Research Article

Test Point Selection Method for Analog Circuit Fault Diagnosis Based on Similarity Coefficient

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The demand for testability analysis has increased with the integration densities and complexity of circuits. As an important part of testability analysis, the test point selection method needs to be researched in depth. A new similarity coefficient criterion is proposed to determine the fault isolation degree because output responses of a circuit with component tolerance are approximately subject to the normal distribution. Then, a new test point selection method is proposed based on the fault-pair similarity coefficient criterion information table. Simulation experiments are used to validate the accuracy of the proposed method in terms of the optimum test point set and fault isolation degree. The results show that the proposed method improves the performance of test point selection by comparing with the other reported methods.

1. Introduction

Testability analysis is an important research topic for fault diagnosis in analog circuits. It performs test generation and test point selection in order to improve observability of a circuit under test (CUT). Test generation technique is used to gain the optimal test excitation signals for a CUT and test point selection technique is used to search the optimal test point set for a CUT. This paper mainly studies the test point selection method.

Generally, a CUT often includes many test points, but not every test point in the CUT is necessary or measurable. The optimal test point selection technique can reduce the fault dictionary dimension and save the computational cost by eliminating redundant and immeasurable test points. The total test cost of the CUT can be reduced greatly. Although the exhaustive search method can select a global minimum test point set, the papers [1–3] pointed out that the method is NP-hard and only suitable for small scale analog systems because of its high computational cost. Now, test point selection for analog circuit has become very difficult due to the high dense packages of chips and complex electronic system. The compromise approach is to find a local minimum test point set [1, 3].

There have been many researches about test point selection methods in the past years. A heuristic method for test points selection based on the concept of confidence levels was proposed in paper [4]. The concept of ambiguity sets and developed logical rules to select test points was proposed by Hochwald and Bastian [5]. Lin and Elcherif [6] proposed two heuristic methods based on the criteria proposed by Hochwald and Bastian. Van Spaandonk and Kevenaar [7] combined the decomposition method of system sensitivity matrix and an iterative algorithm to search a set of test points for analog circuits. Prasad and Babu [8] proposed four algorithms based on inclusive approaches and exclusive approach. An entropy index method was proposed to search for a local minimum test point set [1]. A genetic algorithm was proposed to determine the optimal test point set, which effectively enabled the results to avoid being trapped into local minimums [9]. In paper [10], the test point selection procedure was transformed into a graph node expanding procedure and utilized entropy of information to guide graph search, and the method is subsequently improved by Gao et al. [11]. A greedy randomized adaptive search algorithm was proposed to find the global optimal test point set [12]. A multiobjective fruit fly optimization algorithm was proposed to enhance the global test point selection ability [13]. All

test point selection methods reported above are based on an integer-coded dictionary technique.

Generally, analog CUT output values change in intervals because an analog signal has continuity and parameters of analog component have tolerances. Hence, the responses of some analog circuit faults usually overlap each other. In order to discriminate these ambiguous faults and construct an integer-coded dictionary for analog circuit, the ambiguity set and the ambiguity gap (i.e., a diode drop 0.7 V) between ambiguity sets were introduced by Hochwald and Bastian firstly [5]. Subsequently, most of test point selection algorithms employ 0.7 V as the ambiguity gap, but it is proved by many practical test results that 0.7 V is not always effective and accurate [2, 3]. In paper [14], 0.2 V was chosen as the ambiguity gap and an accurate fault-pair Boolean table technique for the test point selection was proposed, which overcame the shortcoming of the traditional integer-coded table that only a part of the faults can be isolated. In paper [2], ambiguity gaps were determined by means and variances of the circuit responses because the tolerances of component parameters obey the normal distribution. According to the normal distribution characteristics, an overlapped area method was proposed to improve the accuracy of selecting the optimal test point set. Subsequently, the fault-pair isolation table technique was proposed by Zhao and He to guide the test point selection algorithm. The table consisted of the isolation probability of fault-pairs, which was gained by calculating ambiguity gap [3].

This paper proposes a similarity coefficient criterion to compute each fault-pair isolation capability. The larger the coefficient is, the higher the isolation probability of a fault-pair is. According to the trait of a similarity coefficient criterion, the fault-pair similarity coefficient criterion information table is constructed and a new test point selection method is proposed. And then the proposed method is validated by two filter benchmark circuits in terms of the optimal test point set and fault isolation degree. The results show that the new method is effective and accurate.

The remainder of this paper is arranged in the following order. Section 2 introduces the new method to construct the fault-pair similarity coefficient criterion information table. Then a new test point selection algorithm is proposed based on the table. The simulation details are described and the simulation results are discussed in Section 3. In the end, brief conclusions are summarized in Section 4.

Nomenclature of the paper is listed in Nomenclature.

2. New Test Point Selection Method

2.1. Similarity Coefficient Criterion. The core idea of the similarity coefficient criterion is to estimate the overlapping degree of a fault-pair. Assume that there are two faults f_i and f_j , and their samples follow the normal distribution. The probability density function curves are $f_i(x)$ and $f_j(x)$, respectively. Three pairs of fault curves with different overlapping degree are shown in Figure 1. Because $f_i(x)$ and $f_j(x)$ are one-dimensional nonnegative real functions, they satisfy the condition of Cauchy-Schwarz inequality. The following inequality can be deduced according to Cauchy-Schwarz inequality [15]:

$$0 \leq \frac{\int f_i(x) f_j(x) dx}{\sqrt{\int f_i^2(x) dx} \sqrt{\int f_j^2(x) dx}} \leq 1. \quad (1)$$

The similarity coefficient criterion C_s is defined as the following mathematical formula:

$$C_s = 1 - \frac{\int f_i(x) f_j(x) dx}{\sqrt{\int f_i^2(x) dx} \sqrt{\int f_j^2(x) dx}}, \quad (2)$$

so its interval is from 0 to 1. If the curves $f_i(x)$ and $f_j(x)$ almost coincide with each other as shown in Figure 1(a), f_i and f_j cannot be isolated and $C_s = 0$. If the curves $f_i(x)$ and $f_j(x)$ are partially overlapping as shown in Figure 1(b), faults f_i and f_j cannot be isolated partially and $0 < C_s < 1$. If the curves $f_i(x)$ and $f_j(x)$ are not overlapping absolutely as shown in Figure 1(c), faults f_i and f_j can be isolated completely and $C_s = 1$. For example, assume that the mean and variance of fault f_1 are 3.32 and 0.24; the probability density function of fault f_1 is expressed as

$$f_1(x) = \frac{1}{0.24 \times \sqrt{2\pi}} \exp \left\{ -\frac{(x - 3.32)^2}{2 \times (0.24)^2} \right\}; \quad (3)$$

assume that the mean and variance of fault f_2 are 4.33 and 0.13:

$$f_2(x) = \frac{1}{0.13 \times \sqrt{2\pi}} \exp \left\{ -\frac{(x - 4.33)^2}{2 \times (0.13)^2} \right\}. \quad (4)$$

According to formula (2), the calculation of C_s is 0.999. If C_s is rounded to 2 decimal places, $C_s = 1$ and the fault-pair (f_1, f_2) can be isolated.

2.2. Fault-Pair Similarity Coefficient Criterion Information Table. According to Luo's method [2], a fault dictionary is constructed with the mean and standard variance values of fault samples. If the fault dictionary is composed of N_F fault modes and N_T test points, the proposed fault-pair similarity coefficient criterion information table has $C_{N_F}^2 = (N_F \cdot (N_F - 1))/2$ rows of fault-pairs on the basis of combination formula and N_T columns of test points. Assume that a test point of the k th column is n_k and the fault-pair of the l th row is f_i and f_j in the table; the mean and standard variance of f_i and f_j samples of a CUT on the test point n_k can be found in the k th column of the fault dictionary. And then, the similarity coefficient criterion $C_{sl}(n_k)$ of the normal distribution curves $f_i(x)$ and $f_j(x)$ on the test point n_k can be calculated by formula (2). Therefore, the data in cells of the table is similarity coefficients' criterion of all fault-pairs. In order to enhance the accuracy and the efficiency of test point selection, two rows of information, $CI(n_k)$ and $CI_s(n_k)$, and one column of information, NT_l , are added to the proposed table. $CI(n_k)$ is the sum of $C_{sl}(n_k)$'s which equals 1 in column n_k and indicates that test point n_k can isolate the total of fault-pairs. $CI_s(n_k)$ is the sum of $C_{sl}(n_k)$'s which are not equal to 1 and indicates the isolation capability of all overlapping fault-pairs in the column n_k . NT_l is the total of 1's in the l th row and indicates all test points that can isolate the l th fault-pair. Hence, the proposed fault-pair similarity coefficient criterion information table has $C_{N_F}^2 + 2$ rows and $N_T + 1$ columns.

FIGURE 1: Probability density function curves $f_i(x)$ and $f_j(x)$.

2.3. Criteria, Steps, and Complexity of the New Algorithm. The new algorithm is proposed based on the fault-pair similarity coefficient criterion information table. $NT_l = 1$ means only one test point isolates the fault-pair in the l th row, so the test point is removed from the candidate test point set S_C and added to the optimal test point set S_{opt} . If a test point having $\max_k(CI(n_k))$ means that it can isolate the maximal number of fault-pairs, it is selected from S_C and added to S_{opt} . If several test points have the same $CI(n_k)$, $CI_s(n_k)$'s of these test points are compared and the test point with $\max_k(CI_s(n_k))$ is added to S_{opt} . Based on the above criteria, steps of the new algorithm are given as follows.

Step 1. S_{opt} is initialized to a null set. It is constructed that a fault dictionary has N_F rows and N_T columns based on mean and standard variance of fault samples.

Step 2. A fault-pair similarity coefficient criterion information table based on the fault dictionary is constructed.

Step 3. Look up the fault-pair (i.e., row) that corresponds to $NT_l = 1$; the corresponding test point is added to S_{opt} because only it can distinguish the l th fault-pair. The other fault-pairs (i.e., rows) isolated by the test point are deleted from the fault-pair similarity coefficient criterion information table, and then the test point (i.e., column) is also deleted from the table. Until all the fault-pairs and all the test points corresponding to $NT_l = 1$ have been dealt with completely, the algorithm goes to Step 5. If no NT_l equals 1, the algorithm goes to Step 4 directly.

Step 4. $CI(n_k)$ of each test point in the fault-pair similarity coefficient criterion information table is calculated, and the test point with $\max_k(CI(n_k))$ is added to S_{opt} . If several test points have the same $\max_k(CI(n_k))$, their $CI_s(n_k)$'s are compared and the test point with $\max_k(CI_s(n_k))$ is added to S_{opt} .

After the corresponding fault-pairs and the corresponding test point are deleted from the table, the algorithm goes to Step 5.

Step 5. Check whether the selected test points can isolate all fault-pairs in the table or the remainder fault-pairs cannot be isolated anyhow. If yes, S_{opt} is outputted and the algorithm terminates; else, the algorithm goes back to Step 3.

The calculation of complexity of the new algorithm is similar to that of literature [3]. The result of complexity is

$$O(N_F \cdot N_T + N_F^2 \cdot N_T + m(2N_F^2 + N_F^2 \cdot N_T)), \quad (5)$$

that is, $O(m \cdot N_F^2 \cdot N_T)$, where m is the number of test points that are selected into S_{OPT} .

3. Experiment Circuit and Simulation Results

3.1. Experiment on the Leapfrog Filter Circuit. The simulation CUT is a leapfrog filter, which is a benchmark circuit of ITC97. The nominal value of each component is labeled in Figure 2 and the tolerances of resistor and capacitance are set as 5% and 10%, respectively. It is reported that single hard faults account for approximately 90% of all analog faults occurring in practice [3], so 16 single hard faults $f_2 \sim f_{17}$ are examined on the simulation CUT. The normal mode is labeled as f_1 and all modes are listed in Table 1. 1Ω resistor is used to represent the short circuit fault and $1\text{M}\Omega$ resistor is used to represent the open circuit fault in circuit simulation. All modes are simulated by OrCAD/PSPICE16.6 and 1 kHz; 5 V sinusoidal signal is chosen as the stimulus of circuit simulation. The number of runs is set to 50 and tolerance distribution is set as Gaussian in Monte Carlo analysis. Because each mode takes 50 samples by Monte Carlo analysis,

FIGURE 2: Schematic of a leapfrog filter circuit.

TABLE 1: Fault modes of the first CUT.

Label	Fault
f_1	Normal
f_2	R_1 open
f_3	R_3 open
f_4	R_4 open
f_5	R_6 open
f_6	R_7 open
f_7	R_8 open
f_8	R_{10} open
f_9	R_{11} open
f_{10}	R_{12} open
f_{11}	R_{13} open
f_{12}	C_1 open
f_{13}	C_4 open
f_{14}	C_1 short
f_{15}	C_2 short
f_{16}	C_3 short
f_{17}	C_4 short

all 600 sample datasets are obtained from 12 test points of the simulation CUT for each mode.

According to criteria and steps of the new algorithm, the algorithm firstly starts the initialized work. S_c is initialized as $\{n_1, n_2, \dots, n_{12}\}$ and S_{opt} is initialized to a null set, and the fault dictionary as shown in Table 2 is constructed based on mean and standard variance of the test point voltage maximum values of fault samples.

Secondly, the fault-pair similarity coefficient criterion information table is constructed based on the fault dictionary. Table 3 shows a part of the proposed table. The similarity coefficient $C_{sl}(n_k)$ equals 1 that indicates the fault-pairs can be isolated on the test point n_k completely. If $C_{sl}(n_k)$ equals 0, the fault-pairs cannot be isolated on the test n_k anyhow. If the value of $C_{sl}(n_k)$ is between 0 and 1, this indicates the fault-pairs can be isolated on the test point n_k partly. For example, the 2nd fault-pair (f_1, f_3) in Table 3 includes the three kinds of similarity coefficient values.

Thirdly, the corresponding test points $\{n_2, n_6, n_{10}, n_{12}\}$ are added to S_{opt} because NT_l equals 1. After deleting the corresponding test points and the corresponding fault-pairs from the fault-pair similarity coefficient criterion information table, the size of the table as shown in Table 4 reduced greatly.

Fourthly, the end conditions of the algorithm cannot be satisfied, so it goes to Step 3. No NT_l equals 1, so the algorithm goes to Step 4 and calculates $CI(n_k)$ and $CI_s(n_k)$

TABLE 2: Fault dictionary of the first CUT (unit: V).

	$n_1(\mu_1, \sigma_1)$	$n_2(\mu_2, \sigma_2)$	$n_3(\mu_3, \sigma_3)$	$n_4(\mu_4, \sigma_4)$	$n_5(\mu_5, \sigma_5)$	$n_6(\mu_6, \sigma_6)$	$n_7(\mu_7, \sigma_7)$	$n_8(\mu_8, \sigma_8)$	$n_9(\mu_9, \sigma_9)$	$n_{10}(\mu_{10}, \sigma_{10})$	$n_{11}(\mu_{11}, \sigma_{11})$	$n_{12}(\mu_{12}, \sigma_{12})$
f_1	0.00	0.00	2.66	0.36	0.00	0.00	4.09	0.63	0.00	0.00	0.00	0.00
f_2	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
f_3	0.00	0.00	4.14	0.26	0.00	0.00	6.28	1.03	0.00	0.00	0.00	0.00
f_4	0.00	0.00	4.02	0.25	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
f_5	-7.32	0.22	-13.22	0.00	-13.22	0.00	-13.22	0.00	-13.22	0.00	-13.22	0.00
f_6	0.00	0.00	4.61	0.37	0.00	0.00	4.63	0.41	0.00	0.00	0.00	0.00
f_7	0.00	0.00	2.90	0.99	0.00	0.00	0.02	0.84	0.00	0.00	0.00	0.00
f_8	0.00	0.00	3.00	1.02	0.00	0.00	0.00	0.84	0.00	0.00	0.00	0.00
f_9	0.00	0.00	4.33	0.42	0.00	0.00	1.56	0.70	0.00	0.00	0.00	0.00
f_{10}	0.00	0.00	2.92	1.00	0.00	0.00	0.00	0.82	0.00	0.00	0.00	0.00
f_{11}	0.00	0.00	4.70	0.36	0.00	0.00	4.75	0.43	0.00	0.00	0.00	0.00
f_{12}	0.00	0.00	2.49	0.32	0.00	0.00	3.72	0.41	0.00	0.00	0.00	0.00
f_{13}	-7.25	0.30	-13.22	0.00	-13.22	0.00	-13.22	0.00	-13.22	0.00	-13.22	0.00
f_{14}	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
f_{15}	0.00	0.00	4.14	0.34	0.00	0.00	3.93	0.39	0.00	0.00	0.00	0.00
f_{16}	0.00	0.00	4.85	0.50	0.00	0.00	4.85	0.51	0.00	0.00	0.00	0.00
f_{17}	0.00	0.00	2.91	1.00	0.00	0.00	7.18	0.85	0.00	0.00	0.00	0.00

TABLE 3: Continued.

Number	Fault-pair	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}	n_{11}	n_{12}	NT_I
121	(f_{11}, f_{17})	0	0.81	0	0.97	0	0.98	0	0.49	0	0.36	0	1	1
122	(f_{12}, f_{13})	1	1	1	1	1	1	1	1	1	1	1	1	12
:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
135	(f_{15}, f_{17})	0	0.6	0	1	0	1	0	1	0	1	0	1	5
136	(f_{16}, f_{17})	0	0.8	0	0.93	0	0.96	0	1	0	1	0	0	2
	$CI(n_k)$	30	68	44	78	31	90	30	92	30	100	30	104	
	$CI_s(n_k)$	0.04	30.31	0	34.58	0	26.62	0.53	15.25	0.04	13.65	0.01	9.05	

TABLE 4: Reduced fault-pair similarity coefficient criterion information table of the first CUT.

Number	Fault-pair	n_1	n_3	n_4	n_5	n_7	n_8	n_9	n_{11}	NT_1
11	(f_1, f_{12})	0	0	0.15	0	0	0.39	0	0	0
38	(f_3, f_{10})	0	0	0.23	0	0	0.06	0	0	0
39	(f_3, f_{11})	0	0	0.67	0	0	0.22	0	0	0
90	(f_7, f_{16})	0	1	0.93	0	0	1	0	0	2
	$CI(n_k)$	0	1	0	0	0	1	0	0	
	$CI_s(n_k)$	-	0	-	-	-	0.67	-	-	

TABLE 5: Remainder fault-pair similarity coefficient criterion information table of the first CUT.

Number	Fault-pair	n_1	n_3	n_4	n_5	n_7	n_9	n_{11}	NT_1
11	(f_1, f_{12})	0	0	0.15	0	0	0	0	0
38	(f_3, f_{10})	0	0	0.23	0	0	0	0	0
39	(f_3, f_{11})	0	0	0.67	0	0	0	0	0
	$CI(n_k)$	0	0	0	0	0	0	0	
	$CI_s(n_k)$	-	-	-	-	-	-	-	

TABLE 6: Results of comparison experiment with the other reported methods.

Method	S_{opt}	Fault isolation degree	Number of remainder fault-pairs
Starzyk et al.'s [1]	$n_2, n_4, n_5, n_6, n_{10}, n_{12}$	10	-
Golonek and Rutkowski's [9]	$n_2, n_5, n_6, n_{10}, n_{12}$	10	-
Luo et al.'s [2]	$n_2, n_5, n_6, n_{10}, n_{12}$	10	-
Zhao and He's [3]	$n_2, n_4, n_6, n_{10}, n_{12}$	11	3
Yang et al.'s [14]	$n_2, n_4, n_5, n_{10}, n_{12}$	12	3
New method (1.00)	$n_2, n_6, n_8, n_{10}, n_{12}$	12	3
New method (0.95)	n_2, n_6, n_{10}, n_{12}	12	3

of each remainder test point. After comparing $CI(n_k)$'s of the remainder test points, $CI(n_3)$ and $CI(n_8)$ are found to be the same and their values are 1. In order to select the better test point, $CI_s(n_3)$ and $CI_s(n_8)$ are compared. Because $CI_s(n_8)$ of n_8 is larger than $CI_s(n_3)$ of n_3 , n_8 is added to S_{opt} . After deleting (f_7, f_{16}) and n_8 , the algorithm goes to Step 5.

Finally, no fault-pair can be isolated by the remainder test points, so the algorithm stops and the final S_{opt} is $\{n_2, n_6, n_8, n_{10}, n_{12}\}$. The final fault-pair similarity coefficient criterion information table is shown in Table 5. The fault-pairs (f_1, f_{12}) , (f_3, f_{10}) , and (f_3, f_{11}) (i.e., five faults f_1, f_3, f_{10}, f_{11} , and f_{12}) cannot be isolated.

3.2. Comparison Experiment. The comparison experiment of accuracy is made between the proposed method and five reported methods. The interval parameter 1.96 is usually used to determine ambiguity gaps [2, 3]. According to the normal distribution theory, the probability is 95% when the interval parameter is 1.96. The same ambiguity gap (i.e., $[u_i - 1.96\sigma_i, u_i + 1.96\sigma_i]$) is adopted in the five reported methods for comparison under the same condition. The new method needs integral operation in the interval $(-\infty, +\infty)$ to solve C_s , and then the threshold value of C_s should be set to distinguish whether the fault-pair can be isolated or not. The threshold values 1.00 and 0.95 are set in new method to compare with other methods. The comparison results of these methods are listed in Table 6.

As can be clearly seen from Table 6, three methods which adopt the integer-coded fault dictionary have the same fault isolation degree, but their fault isolation degree is smaller than those of other three methods which adopt fault-pair.

When the threshold value of the new method is set as 1.00, all the methods except Starzyk's method obtain the same size of test points set. However, the new method and Yang's method have the largest fault isolation degree. When the threshold value of the new method is set as 0.95, the new method has the smallest test point set. Therefore, the new method is accurate and effective.

3.3. Experiment with Different Threshold of C_s on the Active Filter Circuit. The second simulation CUT is shown in Figure 3. A 1 kHz, 4 V sinusoidal signal is chosen as the stimulus of circuit simulation. The tolerances of resistor and capacitance, parameters of Monte Carlo analysis and fault mode setting method, are the same as the first CUT. 20 single hard faults $f_2 \sim f_{21}$ and normal mode f_1 are tested on the CUT. All modes are listed in Table 7. According to samples of the active filter circuit, a fault dictionary is constructed and shown in Table 8.

C_s is solved by integral operation in the interval $(-\infty, +\infty)$ according to formula (2). Because theoretically the probability density function curves of any fault-pair are overlapping in the interval $(-\infty, +\infty)$ and the value of C_s

FIGURE 3: Schematic of active filter circuit.

TABLE 7: Fault modes of the second CUT.

Label	Fault
f_1	Normal
f_2	R_1 short
f_3	R_1 open
f_4	R_2 short
f_5	R_2 open
f_6	R_3 open
f_7	R_5 short
f_8	R_5 open
f_9	R_6 short
f_{10}	R_6 open
f_{11}	R_7 open
f_{12}	R_8 open
f_{13}	R_9 open
f_{14}	R_{10} open
f_{15}	R_{11} open
f_{16}	R_{12} open
f_{17}	C_1 open
f_{18}	C_2 short
f_{19}	C_3 short
f_{20}	C_4 open
f_{21}	C_4 short

is less than 1, the threshold value of C_s should be set in practical application. The test results with different threshold value are shown in Table 9. The threshold value 1 is obtained by rounding it to 2 decimal places for C_s . In Table 9, the larger threshold values have more fault-pairs that cannot be isolated because the overlapped area of probability density function curves increases. Under threshold values 0.9, 0.92, 0.94, 0.96, and 0.98 conditions, the fault isolation degrees and isolated fault modes are the same which illustrates that the

increased fault-pairs that cannot be isolated originate from the same ambiguity fault set. However, the test point set of threshold value 0.9 is the smallest among these threshold values. $\{n_1, n_8, n_9, n_{11}\}$ can be selected as the optimal test point set to diagnose the CUT in practice.

4. Conclusion

This paper uses the similarity coefficient criterion to construct a fault-pair similarity coefficient criterion information table. According to the table, the optimal test point set S_{opt} is obtained. By analysis, the complexity of the algorithm is proved to be $O(m \cdot N_F^2 \cdot N_T)$. The feasibility and validity of the proposed method have been verified by the simulation experiments, and the accuracy of the proposed method has been demonstrated by the comparison experiment with the other reported methods. The results indicate that the proposed method achieves a significant improvement in the optimal test point selection for analog circuit.

Nomenclature

f_i :	The i th fault
f_j :	The j th fault
C_s :	Similarity coefficient criterion
N_T :	Number of candidate test points
N_F :	Number of all the faults
n_k :	The k th test point
$C_{sl}(n_k)$:	Similarity coefficient criterion in the l th row and column n_k
$CI(n_k)$:	Total number of 1's in column n_k
$CI_S(n_k)$:	Sum of all overlapping fault-pair similarity coefficient criterion information in column n_k
NT_l :	Total of 1's in the l th row
S_{OPT} :	Optimal test point set
S_C :	Candidate test point set.

TABLE 8: Fault dictionary of the second CUT (unit: V).

	$n_1(\mu_1, \sigma_1)$	$n_2(\mu_2, \sigma_2)$	$n_3(\mu_3, \sigma_3)$	$n_4(\mu_4, \sigma_4)$	$n_5(\mu_5, \sigma_5)$	$n_6(\mu_6, \sigma_6)$	$n_7(\mu_7, \sigma_7)$	$n_8(\mu_8, \sigma_8)$	$n_9(\mu_9, \sigma_9)$	$n_{10}(\mu_{10}, \sigma_{10})$	$n_{11}(\mu_{11}, \sigma_{11})$
f_1	4.00	0.49	2.81	0.5	3.11	0.61	2.75	0.57	2.75	0.57	3.82
f_2	3.94	0.03	2.75	0.15	3.05	0.28	2.66	0.26	2.66	0.26	3.53
f_3	-6.22	0.17	-6.22	0.17	0.00	0.00	-0.06	0.00	-0.05	0.00	7.17
f_4	3.61	0.17	3.61	0.17	4.03	0.36	3.52	0.32	3.52	0.32	4.97
f_5	2.83	0.13	-6.13	0.16	0.00	0.00	-0.06	0.00	-0.05	0.00	7.23
f_6	2.76	0.14	1.90	0.20	1.15	0.15	1.11	0.14	1.11	0.14	5.57
f_7	4.13	0.42	2.93	0.41	0.00	0.00	-0.06	0.00	-0.05	0.00	7.29
f_8	3.97	0.32	2.84	0.34	3.72	0.51	3.24	0.45	3.24	0.45	5.11
f_9	4.13	0.41	2.91	0.4	2.34	0.38	0.00	0.00	0.00	0.00	7.19
f_{10}	4.33	0.55	3.13	0.55	1.38	0.38	6.52	0.15	6.55	0.15	10.2
f_{11}	4.14	0.42	2.84	0.42	3.23	0.51	2.83	0.47	2.83	0.47	4.74
f_{12}	4.16	0.44	2.97	0.43	2.72	0.44	1.79	0.32	2.60	0.12	10.2
f_{13}	4.01	0.41	2.89	0.43	3.15	0.49	2.77	0.47	2.77	0.47	3.57
f_{14}	3.94	0.53	2.79	0.52	2.49	0.54	-2.12	0.39	-5.86	0.21	10.2
f_{15}	4.08	0.44	2.85	0.42	3.19	0.52	2.8	0.47	2.80	0.47	4.40
f_{16}	4.08	0.42	2.90	0.43	3.19	0.51	2.78	0.46	2.79	0.47	4.42
f_{17}	2.53	0.09	1.80	0.16	2.04	0.2	1.74	0.18	1.74	0.18	4.36
f_{18}	1.80	0.06	0.00	0.00	0.00	0.00	-0.06	0.00	-0.06	0.00	7.27
f_{19}	4.32	0.44	3.13	0.43	4.99	1.03	4.99	1.03	5.03	1.07	7.97
f_{20}	4.01	0.49	2.83	0.5	4.31	0.78	-0.06	0.00	-0.05	0.00	7.31
f_{21}	4.13	0.44	2.85	0.46	3.47	0.57	3.47	0.57	3.48	0.57	5.07

TABLE 9: Test results with different threshold value of C's for the second CUT.

Different threshold value	S_{opt}	Fault isolation degree	Isolated fault modes	Number of remainder fault-pairs
0.90	n_1, n_8, n_9, n_{11}	13	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{18}, f_{20}$	14
0.92	$n_1, n_3, n_8, n_9, n_{11}$	13	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{18}, f_{20}$	15
0.94	$n_1, n_3, n_8, n_9, n_{11}$	13	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{18}, f_{20}$	16
0.96	$n_1, n_3, n_7, n_8, n_9, n_{11}$	13	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{18}, f_{20}$	17
0.98	$n_1, n_3, n_7, n_8, n_9, n_{11}$	13	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{18}, f_{20}$	20
1	$n_1, n_3, n_7, n_8, n_9, n_{11}$	11	$f_3, f_5-f_7, f_9-f_{10}, f_{12}, f_{14}-f_{16}, f_{18}, f_{20}$	27

Conflicts of Interest

The authors declare that they have no conflicts of interest in connection with the work submitted.

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