Automated Selection of Test Frequencies for Fault Diagnosis in Analog Electronic Circuits

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***Abstract*—This paper suggests three novel methods for selecting the frequencies of sinusoidal test signals to be used in fault diagnosis of analog electronic circuits. The first and second methods are based on a sensitivity analysis and show to be particularly effective in linear circuits where a priori information and designer experience can be exploited. Conversely, the third method selects the input frequencies to be used for diagnostic purposes without requiring any hypothesis about the circuit or testing design background. As such, the method is particularly appealing in complex—possibly nonlinear—circuits where the designer experience is of little value and an effective "blind" approach saves both designer and testing time. The suggested frequency selection methods are then contrasted to each other against performance and computational complexity.**

***Index Terms*—Analog circuit diagnosis, test frequency selection.**

I. INTRODUCTION

THE paper addresses the automated single fault location issue in analog electronic circuits by considering the simulation before test approach (SBT) [1]–[10] and the harmonic analysis [1]. Fault diagnosis is carried out by comparing the actual circuit under test (CUT) response (when the circuit is excited by a predefined set of sine waves) with a set of labeled response examples contained in a fault dictionary (previously built by simulating the circuit both under regular functioning and faulty conditions). Fault detection and isolation is achieved with a classifier, which makes a decision based on the signature differences between the actual CUT responses and the stored ones.

Here, we follow the harmonic analysis framework which requires that the input stimuli exciting the CUT are sinusoidal signals at different frequencies; solutions based on the wide band stimuli approach (e.g., white noise [10] or arbitrary waveforms [7]) are more efficient in terms of analysis time but provide a reduced signal-to-noise ratio (SNR) and require a more complex test setup.

It is well known that simulation after test (SAT) and SBT are alternative approaches to the fault diagnosis in analog circuits [11]. The SAT diagnosis involves a mathematical description of the circuit during test [12] that enables to explicitly solve for the values of internal parameters of the CUT from a sufficiently large set of independent measurements. SAT methods require costly circuit simulations to be carried out in real time and, as such, are time-consuming procedures. This problem is solved by SBT techniques which, conversely, require a very short time to implement the test phase. Moreover, SBT techniques are more versatile: they can be used in any domain (parameters, frequency and time) and for any circuit (linear or nonlinear) provided an efficient simulation engine (e.g., those used in analog circuit design). In a way, the main disadvantage of a SBT approach is related to the computational effort required to simulate off-line a sufficiently large set of fault conditions; nevertheless, this computational effort is required only once, before any test activity is considered.

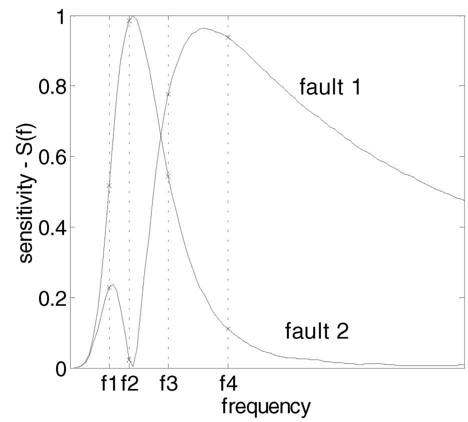

Fig. 1. Sensitivity curves corresponding to two single fault conditions.

The SBT approach in the diagnosis of analog electronic circuit can be summarized in three steps:

- Selection of a suitable set of stimuli exciting the CUT; stimuli must be chosen to maximally amplify the presence of faults (within the harmonic analysis this step requires selection of the sinusoidal stimuli frequencies).
- Selection of the parameters/features to be considered for constructing the fault dictionary (e.g., test node voltage magnitudes or phases, current magnitudes or phases).
- Design and configuration of the classifier by using the fault dictionary.

The construction of the fault dictionary and configuration of the classifier are hence two fundamental topics in the SBT diagnosis analysis and their optimization represents a critical issue.

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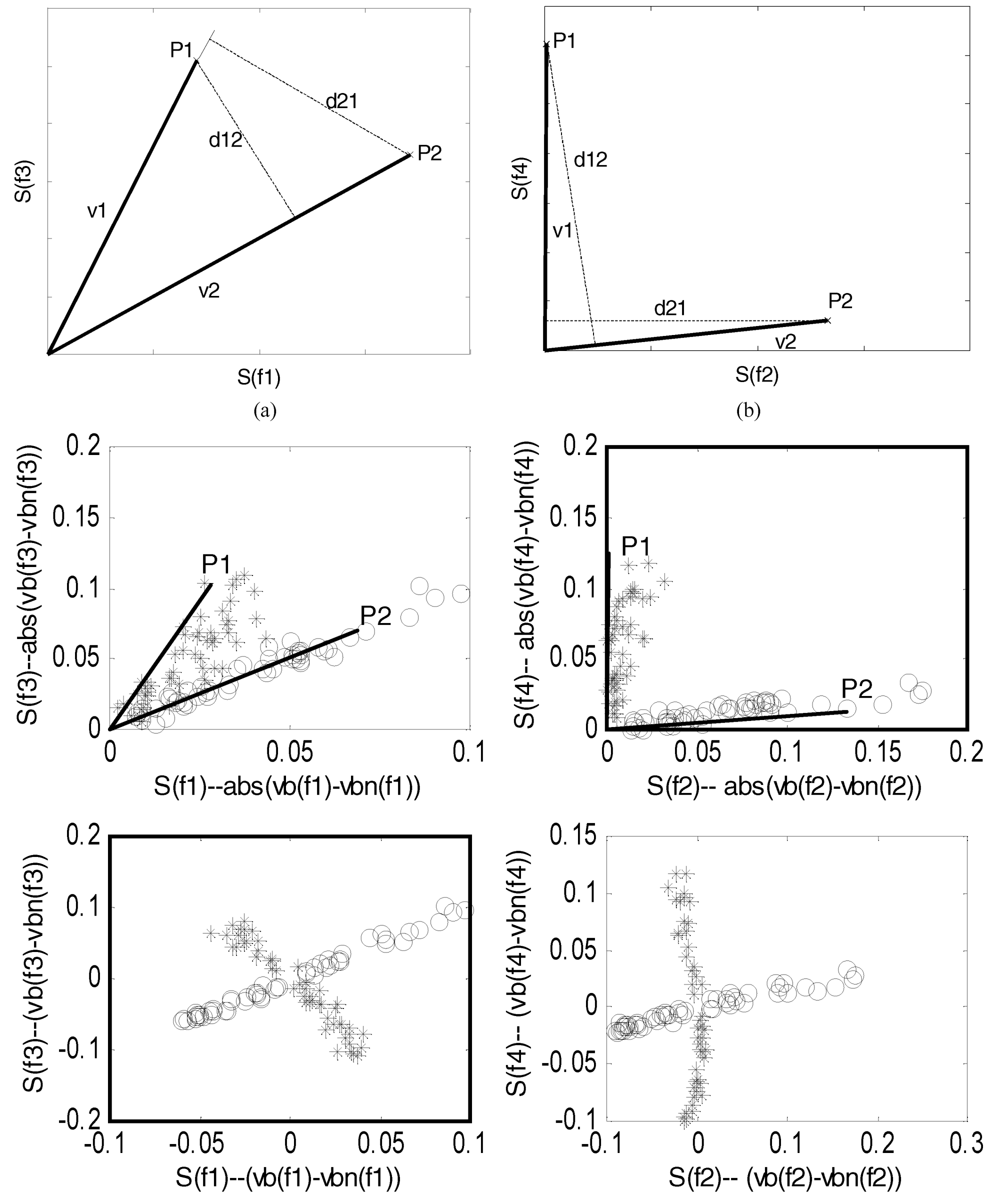


(c)

Fig. 2. Faults are those characterized in Fig. 1. (a) Representative points for the two faults in plane f_1, f_3 (b) Representative points for the two faults, in plane f_2, f_4, (c) Representative points and vectors superimposed to fault signatures (fault 1, circles; fault 2, stars).

While classifier performance optimization is a well known problem, e.g., see [14]–[16], optimization of the dictionary fault in terms of number and relevance of the signatures to be inserted in is still a challenging issue [2]–[9] which strongly depends on the test signals.

The fault dictionary must be as small as possible to reduce the diagnosis procedure complexity and large enough to provide a satisfactory coverage of the fault/fault-free space to grant fault detection and localization accuracy.

The automatic selection of test waveforms is carried out in the technical literature with different approaches [2]–[9] aiming at an efficient fault diagnosis. In [6], fault observabilty is reached by taking into account also fault masking while [5] addresses test sine waveforms selection by minimizing the risk of false rejection and false acceptance of a CUT. A different approach has been suggested in [4] where test waveforms to be considered have spectra maximizing a testability function in the frequency domain. Anyway, in these papers test inputs are selected without considering fault isolation optimization, i.e., the fault signature discrimination ability.

Differently, we address the problem of selecting the test signals by maximizing the system performance in terms of fault isolation. This can be achieved by selecting a set of sine waveforms able both to highlight faults and produce different signatures for different faults, hence ensuring efficient fault isolation. The three novel methods for frequency selection support an automated SBT diagnosis framework for the selection of test stimuli and the development of the subsequent classifier

TABLE I

COMPARISON AMONG COMPUTATIONAL COMPLEXITIES FOR THE DESCRIBED METHODS. N_E =TOTAL NUMBER OF EXAMPLES IN THE FAULT DICTIONARY, N_g FAULT NUMBER, g COMPLEXITY OF THE TRANSFER FUNCTION OF THE CUT CALCULATION, D NUMBER OF POSSIBLE FREQUENCIES, N NUMBER OF SIMULATION RUNS FOR THE EVALUATION OF THE SENSITIVITY (RANDOMIZED ALGORITHM APPROACH), M NUMBER OF BEST FREQUENCY SETS SELECTED AT EACH STEP OF THE SELECTION ALGORITHMS, H NUMBER OF HIDDEN UNITS IN THE RBF CLASSIFIER

	Method I (Fuzzy +RBFN)	Method II (functional +RBFN) (first iteration in a bi-dimensional space)	KNN + LOO (first iteration in a bi-dimensional space)
Contribution #1	Sensitivity Computation for a selected frequency: $O(gN_f DN)$	Sensitivity Computation: $O(gN_f DN)$	$O(MN_E^2 D^2)$
Contribution #2	Test Frequencies Selection: $O(N_f D)$	Test Frequencies Selection: $O(MN_f^2 D^2)$	
Contribution #3	RBFN training (without clustering): $O(N_E^3)$	RBFN training (Fuzzy C Mean clustering): $O(H^3 + N_E^2 / N_f)$	

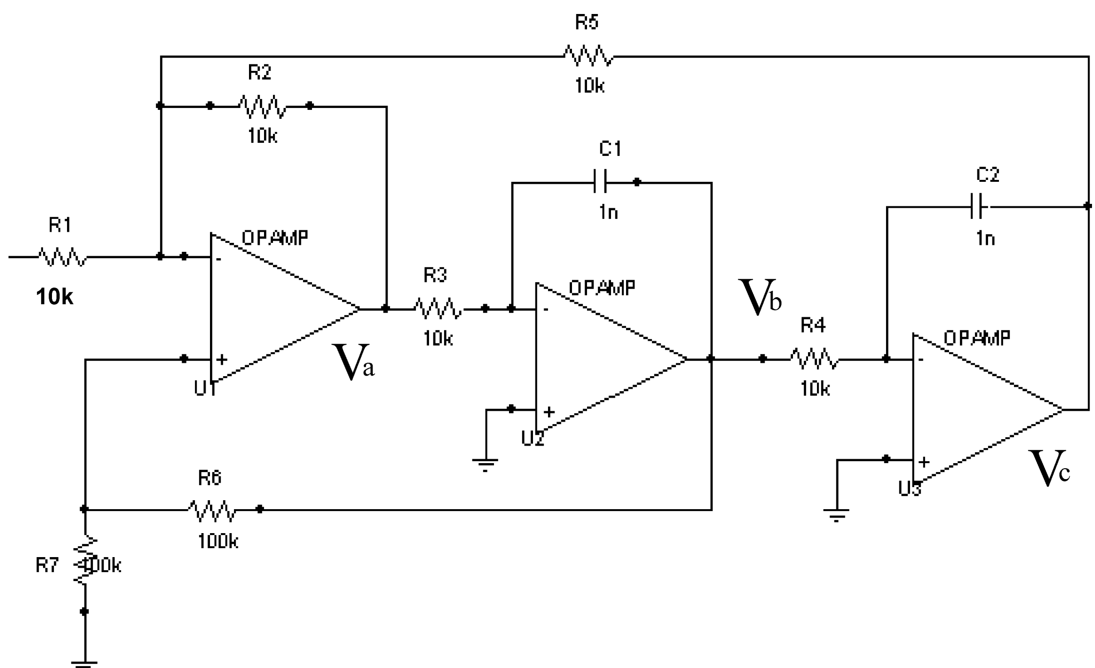


Fig. 3. CUT: Biquad filter-fault classes: *Group 1 – R6, R7 faulty; group 2: R3, C1 faulty; Group3 – R4, C2 faulty; Group 4: R5 faulty; Group 5 – R2 faulty; Group 6: R1 faulty; Group 7: no faulty components (fault-free condition).*

here implemented with a radial basis function neural network (of course, any other classification method can be considered instead).

More in detail, the first two methods are based on a sensitivity analysis. The former, which extends the work carried out in [16], selects frequencies by relying on fuzzy-rules; the latter by maximizing a suitable figure of merit. The third method operates in a blind way without requiring—or using—any information about the circuit nature. As such, it is particularly appealing in nonlinear analog circuits where the test designer background is of little help. The method is general and can be applied to select any test stimuli feature other than frequency as required by the harmonic analysis, e.g., amplitude and time duration or any other feature characterizing the test signal.

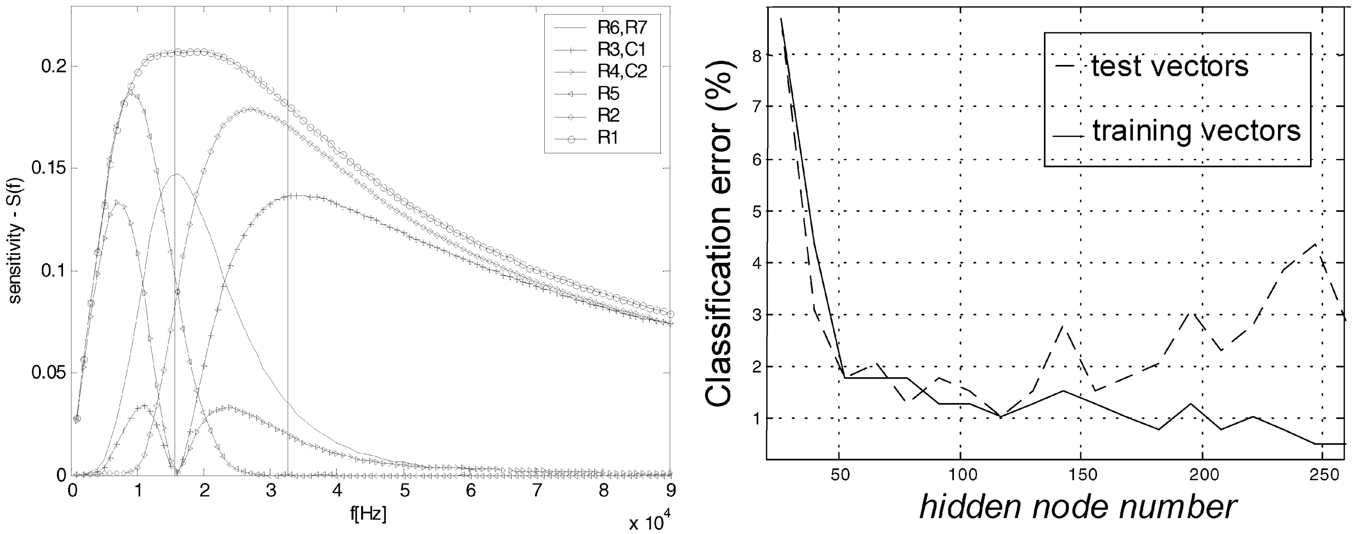


Fig. 4. (a) Sensitivity curves for the CUT of Fig. 3 (bandpass output); the test frequencies selected by the functional method are shown. (b) Training and test errors of the RBFN classifier for the bandpass circuit.

The structure of the paper is as follows. Section II presents the novel methods for input frequency selection. Application and comparison of the methods suggested in Section II is carried out is Section III by taking into account both diagnosis performance (fault classification error) and algorithm complexity. Experimental results are finally given in Section IV.

II. Selecting the Optimal Test Frequencies

The first two methods for frequency selection suggested in this paper are based on the analysis of the circuit output sensitivity, while the third one is somehow blind, since selection of the optimal test signal frequencies is performed by analysing a set of signal output examples. A similar approach was presented in [8] where the authors compute a transient test stimulus with the objective of maximizing the isolation capability of the test system by means of genetic algorithms. Here, differently, by using sinusoidal test signals we significantly simplify both test system and setup.

A. Selection Based on Sensitivity Analysis (Methods I and II)

Methods I and II are based on a sensitivity analysis and, more specifically, on the evaluation of the sensitivity of the measured output value with respect to perturbations induced by the faulty components.

Hence, once defined the fault set (N_f possible fault classes affecting the CUT), and the CUT parameters variations responsible for each fault (hence, generating N_f sets of CUT parameters), N_g sensitivity functions need to be evaluated for each considered output parameter. Each sensitivity curve shows, as function of the frequency within the circuit bandwidth, the sensitivity value of the envisaged output in correspondence with the specific fault class.

Method I: Once obtained a fine sampling for the output parameter sensitivity, a set of fuzzy rules can be constructed to select the optimal set of test frequencies according to the following rules.

TABLE II
PERCENTAGE OF ERRORS PROVIDED BY METHOD II. TEST SET: 60 EXAMPLES PER FAULT CLASS, UNIFORM RANDOM DISTRIBUTION IN THE INTERVAL $X_n \pm [0.01X_n, 0.4X_n]$

Error types	Mean number of errors
Correct detection/correct location	97.5%
Correct detection/wrong location (faults detected but attributed to a different fault class)	1.6 %
Missed detection (faults that are not detected and fault-free circuits that are classified as faulty)	0.9%

Rule 1: IF (ONE OF THE SENSITIVITIES is LARGE) THEN (THE DETECTABILIY is LARGE).

Rule 2: IF (ONE OF THE SENSITIVITY DIFFERENCES is LARGE) THEN (THE DETECTABILITY is LARGE).

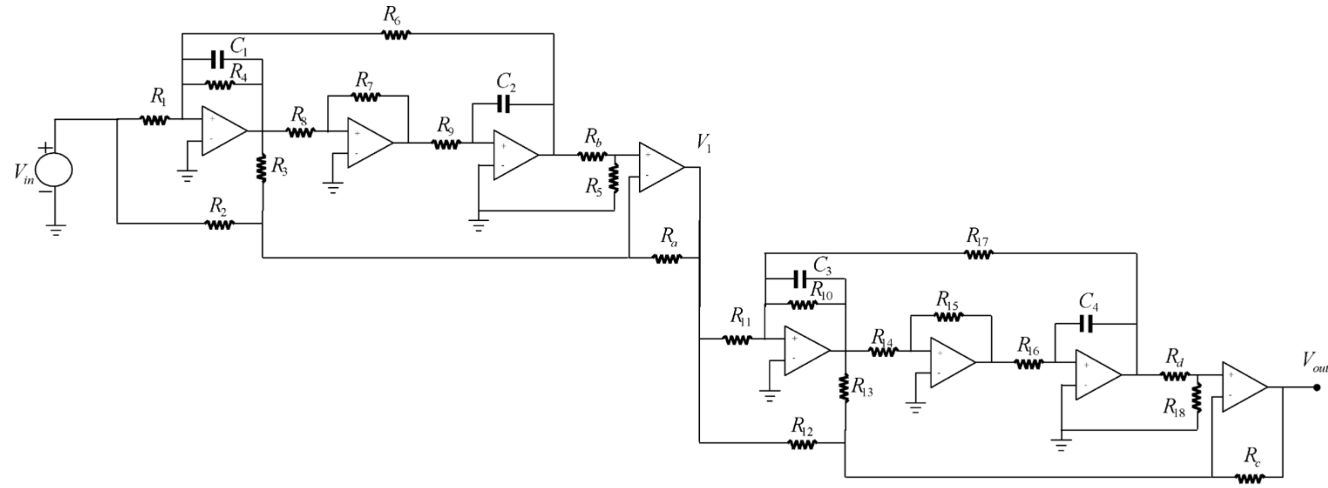
These rules simply translate the intuitive consideration that it is possible to distinguish a fault iff each sensitivity pattern (at the considered frequencies) shows a behavior different from the others.

The fuzzy output response (detectability) represents a measure of the ability to identify and localize faults. The maximum of the fuzzy output response corresponds to those frequencies with the best efficiency in terms of fault diagnosis.

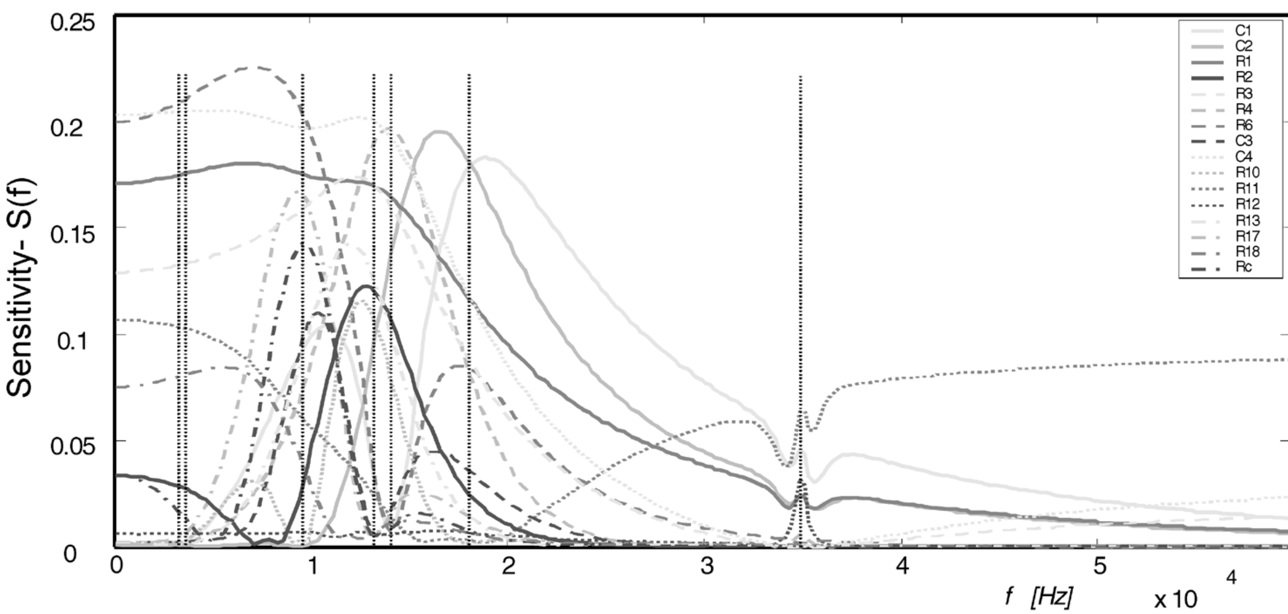
Fig. 1 shows an example for the sensitivity curves $S(f)$ associated with two faults (fault 1 and fault 2) as a function of the frequency f. Rule 1 applied to the sensitivity curve "fault 2" suggests that frequency $f2$ must be selected for diagnosis.

Method II: The second method is based on the design of a proper figure of merit to measure the diversity of the signatures belonging to different faults. The n frequencies maximizing such a figure of merit are those to be selected and constitute the optimal set of test frequencies.

The figure of merit derives from the nature of the testing problem and requires introduction of the representative point concept. We define the representative point for the ith fault to be a curve evaluated at one of the n considered frequencies.



(a)



(b)

Fig. 5. (a) Low-pass filter – $C1 = 10$ nF; $C2n = 10$ nF; $R1 = 182$; $R2 = 11.1\ k$; $R3 = 100\ k$; $R4 = 1570$; $R5 = 1\ k$; $R6 = 440$; $R7 = 10\ k$; $R8 = 10\ k$; $R = 2640$; $Ra = 1\ k$; $Rb = 5.41\ k$; $C3 = 10$ nF; $C4 = 10$ nF; $R10 = 1312$; $R11 = 1\ k$; $R12 = 111.1\ k$; $R13 = 600\ k$; $R14 = 10\ k$; $R15 = 10\ k$; $R16 = 2320$; $R17 = 820$; $R18 = 1\ k$; $Rd = 72.4\ k$; $Rc = 10\ k$; fault classes: *Group 1 – C1;, Group 2 –C2, R7, R8, R9; Group 3 – R1, R5, Rb; Group 4 – R2, Ra; Group 5 – R3; Group 6 – R4; Group 7 – R6; Group 8 – C3; Group 9 – R14, C4, R15, R16; Group 10 – R10; Group 11 – R11; Group 12 – R12=; Group 13 – R13; Group 14 – R17; Group 15 – R18, Rd; Group 16 – Rc.; Group 17-Fault free.* (b) Low-pass filter fault sensitivities.

More intuitively, the representative point indicates the mean position of the signatures associated with the ith fault.

We discovered that the distribution of the representative points in the selected space allows the designer for evaluating the complexity of the classification task by using the selected test frequencies. Hence, by studying the distribution of the representative points in all the considered n-dimensional spaces it is possible to find the best set of frequencies necessary for the signature classification.

It is obvious that if these points are separate the average variations induced by the associated faults on the circuit response with respect to the nominal one can be distinguished if observed at these frequencies. Hence, by considering a figure of merit that synthetically describes the geometric distribution of the representative points for all the considered n-dimensional spaces it is possible to find the best set of frequencies for signature classification.

To derive the appropriate figure of merit we refer to Fig. 1 where the sensitivity curves, obtained by the method presented in [1] and [17] and associated with the two envisaged faults are shown. Once selected n frequencies and considered the CUT with the faulty situation depicted in Fig. 1, the representative points for the two faults (P1 for fault 1 and P2 for fault 2) are those of Fig. 2(a) and (b). The figures show two bidimensional spaces defined by different couples of frequencies. It can be seen that, if vectors $v1$ and $v2$ (characterized by joining the extremes P1 and P2 with the origin of the axis) have a large angular distance [e.g., refer to Fig. 2(b)] then the representative points are significantly distinct as well. This implies that the two faults are highly distinguishable. To further clarify this concept we also

TABLE III

COMPARISON AMONG COMPUTATIONAL COMPLEXITIES FOR THE DESCRIBED METHODS AND FOR THE CUT OF FIG. 3. N_E (NUMBER OF EXAMPLES IN THE FAULT DICTIONARY) = 420 (60 EXAMPLES PER FAULT CLASS)), N_f (NUMBER OF FAULTS) = 7, g (COMPLEXITY OF THE TRANSFER FUNCTION OF THE CUT CALCULATION) = 47 Flops, D (NUMBER OF POSSIBLE FREQUENCIES) = 20, N (NUMBER OF SIMULATION RUNS FOR THE EVALUATION OF THE SENSITIVITY) = 300, M (NUMBER OF BEST FREQUENCY SETS SELECTED AT EACH STEP OF THE SELECTION ALGORITHMS) = 5, H = 140 RBF HIDDEN UNIT NUMBER

	Method I (Fuzzy +RBFN)	Method II (functional +RBFN) (first iteration in a bi-dimensional space)	KNN + LOO (first iteration in a bi-dimensional space)
Contribution #1	Sensitivity Computation: 81.57 Mflops	Sensitivity Computation: 81.57 Mflops	2290 Mflops
Contribution #2	Test Frequencies Selection: 10^{-2} Mflops	Test Frequencies Selection: 0.6 Mflops	
Contribution #3	RBFN training: 14 Mflops	RBFN training: 14 Mflops	

refer to Fig. 2(c) that provides the signatures obtained for the sample circuit under the two considered fault conditions (stars and circles) superimposed to the representative points and vectors. The signatures are evaluated as deviations from the nominal value of the output voltage amplitude $Vb(f)$ at the given frequencies. They can be obtained by generating the deviations of the faulty component values with an uniform distributions affecting the circuital parameters outside the tolerance ranges up to 40% of the nominal values, while fault free components are characterized by values randomly distributed in the tolerance ranges for the parameters.

We note that the angular distance between v_1 and v_2 affects the discrimination ability of the two faults while the vector magnitude accounts for the sensitivity magnitude, i.e., the distance from the nominal condition.

The figure of merit for frequency selection is therefore based on the sum of the distances of each representative point from the lines joining the origin with the representative points of all other faults [e.g., in Fig. 2(a) and (b) we have to refer to distances d_{12} and d_{21}].

The frequency selection algorithm can be summarized as follows:

1. Consider a set of frequency $(f_1, f_2 \dots . f_N)$ and the sensitivities associated with the N_f fault classes

$$(S_1(f_1), S_1(f_2) \dots ., S_1(f_N)); (S_2(f_1), S_2(f_2) \dots, S_2(f_N)) \dots ; (S_{N_f}(f_1), S_{N_f}(f_2), \dots, S_{N_f}(f_N)).$$

2. For all couples (f_i, f_j) $(i, j = 1, \dots, N$, $i \neq j)$ evaluate the distance, d_{kl}, of each point $P_k = (S_k(f_i), S_k(f_j))$ $(k = 1, \dots, N_f)$ from the lines joining the origin (0,0) with points $P_l = (S_l(f_i), S_l(f_j))$ $(l = 1, \dots, N_f l \neq k)$; evaluate $F_2(f_i, f_j)$ as the sum of these distances, i.e., $F_2(f_i, f_j) = \sum_{k,l=1, l \neq k}^{N_f} d_{\text{kl}}$.

3. Select the M couples (f_{am}, f_{bm}) $(m = 1, \dots, M)$ characterized by the larger value of $F_2(f_i, f_j)$.

4. Add to each of the M frequency couples a frequency, hence obtaining $M^*(N-2)$ frequency triplets (f_{am}, f_{bm}, f_p) $(m = 1, \dots, M$ and $p = 1, \dots, N$, $am \neq bm \neq p)$; repeat the procedure described in the above steps, i.e., evaluate the distance d'_{kj} of each point $P_k = (S_k(f_{am}), S_k(f_{bm}), S_k(f_p))$ $(k = 1, \dots, N_f)$ from the lines joining the origin (0,0) with the points $P_l = (S_l(f_{am}), S_l(f_{bm}), S_l(f_p))$ $(l = 1, \dots, N_f l \neq k)$. Evaluate F_2 as the sum of these distances. Select the M frequency triplets characterized by the larger value of $F_3(f_{am}, f_{bm}, f_p)$.

5. Proceed iteratively by adding to each of the M K-uples another frequency component and apply again steps 4 and 5.

6. Stop the iterations when the improvement in the figure of merit is below a given threshold. Select the K-uple with the largest value of F_K; such K-uple becomes the set of test frequencies.

After having selected the test frequencies by means of method I or II the fault dictionary can be constructed by simulating K fault examples for each of the possible N_f fault classes. The obtained signatures can then be used to configure the classifier solving the faulty detection and placement problem [1].

B. Blind Selection (Method III)

A methodology based on a sensitivity analysis (frequency relevance) has been developed to solve the frequency selection problem. The method is blind in the sense that the frequency selection problem is solved without requiring particular assumptions about the structure of the circuit, which can be either linear

TABLE IV
EXPERIMENTAL RESULTS FOR THE CUT IN FIG. 3

Faulty Resistor (nominal value)	Resistance values (kΩ) Measured by HP 34401A	Number of Correct detections/correct locations
Group 1 R7 (100 kΩ)	72.04, 76.22, 81.44, 92.92, 94.21 108.47, 120.55, 131.79, 141.29, 151.23	10 (all)
Group 2 R3 (10 kΩ)	6.99,7.90, 8.44, 9,02, 9.28 11.02, 12.66, 13.33, 14.67, 15.49	10 (all)
Group 3 R4 (10 kΩ)	6.44,7.22, 8.17, 9.07, 9.43, 11.03, 12.05, 13.24, 14.39, 15.61	10 (all)
Group 4 R5 (10 kΩ)	5.96, 6.67, 7.01, 8.21, 9.11, 11.21, 13.23, 14.81, 15.33, 15.63	10 (all)
Group 5 R2 (10 kΩ)	7.01,7.72, 8.12, 8.87, 9.33 10.98, 12.91, 13.01, 13.55, 14.63	10 (all)
Group 6 R1 (10 kΩ)	7.51, 7.85, 8.02, 8.52, 9.37, 11.64, 12.63, 13.11, 13.25, 14.04	10 (all)

or nonlinear. The unique information needed is the voltages measured at the circuit test points. The basic idea supporting the method is that a frequency is relevant to the whole diagnosis task if it improves the fault detection and location subproblems. The frequency selection problem is therefore strictly related to the diagnosis performance: the optimal frequency set is the one characterized by the minimum cardinality yet minimizing the diagnosis classifier. As stated, the frequency selection problem is NP-hard in the sense that all possible classifiers receiving all the possible groups of frequency should be envisaged. Moreover, once a candidate set of frequency is selected we have to configure a classifier, operation requiring a time consuming training phase.

We suggest a methodology solving the frequency selection problem with a Poly-time complexity in the number of frequencies. The methodology, suggested in [18] to identify the set of features relevant in a quality analysis problem, has been suitably adapted to the test frequency selection problem.

The constructive method for frequency selection contains two core problems:

1) identification of a subset of candidate test frequency
2) generation of a classifier to test the diagnosis performance of the candidate subset.

The first problem is solved by means of an effective heuristic, which groups test frequencies based on their effectiveness so as to generate candidate solution. The second step which, de facto, is a performance evaluation problem, takes the candidate solution and develops a diagnosis classifier. Afterwards, the performance of the classifier must be evaluated. The time consuming aspects associated with selection of the best classifier topology (e.g., think of a neural classifier) and the subsequent training phase have been solved by resorting to statistically-based approaches. In particular, we consider a K-mean nearest neighborhoods (KNN) classifier [15] and we assume that it effectively estimates the optimal Bayes's classifier (i.e., the analysis is optimistic); the hypothesis holds when the number of data is sufficiently large [15].

TABLE V
PERCENTAGE ERRORS OBTAINED BY METHOD II. TEST SET: 60 EXAMPLES PER FAULT CLASS, UNIFORM RANDOM DISTRIBUTION IN THE INTERVAL $X_n \pm [0.01X_n, 0.4X_n]$

Error type	Mean number of errors
Correct detection/correct location	92%
Correct detection/wrong location (faults detected but attributed to a different fault class)	6.5 %
Missed detection (faults that are not detected and operating circuits that are classified as faulty)	2%

The immediate advantage of a KNN over other consistent classifiers of neural type (e.g., feedforward and radial basis function NNs) is that it does not require a proper training phase (the classifier is immediately configured on the data set [14]). Since the subsequent selection of the set of test frequencies is based on diagnosis performance it is extremely important to obtain an accurate estimate of the performance for the diagnosis classifier. Due to the limited number of data a proper cross-validation technique cannot be adopted in the sense that the performance estimate may not be enough accurate. A leave one out (LOO) validation technique has been considered which estimates the performance of the ensemble of classifiers receiving the candidate test frequency set (a 95% of confidence has been considered, see [6]).

As a consequence of the considered framework, the performance estimate of the final classifier is accurate with high probability: the relative accuracy among different classifiers (i.e., sets) is finally used to suggest a new candidate set of test frequencies. The classifier maximizing the LOO performance is the best one for the particular diagnosis problem. The interesting related effect is that the frequencies it receives are the most relevant ones to solve the envisioned application and the obtained classifier is the one to be used also to solve the diagnosis problem. The final algorithm implementing the test frequency selection can be summarized as follows:

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1. Denote U by the set containing all
possible test frequencies.
2. Build N subsets U_i of U each con-
taining a test frequency.
3. For each U_i estimate the LOO perfor-
mance of all N KNN classifiers receiving
U_i as input.
4. Select those U_is yielding a performance
above a threshold;
 if only one U_i is selected goto 5
  else build their union U_i and goto 3
5. Try to integrate in U_i all frequencies
one by one. A frequency is inserted in U_i
solely if it improves the classifier per-
formance.
6. Set U_i comprises the optimal set of
test frequency and the associated classi-
fier is the optimal diagnosis classifier.
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III. Complexity of the Test Frequency Selection Methods

The complexity of the suggested methods has been evaluated by taking into account the contributions associated with the time-consuming phases needed to solve the diagnosis problem. Methods I and II are characterized by the three subphases: sensitivity analysis, test set selection and diagnosis classifier construction. Conversely, from its nature, method III is characterized by a single phase, which receives all data and outputs the optimal classifier with the optimal test frequencies.

The complexities of the methods with respect to the different phases are given in Table I. More in detail, as far as method I and II are concerned, we consider the three different contributions aforementioned. The first one, that accounts for the evaluation of the sensitivity curves, was calculated by referring to the method presented in [17] and based on Montecarlo simulations (N is the number of runs used in the Montecarlo simulation). The second contribution is given by the complexity of the sensitivity curve analysis algorithm as performed by the fuzzy system or by the evaluation of the figure of merit (this term is, in general, very low when compared with the first contribution). For these two methods we report in the table also the contribution associated with the Neural Network training (the training method is described in detail in [1]). It must be underlined that the complexity of the first two methods can be lowered if other sensitivity evaluation techniques are used (in particular, symbolic methods). Here we report the Monte Carlo-based algorithm for its general validity, as it can be applied to any domain (and also in nonlinear applications [17]).

It can be seen that the blind method's complexity depends on the product of the square of the number of possible frequencies (D) and the square of the number of examples (N_E) in the fault dictionary, while the complexities of the other two methods grow linearly with D. As a consequence, by considering a large set of possible test frequencies the complexity of the III method can be very high. Conversely, the first two methods are considerably influenced by the complexity of the sensitivity evaluation that may become dramatically high if the computational burden of a CUT simulation grows. Finally, it can be seen that for RBF training the larger contribution is given by the least mean square solution of a linear system that depends on the cubic power of the number of hidden units of the neural classifier; conversely, the complexity of the blind method depends on the square the examples in the examples in the fault dictionary N_E. This comparison points out that for medium and low complexity linear circuits methods I and II present a significant advantage in terms of processing time while the main advantage of method III resides in its blind approach.

IV. Case Studies

The methodology described in the previous sections has been tested for effectiveness on two linear circuits and a nonlinear circuit. The two linear circuits were chosen among those considered as benchmarks in the related literature (e.g., see [10]); this allows a direct comparison of the obtained results. The third circuit is related to a real-world application studied by the authors.

A. Test Frequency Selection and Diagnosis in Linear Circuits

The first circuit, shown in Fig. 3, is a Biquad filter with a cutoff frequency of 15.9 kHz. Single faults were considered (faults are due to a single parameter variation) and each component tolerance has been fixed to 1%. For this particular application a fault condition is defined as a variation of the magnitude of the transfer function above the 3% of its nominal value. The circuit signature is obtained by measuring the voltage amplitude at the output node Vb. This selection allows a very simple test setup.

By taking into account also the fault ambiguity classes, we obtained six fault classes.

It must be noted that the ambiguity classes can be found with an automated procedure when we use approaches based on the sensitivity curves analysis. In this paper, the tools implementing approaches I or II comprise a sub-program that regroups the faults characterized by the same sensitivity curve shape in a single fault class.

The comparison among the three techniques was performed under the same conditions to grant comparability: the test frequencies were selected among 20 feasible logarithmic spaced frequency values belonging to the [100 Hz, 90 kHz] interval. The analyzed frequency range was selected in order to obtain a sufficiently high SNR when performing measurements. As such, the range is derived from fixing the maximum acceptable filter attenuation.

We considered 60 fault samples for each fault class by randomly sampling the $X_n \pm [0.01X_n, 0.4X_n]$ interval for each n, where X_n is the nominal value of the generic component, non faulty components randomly varied in their tolerance ranges.

Fig. 4(a) shows the sensitivity curves of the CUT. All three methods found out three optimal test frequencies which are very similar; by using the identified test frequencies method I (fuzzy + RBFN) and III (blind method) give a classification error around 3%, while for method II (figure of merit + RBFN) the error is around 2.5%, as it can be seen in Fig. 4(b). The detailed classification results for method II are listed in

TABLE VI

COMPARISON AMONG COMPUTATIONAL COMPLEXITIES FOR THE DESCRIBED METHODS FOR THE CUT OF FIG. 5. N_E [NUMBER OF EXAMPLES IN THE FAULT DICTIONARY) $= 1020$ (60 EXAMPLES PER FAULT CLASS)], N_g (NUMBER OF FAULTS) $= 17$, g (COMPLEXITY OF THE TRANSFER FUNCTION OF THE CUT CALCULATION) $= 1000$ Flops, D (NUMBER OF POSSIBLE FREQUENCIES) $= 20$, N (NUMBER OF SIMULATION RUNS FOR THE EVALUATION OF THE SENSITIVITY) $= 300$, M (NUMBER OF BEST FREQUENCY SETS SELECTED AT EACH STEP OF THE SELECTION ALGORITHMS) $= 5$, $H = 300$ RBF HIDDEN UNIT NUMBER

	Method I (Fuzzy +RBFN)	Method II (functional +RBFN) (first iteration in a bi-dimensional space)	KNN + LOO (first iteration in a bi-dimensional space)
Contribution #1	Sensitivity Computation 1.18 Gflops	Sensitivity Computation: 1.18 Gflops	11.9 Gflops
Contribution #2	Test Frequencies Selection: 10^{-2} Mflops	Test Frequencies Selection: 3 Mflops	
Contribution #3	RBFN training: 650 Mflops	RBFN training: 650 Mflops	

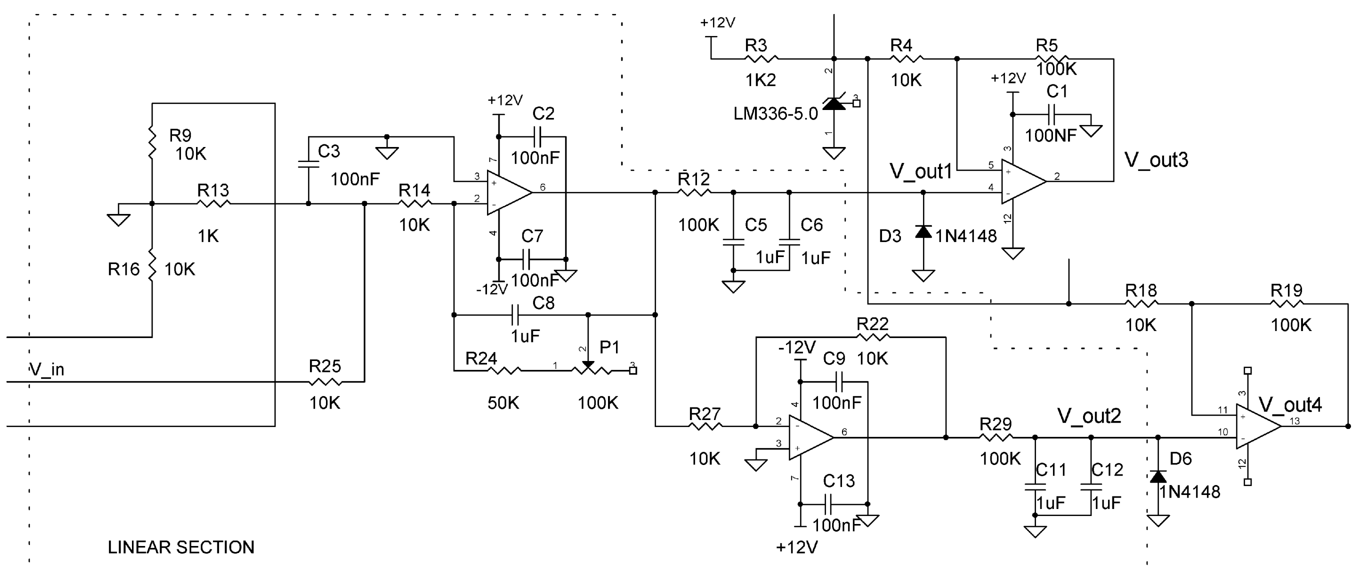

Fig. 6. CUT.

Table II, where the average errors obtained with RBFN's with complexity between 14 and 30 nodes per class are presented.

Very few fault-free circuits (0 for the data set considered) have been classified as faulty ones. We experienced similar results with methods I and III.

The effective computational complexities of the three techniques (in Mflops) based on a Matlab execution are shown in Table II.

The performance in terms of classification errors are very similar for the three approaches but the computational complexity of the blind method is significantly higher in this case since it is characterized by a reduced number of fault classes and a limited CUT complexity. In fact, it can be seen that the sensitivity evaluation step, which is the heaviest contribution in computational complexity for the first two methods is contained.

For these circuits simulation results were confirmed by an experimental test campaign. We considered TL081s for OPAMP's and an automatic measurement system composed of a 6½ Digital multimeters (HP 34 401A) and a signal generator (HP 33120A). We performed ten tests for each class by forcing the resistances to assume values outside their tolerance ranges by means of trimmers. We obtained a 100% correct location of the faults for all testing methods (see Table IV). This excellent result can be explained by noting that for experimental tests the minimum deviation from the nominal value was higher than 5%. It must also be noted that if faults are due to variations above 40% of the nominal value (used to train the classifier) the percentage of correct diagnosis/missed location significantly grows.

The described techniques have been applied also to the circuit depicted in Fig. 5 which represents a fourth order low pass filter with a cut off frequency of 15.85 kHz. Fault conditions were defined as we did in the previous CUT and provided 16 fault classes (also including the fault free one). As in the pre-

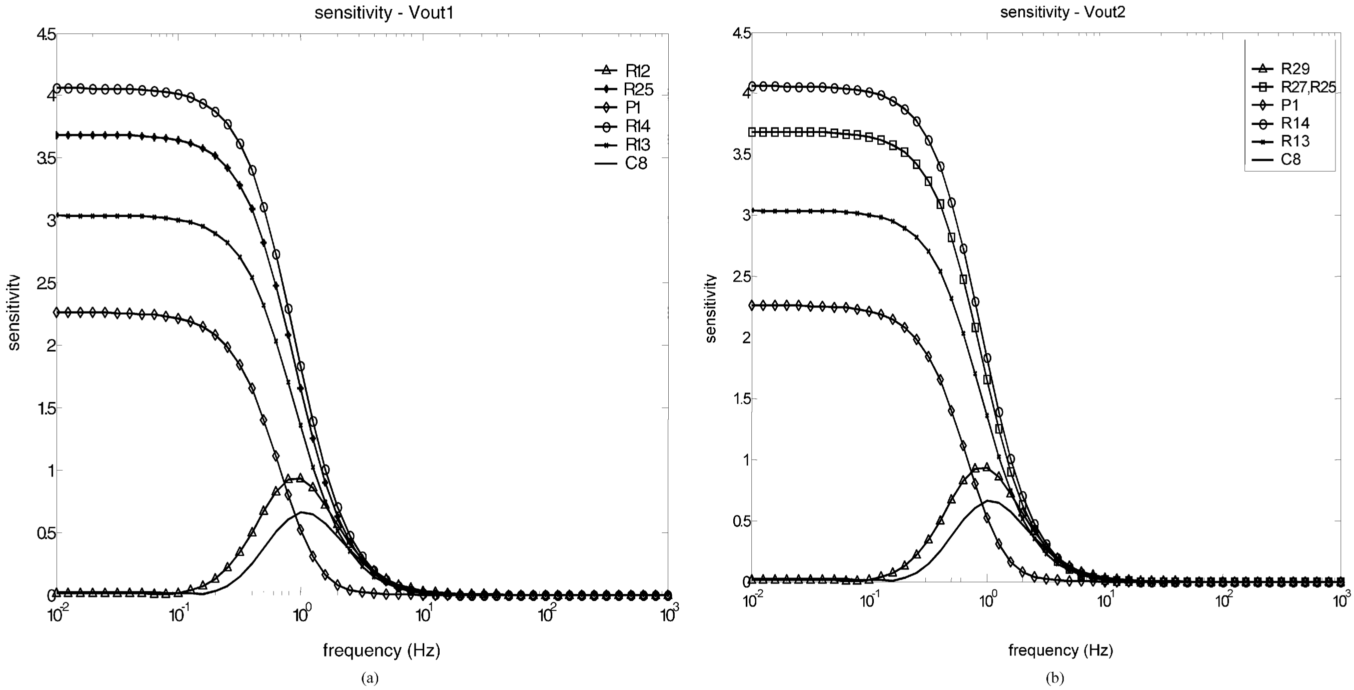

Fig. 7. (a) Sensitivity of voltage amplitude (node V_out1). (b) Sensitivity of voltage amplitude (node V_out2) – Fault classes: *Group 1- R13,R14,R25; Group 2 – R22,R27; Group 3 – P1,R24; Group 4 – C8; Group 5 – R29,C11,C12; Group 6 – R12,C5,C6.*

vious example we considered a grid of 20 logarithmic spaced feasible frequencies sampling the [100 Hz, 60 kHz] interval. For each class 60 fault examples have been considered by randomly extracting the samples from the $(X_n \pm [0.01X_n, 0.4X_n])$ interval a uniform distribution. The measured quantity is the output voltage amplitude.

The fuzzy approach (I) provided eight test frequencies and an error of about 8.5%. Instead, method (II) selected seven frequencies with an error of 8%; method (III) found out nine frequencies [as shown in Fig. 5(b)] with a classification error of about 8%. In particular, Fig. 5(b) shows the low pass filter sensitivity curves set and the frequencies selected for the diagnosis by method II.

As we did for the previous CUT classification results provided by method II are detailed in Table V). In this CUT the classification error is higher than the previous one due mainly to the larger fault class number. In particular, the group 5 fault is characterized by a low sensitivity and, hence, is more troublesome. We discovered similar results with methods I and III.

The estimates for the computational complexities are given in Table VI. It can be seen that with a CUT characterized by a significant complexity the complexities of the three methods get closer, even if the blind method still requires a higher computational effort. It is expected that by increasing the circuital complexity of the CUT the third method is to be preferred also with respect to the computational complexity issue.

B. Test Frequency Selection and Diagnosis in Nonlinear Circuits

The proposed techniques can be extended also to nonlinear circuits. In this case, the harmonic approach can still be used

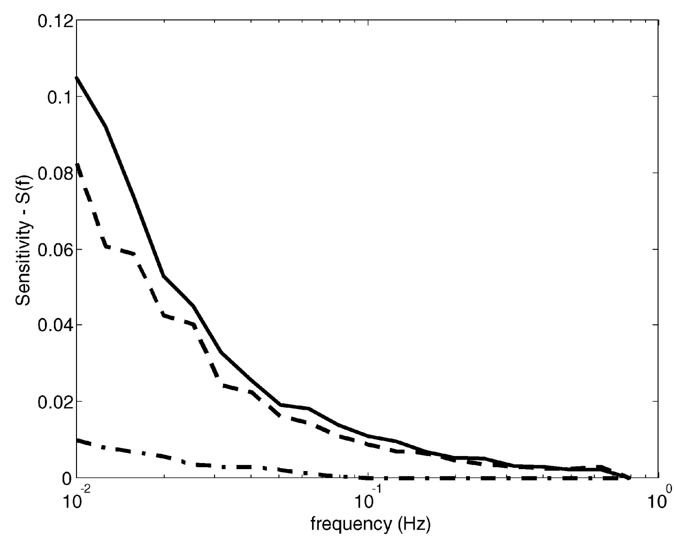

Fig. 8. Sensitivity of switching delay for one comparator, as a function of the stimulus (sine wave) frequency,'—': group 1, '- -': group 2, '.-'group 3.

(obviously also the wave amplitude has to be selected in addition to the frequency) and the output parameter should be selected carefully. In Fig. 6 the CUT is the analog part of an alarm for railways applications, that ensures safety, i.e., isolation from high voltages. Failure detection plays, for this circuit, a fundamental role to grant a good safety level. The cut was designed to detect deviations of the input (V_in) voltage from the reference voltage (12 V). The CUT was divided into two separate subsystems: the linear and the nonlinear sections. The linear subsection consists of two branches containing amplifiers and low pass filters with time constants of about 10 s that cut off transient disturbances. The test stimulus is applied to circuit input V_in, while four measurement points have been selected (V_out1,

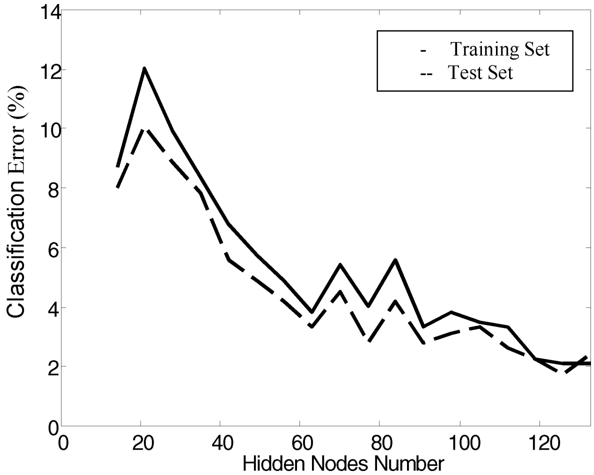

Fig. 9. RBFN classification error (%) for the linear section as a function of hidden node number.

$V\_\mathrm{out}2$, $V\_\mathrm{out}3$, $V\_\mathrm{out}4$). In this case, the harmonic approach was followed, that allows the designer for analysing the linear part as done in the previous two examples (input, V_in, output $V\_\mathrm{out}1$ and $V\_\mathrm{out}2$) where the amplitudes of voltages at the output nodes were considered as the measured entities. Since the nonlinear part consists of comparators, the parameters used for diagnosis are the delays of the switching modules with respect to input zero crossing (evaluated at the two nodes $V\_\mathrm{out}3$, $V\_\mathrm{out}4$).

We assumed a single parametric fault affecting the CUT. CUT output signatures were obtained by PSPICE simulations, by considering tolerances of 1% for resistors and of 5% for capacitors, while the values of faulty components are uniformly and randomly distributed in the range $X_n \pm [0.01X_n, 0.5X_n]$ for resistors and $X_n \pm [0.05X_n, 0.5X_n]$ for capacitors. Sensitivity was obtained as in the previous examples by considering 300 Montecarlo runs.

Fig. 7 shows the sensitivity curves obtained for the magnitudes of voltages $V\_\mathrm{out}1$ and $V\_\mathrm{out}2$. It can be seen that if we measure only a voltage only three faults can be isolated (fault P1 is characterized by a sensitivity similar but not identical to faults in group1 and 2), while by using the two voltages amplitude six fault classes can be detected.

For the nonlinear section we considered the same input stimulus; this enables a simultaneous test for the two circuit sections. The sensitivity curves obtained for this section have been regrouped in three ambiguity groups and are given in Fig. 8.

Also in this case a set of 20 feasible frequencies was obtained by a logarithmic sampling of the frequency range [0.1 Hz, 1 kHz]. Frequencies below 0.1 Hz have been *a priori* discarded to avoid long testing times and stability problems.

The linear and the nonlinear sections were analyzed separately. For the linear section the three methods provides a couple of frequencies with similar values (approximately 0.1 and 1 Hz), and a classification error lower than 3% (results obtained with method II are presented in Fig. 9). The nonlinear section analysis led, with all approaches, to the expected result that only one frequency is needed and that the best frequency for the test is the lowest feasible frequency (in this case 0.1 Hz), while the optimum amplitude of the sine wave was 5 V. In this case the error is around 1% for methods I and II and 2% for the blind method.

V. Conclusion

In this paper, we have proposed three techniques for the identification of the optimal frequencies to be used for constructing the test signals in a simulation before test approach. Results show similar performances with the noticeable advantage of method III over the others due to its completely blind approach, which allows to identify the test frequencies without requiring a priori information about the nature and behavior of the CUT. Conversely, on the computational front, we found that methods I and II present a significant advantage over method III in terms of processing time on medium and low complexity circuits (the advantage reduces when the complexity of the CUT increases). The methods are completely automated and, as such, allow the researcher to develop a fully automated procedure for designing the CUT's diagnosis phase.

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