf	C2-50%	2.5nf

TABLE III
Presentation of levels (Minimum and Maximum) of the accuracy of the Models ARMA, ARX and OE for a Sallen-Key band pass filter.

Model	$(p,q)_{Amax}$	Amax (%)	$(p,q)_{Amin}$	Amin (%)
ARMA	(2,6)	63.42%	(1,9)	13.43%
OE	(8,9)	98.18%	(1,4)	94.36%
ARX	(2,6)	63.42%	(1,9)	13.43%

TABLE IV
Presentation of levels (Minimum and Maximum) of the accuracy of the Models ARMA, ARX and OE for a Four Opamp Biquad High Pass Filter.

Model	$(p,q)_{Amax}$	Amax (%)	$(p,q)_{Amin}$	Amin(%)
ARMA	(9,2)	86.44%	(8,4)	-2.139%
ARX	(9,1)	72.69%	(1,1)	4.964%
OE	(2,5)	97.06%	(9,7)	-3.487

As a fault analysis characteristic, a polynomial order (p,q) investigation is carried on the selected model aiming to find p, q values discrepancies while comparing to those of the healthy

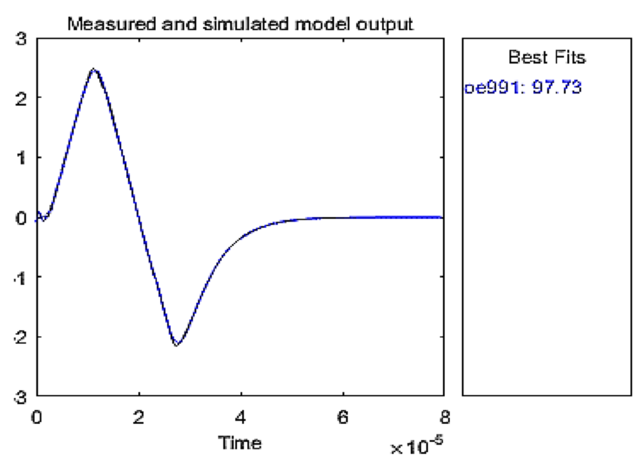


Fig. 8. Plot of measured and estimated orders of OE model of parametric fault F2.

circuit. For each parametric fault we applied the aforementioned approach to estimate its equivalent orders.

In any fault case, a change observed at the output circuit response is interpreted as a change of this characteristic and thus leading to the resulting model polynomial orders (p,q) and coefficients values variations of the resulting model while comparing it to the fault free ones. For instance, in the F2 fault case, the OE model (p,q) are found to be (9,9) and from which a comparison made with the fault free case (F0) has depicted a difference through the p polynomial order passing from 8 to 9, and with a model accuracy of 97.73%, as shown in Fig.8. However, this parameter cannot dissociate the ambiguous faults from each other, for example, faults F2 and F6 that have same polynomial orders (9,9). To solve this troublesome, a use of polynomial coefficients has been intervened as a key solution.

The examination of these coefficients as fault detection features, and from the examination of Table V, revealed impressive fault coverage points and the total distinction of faults. For instance, as fault detection process is concerned, a column by column scan of this table, namely from the F0 column to the F14 one, lets us notice different a_p and b_q values in all operating circuit conditions. This assertion proves that a 100% fault coverage ratio is accomplished successfully. In fact, the examination of this table data of all faults cases has driven us to conclude two main points: a complete absence of the ambiguity problem is achieved with the polynomial coefficients whose values are distinguishable to each other for all the fault free and faulty cases. Though the result is very probing, the task is still very hard to achieve and time consuming, thus a use of fast fault classifier is essential and crucial.

TABLE V

THE COEFFICIENT VALUES *AI(I=1; …;P)* AND BJ(J=1; …;Q) AND *MAXIMUM ACCURACY (***AMAX***)* OF THE SELECTED OE MODEL OF SALLEN-KEY BAND PASS FILTER.

Faults	F0	F1	F2	F3	F4	F5	F6	F7
a1	-0.2163	0.0478	-0.3218	-0.1774	0.1454	-0.0622	-0.1543	0.0341
a2	1.0916	-0.3214	1.7126	0.9225	-0.8565	0.3588	0.6904	-0.2680
a3	-2.0752	0.9261	-3.6925	-1.8595	2.1124	-0.8648	-1.0288	1.0010
a4	1.5579	-1.4800	4.0921	1.6567	-2.7913	1.1167	0.2435	-2.2748
a5	0.2612	1.4155	-2.5126	-0.2713	2.0840	-0.8160	0.8357	3.3564
a6	-1.2093	-0.8095	1.0596	-0.6417	-0.8334	0.3204	-0.7242	-3.2274
a7	0.7445	0.2560	-0.5903	0.4757	0.1395	-0.0528	-0.0220	1.9499
a8	-0.1543	-0.0345	0.3331	-0.1048	0	0	0.2310	-0.6718
a9	0	0	-0.0802	0	0	0	-0.0712	0.1007
b1	-3.7348	-4.8823	-3.9771	-4.2020	-4.6732	-3.8465	-3.6470	-4.4537
b2	3.7923	9.0388	4.7602	5.6583	8.0070	4.5082	3.2466	6.6990
b3	1.4037	-7.2513	0.1454	-1.0502	-5.2093	-0.4791	2.8420	-2.1360
b4	-3.5926	1.5824	-3.2240	-2.6240	-0.4124	-0.9696	-5.3947	-3.8360
b5	-0.2031	0.3310	-0.1706	-0.9673	1.1697	-2.3150	0.1680	2.6115
b6	1.0963	0.9329	2.1319	-4.389	1.0897	2.1640	3.0460	1.5860
b7	1.7379	-0.9496	0.0821	2.5377	-1.3223	1.3091	-0.8916	-1.9999
b8	-2.0788	0.1592	-1.1343	0.2070	0.3508	-1.9136	-0.6557	0.5292
b9	0.5792	0.0390	0.3865	0.1269	0	0.5424	0.2863	0
Amax	**98,18%**	**99.19%**	**97,73%**	**98.74%**	**98.91%**	**98.28%**	**97.75%**	**99.05%**
Faults	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**	**F14**	
a1	-0.1380	-0.1059	0.1222	-0.1660	0.1327	-0.0213	-0.1113	
a2	0.9640	0.6281	-0.6619	1.0064	-0.8700	0.1114	0.6516	
a3	-2.9671	-1.6292	1.4423	-2.6672	2.4565	-0.1987	-1.5934	
a4	5.2669	2.473	-1.5446	4.1196	-3.8778	0.0398	2.0842	
a5	-5.9187	-2.5058	0.7174	-4.2004	3.7100	0.3770	-1.5384	
a6	4.3313	1.8263	0.0549	3.0260	-2.1706	-0.6390	0.6077	
a7	-2.0269	-0.9595	-0.1790	-1.5476	0.7376	0.4936	-0.1004	
a8	0.5579	0.3246	0.0488	0.5080	-0.1250	-0.1947	0	
a9	-0.0695	-0.0515	0	-0.0787	0.0065	0.0318	0	
b1	-4.9285	-4.9221	-4.0743	-4.9086	-4.8524	-4.8666	-4.8384	
b2	9.7193	9.6944	4.9792	9.6413	8.0732	9.4765	9.1338	
b3	-9.5870	-9.5502	0.7259	-9.4718	-2.7567	-9.2294	-8.7526	
b4	4.7299	4.7057	-5.5733	4.6542	-6.9055	4.4958	6.3239	
b5	-0.9338	-0.9278	2.0620	0.9151	7.0269	-0.8762	-7.2548	
b6	0	0	2.8677	0	1.2577	0	8.1019	
b7	0	0	-2.6127	0	-5.1985	0	-5.0625	
b8	0	0	0.6255	0	2.8908	0	1.5049	
b9	0	0	0	0	-0.5356	0	-0.1562	
Amax	**98.16%**	**98.12%**	**98.89%**	**98.2%**	**99.33%**	**98.61%**	**97.55%**	

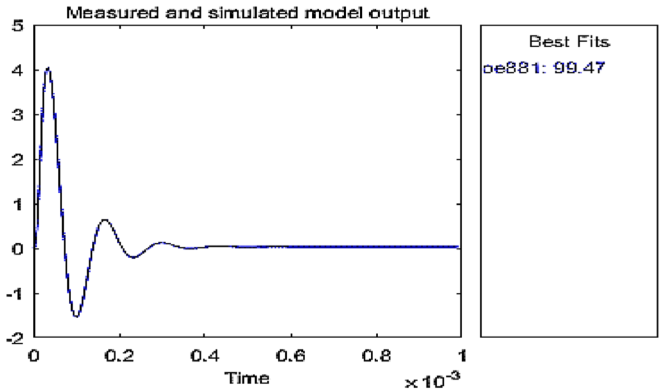


Fig. 9. Plot of measured and estimated orders of OE model of parametric fault F10.

● *Second case study circuit*

In the Biquad circuit case, and due to the higher number of faults taken into account than the previous circuit, we examined only one fault, namely F10 (R5+50%) to highlight the fault modelling process using the OE approach. According to Fig. 9, the effect of this fault manifested according to this approach through the values of the polynomial coefficients and orders according to this approach. The order values p=8 and q=8 allowed the best fitting of the signal providing a model accuracy of 99.47%.

This working sequence is repeated for the fault set of this second circuit. Their OE models having provided the best accuracy (Amax) are maintained for the benefit of the fault classification. The accuracy values of these fault models as well as their polynomial orders and coefficients are also are reported in Table VI.

TABLE VI
THE COEFFICIENT VALUES (P,Q) AND MAXIMUM ACCURACY (**AMAX**) OF THE SELECTED OE MODEL OF OPAMP BIQUAD HIGH PASS FILTER.

Faults	**F0**	**F1**	**F2**	**F3**
(p,q)	(2,5)	(6,4)	(9,8)	(3,4)
A_{max}	97,06%	92,11%	99.31%	99.27%
Faults	**F4**	**F5**	**F6**	**F7**
(p,q)	(9,8)	(7,6)	(9,6)	(9,5)
A_{max}	95.72%	98.7%	95.41%	93,84%
Faults	**F8**	**F9**	**F10**	**F11**
(p,q)	(7,5)	(7,9)	(8,8)	(6,8)
A_{max}	97.74%	97.95%	99.47%	98.68%
Faults	**F12**	**F13**	**F14**	**F15**
(p,q)	(8,5)	(8,4)	(6,9)	(6,9)
A_{max}	97.54%	93.77%	99.41%	99.43%
Faults	**F16**	**F17**	**F18**	**F19**
(p,q)	(9,5)	(9,5)	(8,5)	(9,7)
A_{max}	96.69%	95.46%	95.72%	98.44%
Faults	**F20**	**F21**	**F22**	**F23**
(p,q)	(8,9)	(1,4)	(6,9)	(8,4)
A_{max}	93.12%	95.26%	97.44%	93.01%
Faults	**F24**			
(p,q)	(9,8)			
A_{max}	99.26%			

IV. THE FAULT CLASSIFICATION IMPROVEMENT BY THE GA-SVM COMBINATION APPROACH

The SVM approach play an important role in efficiently classifying datasets even these are non-linear. This data processing is possible due to the use of SVM Kernel Functions. It also disposes of capabilities of preventing the machine learning from over fitting [35]. However if the classifier is dealing with a huge amount of data this will slow the speed of data processing and even affect the accuracy with data points that are useless and redundant as well.

This situation conducts to a poor performance interpreted as more or less significant decline in the overall accuracy of the classifier.

The idea of improving the fault classification haunted our minds and led us to use genetic algorithms, which remain among many others a much desired and competitive optimization approaches.

This task is part of an idea framework serving a selection of the best groups of features that can contribute to raising the accuracy rate of the SVM classifier according to the "one against all" strategy. It is true that the best features are obtained through the Fitness value (FV) counted from the polynomial Kernel function of the SVM that the GA chooses as the Fitness function (FF). This is a polynomial type whose order of which is chosen between 1 and 6 in order to achieve the expected accuracy rate.

This choice is made to highlight the efficiency that the degree of this polynomial function can produce in terms of accuracy. The criterion for stopping the evaluation of the fitness value is established according to the maximum precision reached which is 100% for each class that each best performer can compete among its pairs. This operation is summarized as stipulated in the diagram given in Fig. 10. This hybrid classification approach is carried out according to different process running steps, which are described as follows:

- In first step the data organized in a matrix form are processed simultaneously as training data and test data.

- The second step: the training data processed by GA for optimization purpose generates subgroups of best features with the smallest possible number. It consists of:

1- Random selection of the initial population, which is made up of 18 features in 20 iterations each representing an individual, or a chromosome. This is a bit string sequence coded in binary whose value is 0 or 1 indicating the gene to preserve as a best feature or a feature to be rejected respectively.

2-The classification of best chromosome (best feature) goes through the evaluation of the polynomial kernel function of the SVM model chosen as fitness function. The Fitness value (FV) reached as the difference between the value of this model output and that of the test data (Y_{fit} -Y_{test}) while displaying the highest possible accuracy (AC) of the classifier. The individuals that provide best fitness value are retained as best parent elements for the generational process.

- Third step: for this same population, the GA treatment for searching better chromosomes follows its 3 usual operators of the approach, namely selection, crossing and mutation, whose rate values are fixed beforehand. Parent chromosomes selected by default will give offspring's (new features) replacing their parents according to mutation and crossover rates that can ensure the highest possible classifier accuracy level. This process is repeated from its first phase for the next chromosome within its iteration number of individuals fixed at 20.

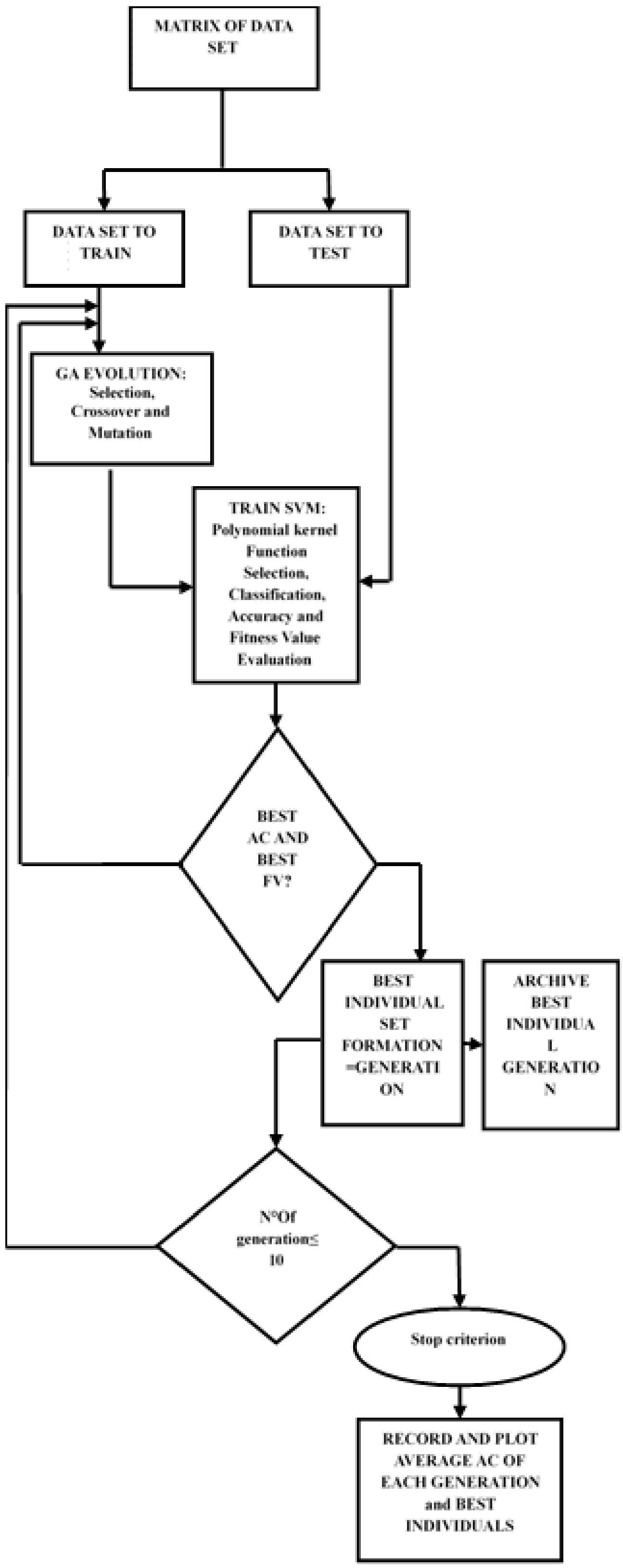


Fig. 10. Flow chart of fault classification and optimization using GA-SVM combination.

- The fourth step: the new chromosomes retained as best ones will constitute the first generation of a new population where an overall precision rate is estimated over all the chromosomes resulting from this population. The number of generation is fixed at 10. This number is judged sufficient for the optimization of the classifier performance since the fitness value is stabilized at same and constant level from the sixth generation and up (see Fig. 10).

- The fifth step: each generation corresponding to a new set of best chromosomes is serving to create next new generation aiming to target the highest AC (100%) with the best FV(FV=0). The genes of the chromosomes that contribute to these values are put into archive for future usage. The process continue until reaching the stop criterion.

The average accuracy is computed for the best individuals of each generation and the FV values as well. This will help to see the classification and the optimization evolution are performed.

V. Results and Interpretation

Combined use of GA-SVM for feature optimization and reduction, using different SVM polynomial kernel functions is intended to improve classifier accuracy and eliminate parameters that cause redundancy and lead to performance drop.

The learning data used by this GA-SVM approach served both the selection of the best features with a reduced number and giving better precision. This says that the kernel function polynomial chosen for the classifier improvement represents also the fitness function whose value maintained for the selection of these features is depending on the level of classifying precision, which must be as high as possible in the classification process. The individuals or the best ones are produced beforehand according to the generational principle. This aims at a selection of parent chromosomes allowing to produce after crossing at a rate of 0.2 to new feature solutions that will undergo a mutation with a probability of 0.01. These offspring representing new best features constitute the first generation and serve to constructing a new population with a better classification accuracy than the previous one. This is evaluated from the calculation of the fitness value from the Kernel polynomial function of the SVM classifier. This generational process will stop at the generation that provides the highest accuracy and the features selected will be identified.

The fitness function (FF) involved in the calculation, considered as a selection criterion for the best feature, is chosen as a kernel function of the polynomial type whose order varies from 1 to 6 in order to highlight the one that provides the best performance of the classifier. On the other hand, the other parameters sigma and C are chosen by default and whose SVM algorithm provides this possibility.

In order to validate the GA-SVM approach proposed in sight to improving the classification process, the two circuits mentioned previously underwent the new experiment, to which detailed study is limited to the classifier whose polynomial Kernel function has led to a better accuracy result. The rest of the classifiers have their results displayed in Tables VII and VIII.

In the Sallen–Key band-pass filter case, we observe in Fig.11 that in the Linear SVM with a polynomial order 1, the fitness value is decreasing from the first generation to the tenth one leading to a mean average fitness value of 9.35% while the best one is about 8.001 % that correspond to a 92% as a classifier accuracy. This has been achieved with some polynomial coefficients as the optimized features obtained and that are (a_2, a_3, a_4, a_6, a_7, a_9, b_1, b_2, b_3, b_4, b_7) as depicted in Fig. 11.

In SVM classifiers with polynomial order superior to 1, the accuracy has been improved in an impressive way reaching a high score value (100%) and with more or less important reduced number of features. For instance, the Quadratic and Cubic SVM classifiers attain an accuracy of 100% with six and four features [a_1, a_5, a_8, b_1, b_3, b_7], [a_5, a_8, b_1, b_5] respectively (see Table VII). Though, among these classifiers, the best of them are achieved got through the Fine, Medium and coarse Gaussian SVMs corresponding to polynomial orders 4, 5 and 6 respectively. They demonstrated a good classifier performance, they scored a 100% as an accuracy level with three best feature sets corresponding to [a_4, b_1, b_5], [a_9, b_2, b_5], and [a_5, b_2, b_4].

TABLE VII
RESULTS OF THE ESTIMATED MODEL OE GA-SVM SALLEN–KEY BAND-PASS FILTER.

OE-GA-SVM	Accuracy	Features (Coefficients ai and bi)
OE-GA-Linear SVM (1)	91.99%	a_2, a_3, a_4, a_6,a_7, a_9, b_1, b_2,b_3, b_4, b_7
OE-GA-Quadratic SVM (2)	100%	a_1, a_5, a_8,b_1, b_3, b_7
OE-GA- Cubic SVM (3)	100%	a_5, a_8, b_1, b_5
OE-GA-Fine Gaussian SVM (4)	100%	a_4, b_1, b_5
OE-GA-Medium Gaussian SVM (5)	100%	a_9, b_2, b_5
OE-GA-Coarse Gaussian SVM (6)	100%	a_5, b_2, b_4

An illustration of the SVM classifier using polynomial order 5 as a Kernel function is given in Fig. 12 where the best fitness value is about a 0.0003 corresponding almost to **100%** of accuracy level.

Concerning the Four opamp biquad high pass filter, the classification process based on the Linear SVM (polynomial order 1) as Kernel function has required too many polynomial coefficients as optimized features as recorded in Table VIII (a_2, a_3, a_4, a_6, a_7, b_1, b_4, b_5, b_6, b_8, b_9) to achieve an accuracy of 88.20% (see Fig. 13). However, in the Coarse Gaussian SVM (polynomial order 6), the least optimized features (a_9, b_2, b_4, b_7) were found to be sufficient to an accuracy achievement of 100% (Fig. 14). In this case, once again the estimated OE model with GA-SVM

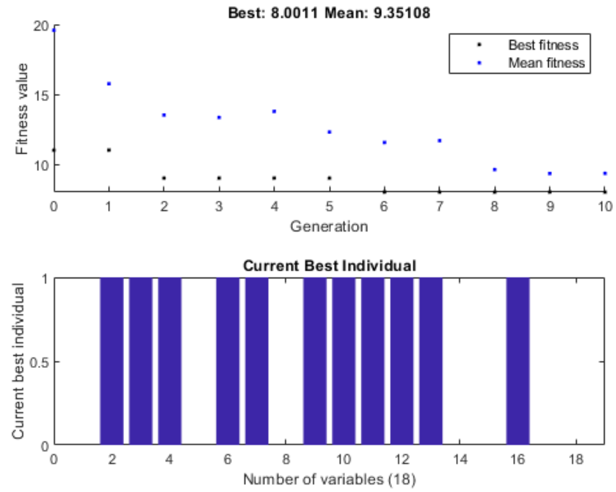


Fig. 11. OE-GA-Linear SVM of Sallen key circuit: Fitness value and best individuals.

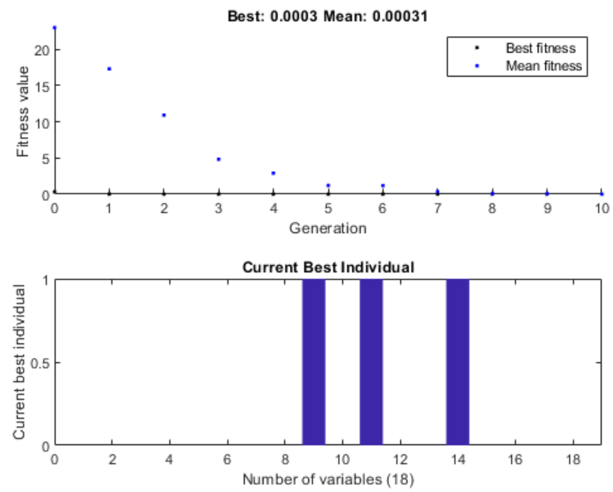


Fig. 12. OE-GA-Medium Gaussian SVM of Sallen key circuit: Fitness value and best individuals.

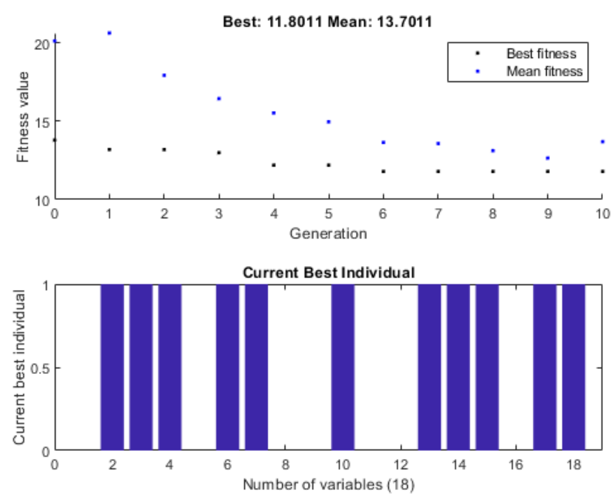


Fig. 13. OE-GA-Linear SVM of Biquad circuit: Fitness value and best individuals.

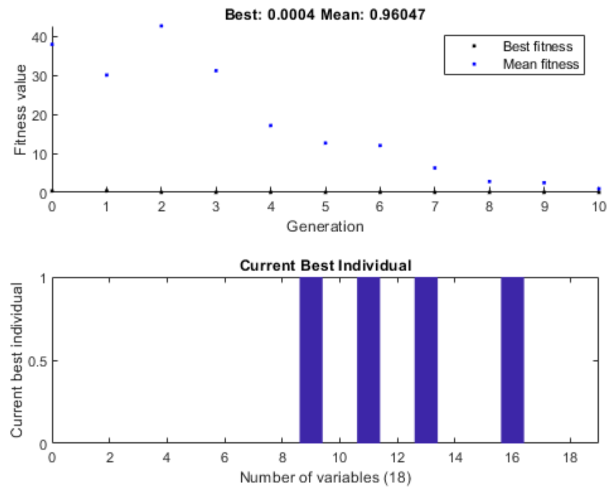


Fig. 14. OE-GA-Coarse Gaussian SVM of Biquad circuit: Fitness value and best individuals.

by the Coarse Gaussian kernel function (polynomial order 6) confirms its performance of the best classifier with low dimensional features and best best classifier accuracy.

TABLE VIII
Results of the estimated model OE with GA-SVM
Four opamp biquad high pass filter.

OE-GA-SVM	**Accuracy**	**Features (Coefficients ai and bi)**
OE-GA-Linear SVM (1)	88.20%	a_2, a_3, a_4, a_6, a_7, b_1, b_4, b_5, b_6, b_8, b_9
OE-GA-Quadratic SVM (2)	100%	a_2, a_3, a_6, a_8, b_1, b_5, b_6,b_7, b_9
OE-GA- Cubic SVM (3)	100%	a_2, a_6 , b_1, b_5, b_8
OE-GA-Fine Gaussian SVM (4)	100%	a_4, a_8, b_4, b_5, b_7
OE-GA-Medium Gaussian SVM (5)	100%	a_9, b_1, b_3, b_4, b_6, b_7
OE-GA-Coarse Gaussian SVM (6)	100%	a_9, b_2, b_4, b_7

In order to validate the proposed paper work and to make it more convincing, we compare it with other research works, made recently with different extracting methods of features and classifiers through the accuracy computation as shown in

Table IX. We find that more means of classification and optimization make it easier to improve the efficiency and accuracy of classifiers. For examples in reference [13] the method gives an accuracy of 99.92% in circuit case 1 and 99% in circuit case 2. Another research work ref. [8], has shown interesting accuracy values reaching 100% and 99.68% in circuit case 1 and circuit case 2 respectively. In our present work the OE method used for feature extraction appears to be 100% effective in detecting and locating all faults. Additionally, its combination with the GA and SVM methods has improved so much both efficiency and accuracy of the classifier. This is said on the basis of an 100% accuracy achievement in the two CUTs and a feature number lowered from 18 to 3 in circuit case 1 and 4 in circuit case 2.

TABLE IX
Results of different methods.

Methods	Accuracy (case 1)	Accuracy (case 2)
Reference 8	100%	99.68%
Reference 13	99.92%	99%
OE-GA-SVM	**100%**	**100%**

VI. Conclusion

In this work we proposed a classifying single parametric faults method for two filtering analog circuits: Sallen–Key bandpass filter and Four Opamp Biquad high pass filter. The proposal is based on the use of estimated system identification (S.I.) output error (OE) model for feature extraction purpose and combination of two methods GA-SVM. The objective behind such a technique is to find a solution for best prediction and detection of faults in these circuits. The feature extracting method consists of identifying parameters the circuit models are built with under faulty and fault free conditions. These model parameters are in fact the polynomial coefficients of the transfer function (TF) deduced from the CUT time domain input and output signals. These famous filtering circuits have served as investigating elements for a model construction purpose and were run in a PSPICE simulator environment. The collected simulation data have been processed with a MATLAB software tool to extract the transfer function coefficients that characterize the circuit models. To preserve the model accuracy, three estimated model approaches were undertaken and are based on ARMA, ARX and OE approaches implemented in a MATLAB S.I. algorithmic tool. The results obtained for these models confirm that the estimated OE model has proven its efficiency when compared to the two others (ARMA and ARX models). From the best fault detection point of view optimal model accuracies of 98.17%, 99.33% and 97.06%, 99.47% have been achieved for both fault free and faulty cases of the two CUTs respectively and no ambiguity problem was encountered with this kind of model as well. These accuracy values have been scored with 18 polynomial coefficients of each. As a result, a huge amount of data was collected covering all faulty circuit conditions and under 20 iterations run for efficiency classifier raison. These results are optimized and classified with combination of GA and SVM methods to obtain a best accuracy of 100% with a dimensional reduction of 3 features in the first circuit case and 4 others in the second one, thus scoring a feature data reduction rate of more than 70%.

In perspective, we plan to broaden this approach in order to touch different analog circuits and to cover all the electrical parameters that can be affected by the presence of faults. Concerning the latter, the study will concern both hard and parametric faults and whether they are singular or multiple in their occurrence.

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