Application of Genetic Algorithms to Analog Fault Diagnosis

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***Abstract* - This paper addresses itself to analog fault diagnosis by means of simulation-before-test approach, the so called dictionary approach. Original diagnostic system for single fault detection, location and identification is built, based on the Genetic Algorithm (GA) technique. The proposed system allows identification of the selected parametric faults at reasonable dictionary size and low computational effort. This feature is not present in classical dictionary. The system effectiveness has been verified by computational examples and the obtained results have confirmed usability of the GA technique to analog dictionary construction**

1 Introduction

Genetic Algorithms (GA) [6-8] imitate natural process selection, crossover, and mutation. GA uses populations (generations), with many individuals (chromosomes), which evolve to solution of problem (coded into individuals). Chromosomes in GA are string of bits (genes) that have constant length usually. Crossover exchanges randomly selected pieces of chromosomes between two parents and creates offspring. Better individuals have more probability of reproduction. Mutation is a negation of randomly selected bit(s). Heredity of coded information in chromosomes allows to build better individuals auguring increasing fitness into next generations. Correct choice of pressure of selection and diversity of population allow to search big space of solution efficiently, owing to hidden parallelism of algorithm. Mutation introduces additional random sampling of the analyzed space, decreasing probability of convergence to local optimum. Application of the well tested, practically verified natural methods allows to solve many difficult problems that need effective optimization techniques. Application of GA to analog fault diagnosis was not well studied yet. In general, two different classes to analog testing can be distinguished: fault driven testing and specification driven (functional) testing. The proposed diagnostic system belongs to the first class, it utilizes GA to single parametric fault detection, location and identification, i.e. it allows not only such fault recognition but also precise estimation of the faulty value. Use of the GA allows great time saving in dictionary construction, when many parametric faults have to be diagnosed.

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2 GA Based Fault Dictionary

In the classical analog fault dictionary only catastrophic faults are considered [1-5]. The proposed dictionary allows also detection, location and identification of the selected parametric faults. The dictionary construction will be presented for dc testing, however the strategy can be easily extended on other testing, such as for example ac testing. Before presenting strategy of the dictionary construction, some basic concepts and notations will be introduced.

Set of the Circuit Under Test (CUT) parameters is denoted by $\boldsymbol{R}=\{R_1,...,R_J\}$. In general, the CUT parameter can be other than resistance R, e.g. control source gain ρ, transistor gain β, etc. The nominal value is denoted by R_j^n and $\Delta R_j = tol \cdot R_j^n$ is the acceptable deviation. Then, the tolerance region is

$$R_j^- = R_j^n - \Delta R_j \le R \le R_j^n + \Delta R_j = R_j^+ ;\ j=1,...,J \quad (1)$$

Single fault is defined as a single parameter deviation outside the tolerance range (1), while other parameters are within their tolerance margins.

In the dc dictionary, node voltages and source current are the CUT measurements: $\boldsymbol{V}=\{ V_1,..,V_M \}$. Set of the identified circuit conditions contains: healthy condition, single catastrophic faults (short circuit=s.c. and open circuit=o.c.) of some elements and single parametric faults of the others. Now, strategy of the dictionary before-test construction and after-test reading (decision taking) will be explained.

2.1 Before -Test Stage

At the before-test stage, each CUT condition is simulated and signatures (measurements) are stored in the dictionary. Signatures of healthy condition and catastrophic faults are designated in a classical way, i.e. for each condition one circuit simulation is performed, GA technique is not involved. To detect, locate and identify selected parametric faults, for each identified parameter R_j ; $j=1,..,J$; functions $V_m(R_j)$; $m=1,...,M$; are designated by means of GA (for the nominal values of other parameters, $R_k=R_k^n$; $k=1,..,J$; $k \neq j$).

These functions are in discrete form, i.e. for discrete values of parameter R_j:

$R_j^{(1)},..R_j^{(i)},...\qquad ;\ R_j^{(i+1)}= R_j^{(i)} + \Delta R_j^{(i)},$

values of all functions V_m are designated:

$V_m[R_j^{(1)}],..,V_m[R_j^{(i)}],..;V_m[R_j^{(i+1)}]=V_m[R_j^{(i)}]+\Delta V_m[\Delta R_j^{(i)}],$

such that each measurement increment $\Delta V_m[\Delta R_j^{(i)}]$ does not exceed the assumed maximum ΔV_m^{max}. The GA performs two functions.

1. For the given value of $R_j^{(i)}$, it finds the most sensitive measurement to R_j change, $V_x[R_j^{(i)}]$.
2. It designates the increment $\Delta R_j^{(i)}$, that provides the assumed maximum deviation ΔV_x^{max}.

Both functions are performed simultaneously. For the given parameter R_j, procedure of finding functions $V_m(R_j)$ is executed in four steps, as described below.

Step 1. $i=1$: $R_j^{(i)}=10^{-6}\Omega$. Circuit simulation, calculation of $V_m[R_j^{(i)}]$; $m=1,..,M$. Random selection of the initial population $\boldsymbol{\Delta R_j^{(i)}}=\{\Delta R_{j1}^{(i)},..,\ \Delta R_{jL}^{(i)}\}$, where L is the assumed size of population, e.g. $L=10$.

Step 2. Circuit simulations for $R_l^{(i+1)}=R_{jl}^{(i)}+\Delta R_{jl}^{(i)}$; $l=1..L$. For each individual $\Delta R_{jl}^{(i)}$ calculation of $V_m[R_j^{(i+1)}]$; $m=1,..,M$; and designation of the most sensitive measurement x. Then, calculation of the fitness function $F_x[\Delta R_{jl}^{(i)}]$.

Step 3. Check of the reproduction stop criteria. If none of them is satisfied, then update of the mating pool, reproduction of the new population $\boldsymbol{\Delta R_j^{(i)}}$ and return to Step 2.

Step 4. Storage of $R_j^{(i+1)}$ and corresponding signature $V_m[R_j^{(i+1)}]$; $m=1,..,M$; in the dictionary. If $R_j^{(i+1)}<R_j^{max}=10^{12}\ \Omega$, then $i=i+1$ and return to Step 2.

Now, Steps 2 and 3 will be explained in details.

Step 2. Increment ΔR_{jl} is coded in 12 bits binary code. Two leftmost bits code the "multiplier" : M, while other ten code the "value" : W.

If $M=1\cdot[00]$, then $\Delta R_{jl}=W1000/1024$.
If $M=100\cdot[01]$, or $M=200\cdot[10]$, or $M=300\cdot[11]$, then $\Delta R_{jl}=M(W+1)1000/1025$.

As can bee seen, the minimum increment (maximum resolution) is $\Delta R^{min}=1000/1024\cong0.98\Omega$. For the example chromosome $C=[10\ 1000101111]$, $M=200$ and $W=559$, and then, increment $\Delta R_{jl}=109.268k\Omega$. For the given $\Delta R_{jl}^{(i)}$ and nominal values of other parameters, the CUT simulation is performed. Next, the most sensitive measurement x with respect to R_j change is designated: $\Delta V_x[\Delta R_{jl}^{(i)}] > \Delta V_m[\Delta R_{jl}^{(i)}]$; $m=1,..,M$; $m\neq x$. Then, for this measurement the following Gauss-type fitness function is calculated:

$$F_x[R_{jl}^{(i)}]=exp(-(\Delta V_x[R_{jl}^{(i)}] - \Delta V_x^{max})^2/(2\ \sigma)) \quad (2)$$

where σ is the assumed variance. This variance has to be selected empirically and for the tested examples $\sigma=0.3$. That way fitness functions have been designated for all chromosomes of the population.

Step 3. In this step two termination criteria are checked. They are as follows.
1. Solution has been found, i.e. for the assumed $\Delta R_{lk}^{(i)}$, single fitness function has reached the assumed limit F^{max} (in tested examples $F^{max}=0.95$ has been assumed) . Then, $R_j^{(i+1)}=R_j^{(i)}+\Delta R_{jk}$.
2. Solution has not been found but the average fitness function $F_a^{(i)}=1/L(\ F_x[\Delta R_{j1}^{(i)}]+..+\ F_x[\Delta R_{jL}^{(i)}]\ )$ does not change over the last few populations, i.e. the assumed i-th initial population does not promise a success. In such case, the best individual ΔR_{jk} is accepted, however $F_x(\Delta R_{jk})<F^{max}$.
If none of the above criteria is fulfilled, then the mating pool is updated, i.e. well adapted chromosomes are included in the pool - the roulette rule is applied [6]. Next, genetic crossing and mutation are applied, the new population of chromosomes is produced and Steps 2-3 are repeated.

Finally, after finding of all discrete relationships $V_m(R_j)$, the total number of circuit conditions is $1+N_1+...+\ N_j$ where N_j is the number of discrete values of parameter R_j. In special case, when only catastrophic faults are identified, $N_j=2$ and signatures are designated after two circuit simulations, as described before. No GA calculations are involved in such case. Two example hypothetical functions have been presented in Fig.1. At $R^{(1)}$ and $R^{(3)}$, ΔV_2^{max} has been reached, while at $R^{(2)}$, ΔV_1^{max} has been reached .

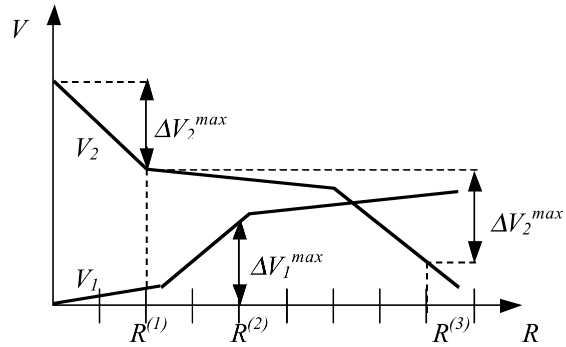

Figure 1: Example hypothetical functions $V_m(R)$, $m=1,2$

2.1 After-Test Stage

At this stage the CUT measurements are compared with stored signatures. First, GO/NO GO check is performed, i.e. CUT measurements are compared with the nominal circuit signature and healthy/faulty decision is taken. The Nearest Neighbor Rule classifier, based on Euclidean distance measure, has been utilized. If the distance (mean square error) is greater than the assumed boundary value $\delta=0.01$, then CUT has been found faulty and fault location and identification are performed next. At first, catastrophic faults are checked. If no catastrophic fault has been found, i.e. all designated distances are greater than δ, then "small" parametric faults (close to the tolerance region faults, i.e. faults from the range $<\Delta R,k\Delta R>$, where k is the assumed small value greater than 1) are checked. If the boundary value δ has not been reached, then "large" parametric faults are checked, i.e. calculated distances are compared with the same boundary value δ. It may happen that the boundary distance δ has been reached by more than one signature. In such case fault has been located with accuracy to group of elements. If size of such group exceeds 5, then diagnosis level remains at GO/NO GO decision (healthy/faulty recognition).

3 Computational Example

To verify the presented strategy of dc dictionary construction and effectiveness of the presented approach some practical examples, have been studied. One of them, originally considered in [5], has been reproduced in Fig.2.

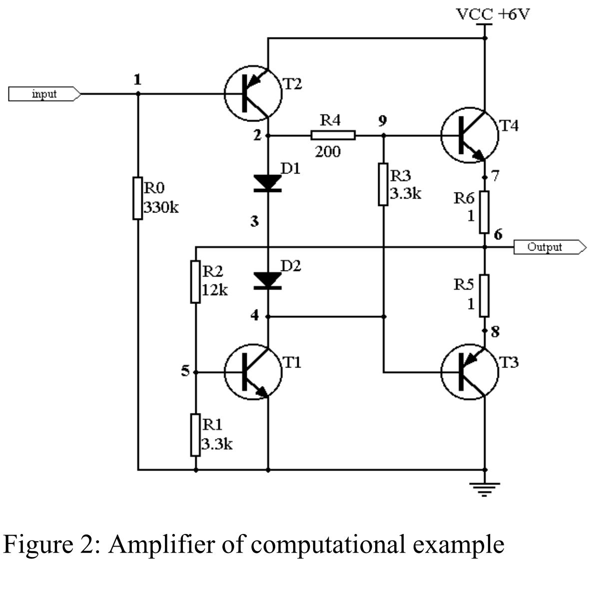

Figure 2: Amplifier of computational example

Set of measurements is $\boldsymbol{V}=[V_1,V_2,V_3,V_4,V_5,I_{cc}]$. Set of identified parameters is $\boldsymbol{R}=[R_0,..,R_4]$, $tol\%=10\%$.

3.1 Before -Test Stage

The dictionary has been constructed to recognize healthy condition, catastrophic faults of all elements (including semiconductors), "large" parametric faults and "small" parametric faults. First, healthy condition and catastrophic faults have been simulated, five faults for each transistor (B-$E_{s.c.}$, C-$B_{s.c.}$, $E_{o.c.}$,$B_{o.c.}$,$C_{o.c.}$) and two faults (s.c. and o.c.) for diodes and resistors, i.e. total of 20+4+10=34 faults. All simulations have been performed by SPICE. Next, $V(R_j)$ relationships have been designated by means of the GA own program. For parametric faults of R , with 1% resolution and search range $<10^{-6}\ \Omega,10^{12}\ \Omega>$, about $3*10^{12}$ simulations are required with a constant step (in the classical approach). Use of the GA, allows to decrease this number to 2041! This large number shows only the GA/classical simulations ratio, i.e. $2041/(3*10^{12})$. Practically, number of GA simulations can be significantly reduced by reasonable increase of the assumed ΔV_m^{max}. Moreover, it should be emphasized that number of GA simulations practically does not depend upon the CUT size and these simulations are performed at the before test stage and at this stage computational time spent is not of the primary importance (reasonable time is practically the only criterion). In Fig. 3 the obtained $V_3(R_1)$ and $I_{cc}(R_1)$ relationships are presented for distinct values of R_1. Values of V_1 are denoted by stars, while values of I_{cc} by dots.

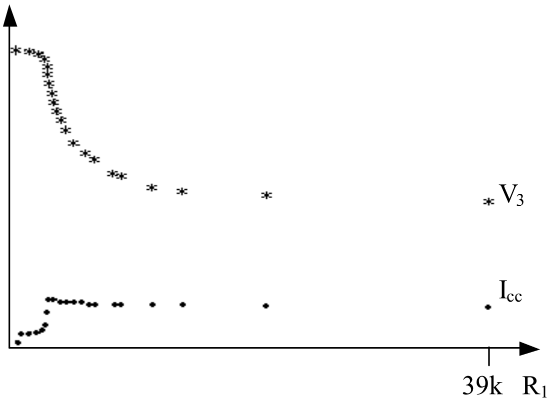

Figure 3: $V_3(R_1)$ and $I_{cc}(R_1)$ relationships for the example amplifier

3.2 After-Test Stage

Total of 2000 simulations have been performed for all circuit conditions, with parameters of fault free elements randomly selected from the tolerance region. First, healthy/faulty recognition has been checked. For healthy circuits, the correct diagnosis has been obtained in 63%, while in the remaining 37% "small" parametric faults have been incorrectly

Table 1: Diagnosis results for selected parametric faults

R \ α	0.1	0.5	2	5	10	50	100	1000
R0	R0=51k	R0=168k	R0=616k	R0=1.4M	R0=3.6M	R0=8.9M	R0=28M	R0=329M
R1	R1=198	R1= 1.4k	R1=6.3k or R2=6k	R1=21k or R2=2.6k	R1=39k or R2=1.9k	R1=170k	*R1=691k*	*R1=2.5G*
R2	R2=1.2k	R2=6.6k or R1=6.3k	R2=23k	R2=61k	*R2=286k or R1=315*	R2=560k	R2=829k	R2=9.1M
R3	R3=264	*R2=11.4k*	*R1=3.2k*	*R2=11.4k*	*R2=11.4k or R1=3.5k*	*R2=11.3k or R1=3.5k*	*R2=11k or R1=3.8k*	*R2=11.3k or R1=3.5k*
R4	*R1=3.4k or R2=11k*	*R3=5k*	*R3=3.1k or R5 O or R4=210 or T3 OB*	R4=1.3k or R3=825	R4=1.3k or R3=825	R4=11.5k	R4=11.5k	R4=152k

identified, i.e. healthy circuit has been diagnosed faulty. Next, catastrophic faults recognition has been checked and 100% correct recognition has been observed, however in some cases recognition was not precise (e.g. open circuit faults of diodes can not be distinguished). Finally, identification of parametric faults has been checked and around 90% of faulty circuits (with "small" and "large" faults) have been diagnosed correctly, i.e. CUT has been diagnosed faulty. The results are presented in Table 1 for selected faulty values of αR_j^n. Faults with incorrect recognition are in shaded fields. Rate of correct identification is 61.4%, however healthy/faulty recognition is 100%. It should be emphasized, that incorrect diagnosis results from the CUT diagnosability limitations rather than weakness of the GA approach. For a voltage divider, increase of one resistance can not be distinguished from decrease of the other, without current measurement . Effectiveness of GO/NO GO check could be improved by removing "very small" parametric faults from the dictionary, e.g. faults from the range $<\Delta R, 2\Delta R>$, or increasing of the assumed increment ΔV^{max}. For other tested examples, the obtained percentages of correct diagnosis were at the same level.

4 Conclusions

New approach to analog fault dictionary construction has been proposed. This approach utilizes GA technique to designate signatures of the CUT parametric faults. Thanks to GA prediction ability, number of simulations and size of fault dictionary have been radically decreased, as compared to parametric faults with constant step of parameter. The constructed dc fault dictionary well describes all possible states of the CUT for single faults. Ability of a parameter value identification for parametric faults is important novel feature of the proposed method. The dc fault dictionary gives limited information about CUT, e.g. it does not allow to identify faults of reactive elements. However, the presented strategy can be easy modified to ac fault dictionary or fault dictionary with non periodic stimulus. The described method of designation of “circuit variable” – “circuit parameter” relationship (in presence of design tolerances of other parameters) has been utilized to dc fault dictionary construction. Other applications to analog circuits analysis and design are possible, e.g. to designate filter amplitude response, i.e. “gain” – “frequency” relationship.

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