Introducing Qualitative Reasoning in fault dictionaries techniques for analog circuits analysis

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Abstract

The aim of this paper is to develop a higher level layer for different analog circuit diagnosis techniques. In particular, two fault dictionary methods have been applied to an analog circuit. The first step towards a qualitative decision is to fuzzyfy the results given by each method. A comparison between the dictionary and the fuzzyfied one shows the great improvement obtained by the method.

Introduction

Although almost all circuits are designed using digital technology, a lot of them have analog components. This is due to the analog nature of input and output signals they have to deal with (audio signals, signals from sensors, etc.). So, analog interfaces as filters, AD/DA converters, PLL (Phase Locked Loop), modulators and demodulators will be needed (Milor 1998), (Wey 1994), (Boyd 1999).

Diagnosis techniques for digital circuits have been successfully developed and automated. But, this is not yet the situation for analog circuits (Mir *et al.* 1994). Analog circuits are more complex to diagnose due to the measures overlapping produced by the components tolerance (Dague 1994),(Duhamel & Rault 1979). These tolerances together with the analog nature of the measured signals, can produce the same symptoms for different failures, producing a set of components as possible diagnosis called *ambiguity groups* (Stenbakken, Souders, & Stewart 1989).

In Next sections a classification of the analog circuits diagnosis and two particular fault dictionary methods applied to a biquadratic filter are shown. Afterwards, the results given by each method will be improved using fuzzy logic in order to cope with tolerance effect. Conclusions and the future work are exposed in the last section.

Diagnosis of analog electronic circuits

Diagnosis of circuits is based on the response circuit analysis to a certain input stimuli. Therefore, it is necessary to generate stimuli signals and to acquire measures in particular circuit nodes. A typical environment for diagnosing electronic circuits, is depicted in Figure 1.

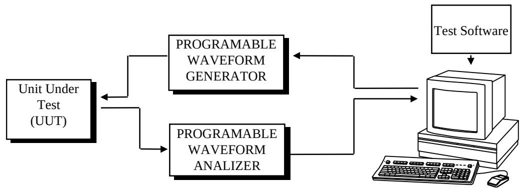

Figure 1: Basic automatic test system structure

There are plenty of methods proposed for diagnosing analog electronic circuits. A possible classification is given in (Bandler & Salama 1985) and a scheme based on it is shown in Figure 2. The block *Artificial Intelligence Techniques* doesn't appear in the original scheme, although it is mentioned in the text. The term *simulation* has to be understood as the process (simulated or real) of taking data from particular faults generated on purpose. Depending on the test stage where the fault simulation is done, the following division can be made: *simulation before test*, where a set of previous simulations will be carried out in order to store particular symptoms and signatures, and *simulation after test*, where these data are calculated after taking the measures. Belonging to the first group, *fault dictionary techniques* and *approximation techniques* can be cited, while the second one encloses *parameter identification techniques*, *fault verification techniques* and some of the *approximation techniques* as well.

The *Artificial Intelligence techniques* could be applied either as a reinforcement of the previous ones or as themselves. *Fuzzy techniques*, *Neural networks*, *Expert systems* and *Case Based Reasoning (CBR)* can be cited among all of them.

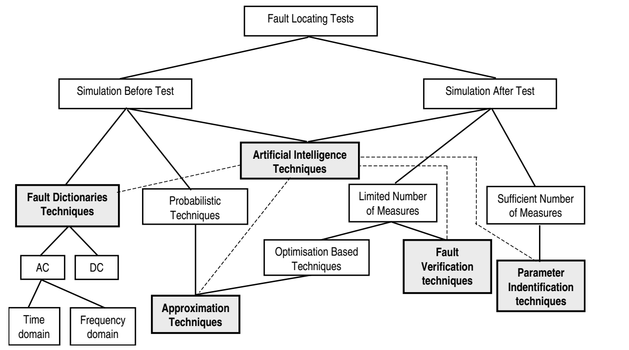

Figure 2: Diagnosis methods classification

In order to select a diagnosis method or methods, it is necessary to fix the type of fault to be detected. This paper is focused on the detection and location of **parametric**, **permanent**, **independent** and **simple** faults. These characteristics are described in detail in (Duhamel & Rault 1979). In particular, fault dictionary techniques are used to approach the problem, because they are simpler and the most commonly used in practice.

Fault dictionary methods

Fault dictionaries are techniques completely based on quantitative calculations. Selected measures are obtained from the faulty system, and stored in a table (dictionary).

Fault set	Measure 1	Measure 2	...	Measure n
Nominal	M10	M20	...	Mn0
Fault 1	M11	M21	...	Mn1
Fault 2	M12	M22	...	Mn2
...	...	...	...	...
Fault m	M1m	M2m	...	Mnm

Table 1: Dictionary appearance

These values will be then compared with the measures obtained from an unknown faulty system. The comparison is typically performed by the neighborhood criterion, obtaining distances, minimizing certain indexes, and so on. So, the method has two steps: The first one is based on simulation in order to built the dictionary; the second one consists of comparing the measures from the unknown faulty system with the stored ones. These techniques have a compromise between testability and dictionary length. When the fault dictionary is made bigger, the scope of faults detected increases as well. On the other hand, if the faults considered to generate the dictionary are a small set, the dictionary will be shortened, and the world of detected faults will be reduced. So, one of the objectives of the diagnosis designer is to built a dictionary with as few measures as possible that gives a good fault diagnosis coverage.

In the following subsections, the effect of tolerances first, and two fault dictionary methods then are described in detail.

Tolerances effect

A lot of systems, and in particular, electronic analog circuits, are seriously affected by tolerances. The following figure shows the deviation in a gain measure considering component tolerances.

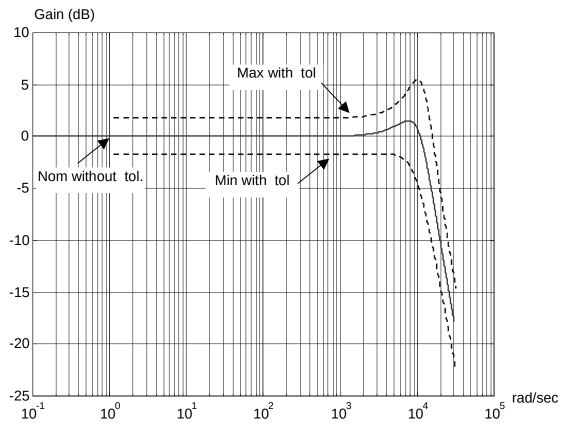

Figure 3: Band produced by tolerance

If the dictionary is obtained by simulation using only the nominal values of the components, the measures got from the real system won't match to the stored ones because of tolerances. A first approach to take tolerances into account is to store intervals instead of just one value, as shown in table .

Fault	Measure 1	...	Measure n
Nom	$[M10_{min} M10_{max}]$	...	$[Mn0_{min} Mn0_{min}]$
F1	$[M11_{min} M11_{max}]$	...	$[Mn1_{min} Mn1_{min}]$
...	...	...	...
Fm	$[M1m_{min} M1m_{max}]$	...	$[Mnm_{min} Mnm_{min}]$

Table 2: Dictionary with intervals

In order to find the maximum and minimum values of the intervals for a particular measure, several simulation runs have to be carried out. According to (Boyd 1999), resistors and capacitors have a gaussian distribution of their values. Therefore, when simulating, the values of the components are randomly changed, inside their $\pm 10\%$ tolerance margin, using the Monte-Carlo method with a gaussian distribution.

It is obvious that increasing the number of Monte-Carlo runs provokes an interval spreading. One of the questions that immediately arises is how many Monte-Carlo runs are necessary to predict a good interval for each measure. After several tests, the authors stated that more than 5000 runs produce outlayers that widen the interval unnecessarily, while the gaussian 3σ deviation from the mean doesn't change. Therefore, 5000 runs for each considered fault, with Monte-Carlo method using gaussian randomly distributed values of the components were used to generate the dictionary intervals. In our case, the simulation was performed using $Matlab^{TM}$.

Frequencial method

For this method, the stimuli signals are sinusoidal waveforms at different frequencies $(f1, f2, ..., fn)$. The measures taken are amplitude, phase or both. The set of frequencies selection at which to perform the measures is based on the one described in (Varghese, Williams, & Towill 1978). It associates a confidence level index to a set of test frequencies selected. This index has to do with the capability of the frequencies to separate and diagnose the proposed set of faults. The faults of interest $(F1, F2, ..., Fn)$ are simulated and the magnitude (Amp) and phase (Ph) responses at these frequencies are stored.

Faults	Amp f1	Ph f1	Ph f2	...	Amp fn
Nominal	$A0_{f1}$	$Ph0_{f1}$	$Ph0_{f2}$	...	$A0_{fn}$
F1	$A1_{f1}$	$Ph1_{f1}$	$Ph1_{f2}$	...	$A1_{fn}$
...	...	...	...	...	...
Fm	Am_{f1}	Phm_{f1}	Am_{f2}	...	Am_{fn}

Table 3: Frequencial dictionary

Then, the algorithm starts calculating the confidence level beginning with a frequency and a measure (module or phase). If the index is not satisfactory (less than a pre-established minimum), more responses and frequencies are introduced. When the confidence level is sufficient, the algorithm stops and provides an optimum set of frequencies and measures to perform.

Temporal method

In this case, the stored data in the dictionary are certain characteristics of the circuit response to a saturated ramp input (Figura 4), as proposed in (Balivada, Chen, & Abraham 1996).

The parameters used to characterize the faults are:

- *Steady state (V_{est})*: Final value at which the output tends to.
- *Overshoot (SP)*: Defined as

$$SP = \frac{V_{\max} - V_{est}}{V_{est}} 100 \tag{1}$$

  where V_{max} is the amplitude maximum value reached at the output.
- *Rising time (tr)*: Time used by the output to rise from the 10% to 90% of the steady state value.

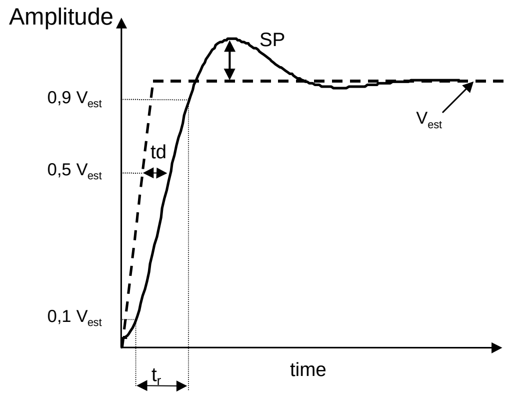

Figure 4: Response parameters to a ramp input

- *Delay time (td)*: Interval of time between the moment that the input and the output get to the 50% steady state value.

In (Balivada, Chen, & Abraham 1996) it is highlighted that choosing a smaller ramp rise time, doesn't imply better diagnostic results. A method to help in the selection of an appropriate ramp rise time is not provided. The dictionary has an appearance like the table

Faults	SP	td	tr	Vest
Nominal	SP0	td0	tr0	Vest0
F1	SP1	td1	tr1	Vest1
...	...	...	...	...
Fm	SPm	tdm	trm	Vestm

Table 4: Temporal dictionary

System under test

The selected system is a biquadratic filter shown in Figure 5. This circuit is used as a benchmark in the bibliography (Balivada, Chen, & Abraham 1996) (Kaminska *et al.*) (Soma 1990).

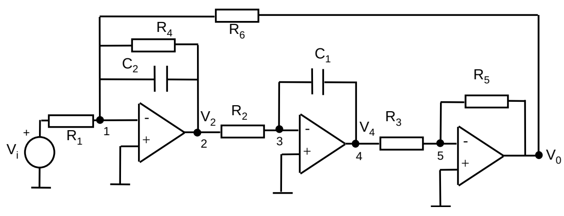

Figure 5: Circuit under test

The nominal values of the components in the example are: R1=2.7K, R2=1K, R3=10K, R4=1.5K, R5=12K, R6=2.7K and C1=C2=10nF. The initial proposed faults to detect are deviations of ±20% and ±50% from the nominal values of the passive components (a set of 32 faults). So, our dictionary has a row for each fault and the nominal case (33 rows). A component is considered faulty when its value differs more than 10% from nominal.

In the following subsections, the two dictionary techniques explained in the previous paragraph are applied to the biquad filter, and the main results are highlighted. In order to reduce the set of measures, it has been considered that only voltage measures at the output V_0 are possible. The frequencial method is described in detail, while for the temporal one, only some results are commented, since both methods are similar.

Frequencial method

Applying this method to the biquad filter, the set of frequencies at which to perform the measures has to be defined first. Implementing the algorithm proposed in (Varghese, Williams, & Towill 1978) to the biquad filter, the following set of measures is derived:

rad/sec.	Amplitude	Phase
9000		X
10000	X	X
65000		X
85000	X	
100000		X

Table 5: Selected set of measures

Observing the table, 6 measures are necessary. For example, taking the fault $R1-20\%$ the following values at V_0 are measured:

Freq.(rad/sec.)	Amplitude (V)	Phase (^{o})
9000		172.17
10000	1.26	171.27
65000		92.89
85000	0.88	
100000		50.19

Table 6: Measures for R1-20%

The dictionary has 33 rows and 6 columns corresponding to the amplitude and phase at V_0 taken at the selected frequencies. Hence, in order to built the dictionary, a set of 33x6 = 198 measures has to be done.

If the component tolerance has been taken into account when generating the dictionary, it has an interval stored (deviations due to tolerance), instead of having a number. For example, for $R1-20\%$ fault, the interval produced by tolerances at the selected frequencies are shown in table 7.

Freq.(rad/sec.)	Amplitude (V)	Phase (^{o})
9000	–	[168.76 175.46]
10000	[0.95 1.57]	[167.47 174.95]
65000	–	[69.08 117.72]
85000	[0.44 1.34]	–
100000	–	[36.80 64.49]

Table 7: Intervals for R1-20%

The same should be done for the rest of the faults, obtaining the dictionary resumed in table 8. As it has been mentioned before, an important overlapping occurs, since the stored intervals overlap at the different frequencies taken.

Fault	Ph9000	Mag10000	...	Ph100000
Nom	[168.78 175.4]	[0.77 1.262]	...	[37.03 64.38]
R1+20	[168.8 175.45]	[0.64 1.05]	...	[36.65 64.76]
R1-20	[168.76 175.46]	[0.95 1.57]	...	[36.8 64.49]
...	...	...	...	...
R5+20	[170.57 176.37]	[0.76 1.266]	...	[39 72.9]
...	...	...	...	...
R6+20	[166.3 174.58]	[0.924 1.51]	...	[35.67 58.47]
...	...	...	...	...
C2-50	[168.94 175.47]	[0.76 1.23]	...	[69.56 102.61]

Table 8: Dictionary for the frequencial method

Once the dictionary is built, a faulty circuit is put under test. If the measures of amplitude and phase at each frequency fall into the intervals obtained for a particular fault, this fault will be taken as possible. Then, for the fault R1-20%, the measures taken (table 6) fall into the six intervals belonging to the faults R1-20, R5+20 and R6+20, the system gives R1, R5 and R6 as a possible faults. The other possible cases have, at least, one of the 6 measures outside the intervals. For example, the measure mag1000 is clearly outside the intervals stored for the cases R1+20 and C2-50. So, the fault is detected, but not diagnosed properly. From the 32 proposed faults, almost all of them are detected but with a great overlapping. Table 10 gives the diagnosis obtained for each provoked fault.

Temporal method

For the circuit of Figure 5, a ramp input with a saturation value of 1 V and a rise time of $100\mu s$ has been chosen. Thus, for the nominal case, the parameters are:

$$SP = 4.81\%,\ td = 16\mu s,\ tr = 75\mu s \text{ and } V_{est} = -1V.$$

As in the frequencial method, this four parameters have to be obtained including the tolerances effect. Then, an interval has been stored for each parameter and fault. For the nominal case, the intervals are shown in table 10.

Similar intervals are stored for each considered fault. The dictionary is like the one shown in table 11.

The diagnosis provided by this method are similar to the frequencial. There are several cases that conclude with a set of possible faulty components, due to

Fault	Diagnosis	Fault	Diagnosis
Nom	All cases	R5+20	All cases
R1+20	All cases	R5-20	Nom,R1,R2
R1-20	R1,R5,R6	R5+50	R2,R3,R5,C1
R1+50	R1,R6	R5-50	R2,R3,R5,C1
R1-50	R1	R6+20	All cases
R2+20	All cases	R6-20	All cases
R2-20	All cases	R6+50	R6
R2+50	R2,R3,R5,R6,C1	R6-50	R6
R2-50	R2,R3,R5,C1	C1+20	All cases
R3+20	All cases	C1-20	All except R6
R3-20	All except C1	C1+50	R2,R3,R5,R6,C1
R3+50	R2,R3,R5,R6,C1	C1-50	R2,R3,R5,C1
R3-50	R2,R3,R5,C1	C2+20	All cases
R4+20	All cases	C2-20	All except R6
R4-20	All cases	C2+50	R4,C2
R4+50	Nom,R1,R4,C2	C2-50	C2
R4-50	R4		

Table 9: Diagnosis for each fault considered

SP(%)	td (μs)
[3.7313 5.888]	[12 21]

tr (μs)	V_{est} (V)
[73 77]	[-1.166 -0.8708]

Table 10: Intervals for nominal case

Fault	SP%	td μs	...	Vest
Nom	[2.42 6.31]	[7.23 23.24]	...	[-1.25 -0.755]
R1+20	[2.43 6.25]	[7.7 23.05]	...	[-1.04 -0.64]
R1-20	[2.50 6.24]	[7.54 23.04]	...	[-1.55 -0.948]
...	...	...	...	...
R5+20	[3.03 6.17]	[4.99 19.3]	...	[-1.25 -0.755]
...	...	...	...	...
R6+20	[1.65 6.25]	[10.07 28.12]	...	[-1.5 -0.91]
...	...	...	...	...
C2-50	[-0.39 2.38]	[7.96 21.58]	...	[-1.25 -0.75]

Table 11: Dictionary for the temporal method

the great overlapping. For example, taking the case R2+20% while other components stay at their nominal value, the parameters measured are:

$$SP = 4.51\%,\ td = 19\mu s,\ tr = 76\mu s \text{ and } V_{est} = -0.99V.$$

With these measures, the final diagnostic gives all possible cases as a diagnosis: Nominal, R1, R2, R3, R4, R5, R6, C1 and C2.

Introducing qualitative reasoning

From the previous examples, it is clear that it is impossible to obtain a sharpen diagnosis about the possible wrong component in the circuit. What is worst, it is difficult to know if the circuit is really faulty or not. For this reason, a tool based on qualitative reasoning will be used. In particular, the results will be refined by means of fuzzy techniques. This means that inputs, outputs, rules and the corresponding operators to combine them, must be defined.

It is expected that the overlapping will be reduced by means of this qualitative reasoning. At the same time, the system is supposed to be able to interpolate between the prototypes described by the rules. So, training the system with the set of faults to detect, it has to predict what would it happen in a new situation. This will be explained for each fault dictionary method in the following paragraphs.

Frequencial method

In the frequencial method, measures at each frequency are taken as fuzzy system inputs (6 inputs are defined). Each fuzzy system input corresponds to the amplitude and phase measures pointed in table 5, and each one compounded by 33 sets, representing the nominal case and the 32 proposed faults to detect. Figure 6 shows the input amplitude at 10000 Hz appearance.

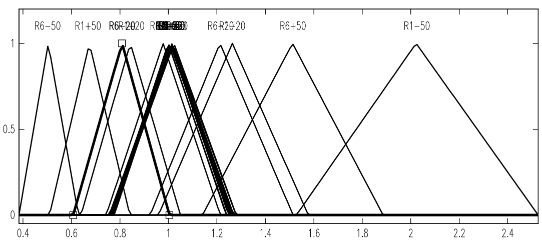

Figure 6: Amplitude measure at 10000Hz.

Membership functions have been taken triangular shaped. Its maximum value corresponds to the value obtained for this measure and fault, while all the other components are at their nominal value. The triangle extremes are the maximum deviation on this value produced by the component tolerance. For example, for the fault R1-50%, the interval extremes corresponding to the magnitude measurement at 10000 Hz are [1.5278

2.5260], and the value obtained without tolerances is 2.022. Figure 7 shows an example comparing a triangular membership function and the real distribution of the output parameter (histogram), when the component values are gaussian distributed. The dotted line represents a gaussian approximation to the output distribution. The abscise magnitude is in Volts.

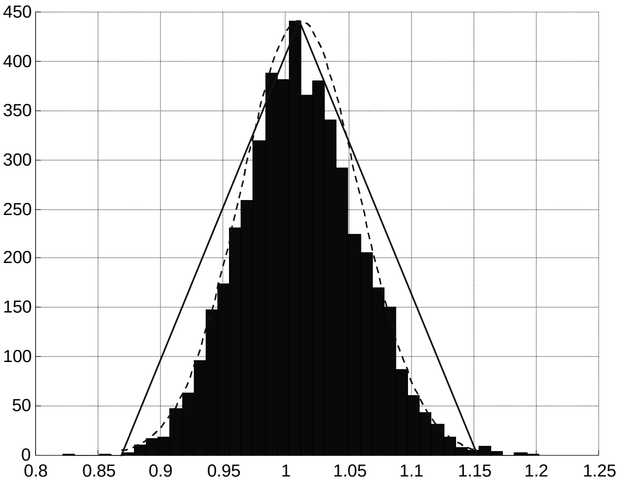

Figure 7: Magnitude at 10000. Nominal case

The previous figure shows that a triangular shaped approximation for the *membership functions* is not bad. Taking gaussian distributions doesn't improve the results significantly, as the authors have tested.

On the other hand, there is one fuzzy system output associated to each component (8 for the biquadratic filter). There will be a set of *membership functions* corresponding to the component at its nominal value and one for each possible deviation considered (±20% and ±50% from the nominal value, giving 5 subsets for each output attribute). So, each output attribute will provide an estimated value for each component. Figure 8 shows the sets considered for the output attribute related to component R1.

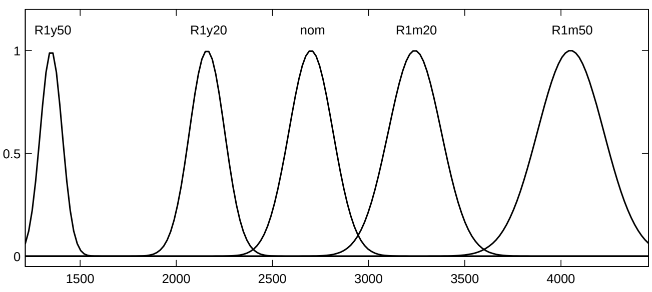

Figure 8: Output attribute sets for R1

Membership functions belonging to the output attributes have a gaussian shape, being this one the typical distribution for electronic components (Boyd 1999).

Rules are simple relations, as the following

if (phase9000 is R1-20)&(mag10000 is R1-20)&(phase10000 is R1-20)&(phase65000 is R1-20)&(phase100000 is R1-20) then (R1 is R1-20)&(R2 is nominal)&(R3 is nominal)&... (C2 is nominal).

The previous rule corresponds to the case R1-20%. The operator '&' is defined by the product function. When measures of table 5 are acquired, they belong to a set in a certain degree. Hence, if one of the 6 measures falls outside at least one of the sets defined for this rule, the final product will be 0, and the rule won't be fired. On the other hand, if each of the 6 measures taken falls into the sets defined by the case R1-20%, this rule will be activated with a value corresponding to the belonging coefficients product. The following figure shows the activated sets in grey color for the case R1-20%.

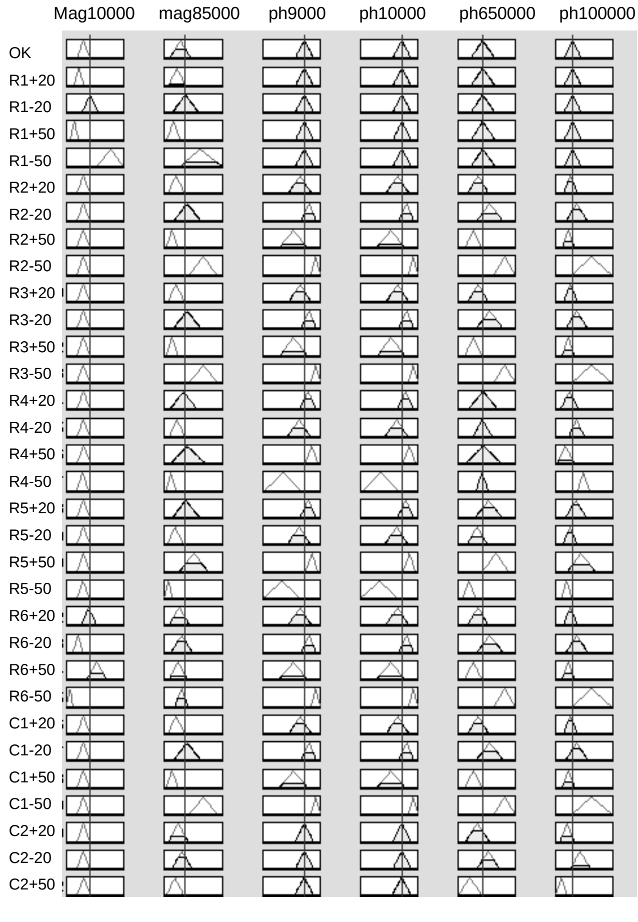

Figure 9: fuzzy input sets activation for R1-20

Analyzing figure 9, it can be seen that the rule corresponding to R1-20% is fired with a belonging coefficient of 1 per each set. Rules corresponding to R4-20%, R5-20% and R6-20% are fired with the membership coefficients of table 12:

Fault	M10K	M85K	ϕ 9K	ϕ 10K	ϕ 65K	ϕ 100K
R1-20	1	1	1	1	1	1
R4-20	0.023	0.85	0.56	0.57	0.98	0.65
R5-20	0.01	0.97	0.55	0.55	0.57	0.70
R6-20	0.83	0.41	0.60	0.60	0.55	0.70

Table 12: coefficients for the other fired rules

If R1-20% was the unique fired rule, the diagnostic would be R1-20% and the other components would have a value belonging to the 10 % tolerance range from nominal. But, due to the overlapping in the sets, sometimes several rules are fired at same time for the same measures set. In this case, the product is the operator selected to combine the fired membership functions. Now, the rules results are added providing the following qualitative set for R1.

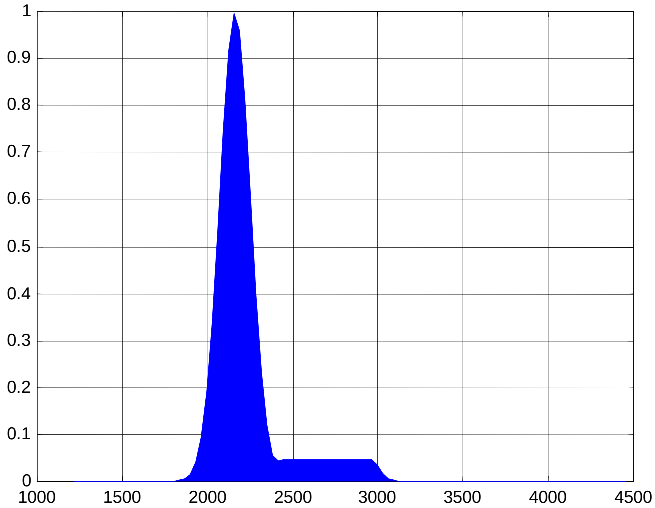

Figure 10: R1 qualitative for R1-20%

A similar figure is obtained for each component. The centroid method is used for giving a final estimated value for each qualitative set. The final outputs for the case R1-20% are:

R1	R2	R3	R4
2223	1000	10000	1504

R5	R6	C1	C2
12010	2757	10nF	10nF

Table 13: Results with fuzzy

Therefore, the conclusion is R1 faulty, since it is the only component that has an estimated value outside the tolerance limits (R1nom=2.7K). For this particular case, fuzzy techniques have allowed to improve the result (diagnostic was R1, R5 and R6 without fuzzy). Doing the same for the other cases table 15 is obtained.

Fault	Diagnosis	Fault	Diagnosis
Nom	Nom	R5+20	R5
R1+20	R1	R5-20	R2,R3,C1
R1-20	R1	R5+50	R5
R1+50	R1	R5-50	R5
R1-50	R1	R6+20	R6
R2+20	R2,R3,C1	R6-20	R6
R2-20	R5	R6+50	R6
R2+50	R2,R3,C1	R6-50	R6
R2-50	R2,R3,C1	C1+20	R2,R3,C1
R3+20	R2,R3,C1	C1-20	All except R6
R3-20	R5	C1+50	R2,R3,C1
R3+50	R2,R3,C1	C1-50	R2,R3,C1
R3-50	R2,R3,C1	C2+20	C2
R4+20	R4	C2-20	C2
R4-20	R4	C2+50	C2
R4+50	R4	C2-50	C2
R4-50	R4		

Table 14: Diagnosis using fuzzy

Comparing the diagnosis provided by the fault dictionary method without fuzzy (table 9) with the method refined introducing the fuzzy concept (table 14), it can be seen that the overlapping has been reduced drastically. There are 4 cases that give a wrong diagnosis: R2-20%, R3-20%, R5-20% and C1-20%. This is because the overlapping fires several rules at the same time, and the centroid averages them giving a wrong value. For example, for the case R2-20%, the qualitative set at the output corresponding to R2 is

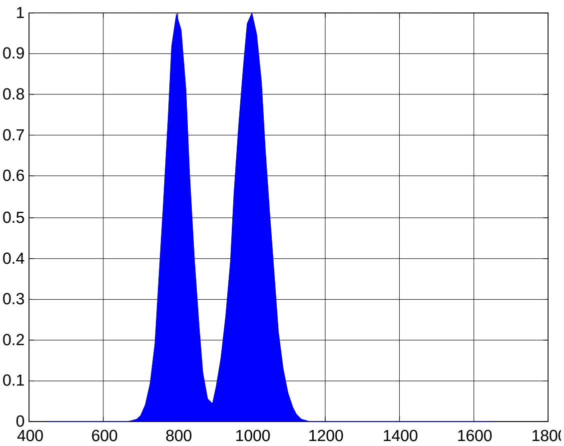

Figure 11: R2 qualitative for R2-20%

The centroid method gives an average of R2=0.911K, therefore, R2 will be considered non faulty. On the other hand, the following qualitative output corresponds to R5

And the centroid method applied to this qualitative set, produces an output R5= 13.58K. So, R5 is considered as faulty. The produced worsening is not seri-

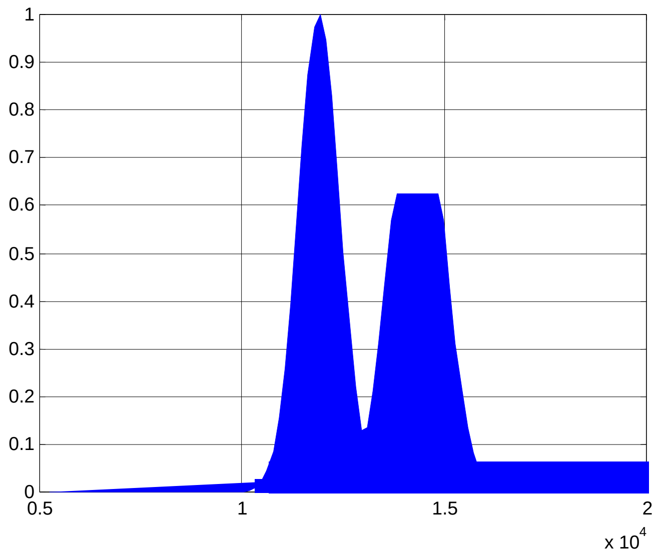

Figure 12: R5 qualitative for R2-20%

Fault	Diag. success	Fault	Diag. success
Nom	68%		
R1+20%	87.35%	R5+20%	63.5%
R1-20%	88.15%	R5-20%	38.7%
R1+50%	100%	R5+50%	93.9%
R1-50%	98.25%	R5-50%	97.05%
R2+20%	64.7%	R6+20%	87.45%
R2-20%	0%	R6-20%	89.8%
R2+50%	94.55%	R6+50%	98.1%
R2-50%	96.4%	R6-50%	98.9%
R3+20%	66.6%	C1+20%	68.9%
R3-20%	0%	C1-20%	0%
R3+50%	95.45%	C1+50%	95.45%
R3-50%	96.4%	C1-50%	97.3%
R4+20%	77.55%	C2+20%	84.2%
R4-20%	87.75%	C2-20%	86.9%
R4+50%	99.1%	C2+50%	98.75%
R4-50%	99%	C2-50%	98.9%

Table 16: Diagnosis success for 2000 runs. Frequencial method

ous, since without fuzzy, it gave much overlapping that makes the situation difficult to diagnose. Something similar happens with the other cases.

As it has been explained in advance, the system has to be able to decide for other unlearned cases. For example, the system was tested with the new cases R1+15%, R6-30%, C2-30% and R3+70%. The diagnosis provided by the system is

Fault	Diagnosis
R1+15%	**R1**
R6-30%	**R6**
C2-30%	**C2**
R3+70%	R2, **R3**, R5, C1

Table 15: Diagnosis for unlearned cases

So, the system does what is expected applying fuzzy, it interpolates to conclude about the new situations proposed giving good results. But, circuit responses for the faults C1+30%, R2+20% and R3+20%, are almost identical, so that it will be impossible to distinguish between them with this method.

It has to be mentioned as well, that tables 14 and 15 have been obtained considering that there is one faulty component at once, while all the others stay at its nominal value. This would be an ideal case. Of course, in a real circuit the components have tolerances, and it should be tested how the diagnosis system cope with this factor. Trying the system with 2000 cases for each considered fault, randomly chosen using Monte-Carlo with a gaussian distribution, the following percentage of successes is obtained for each.

The percentage of success means each time the right component is diagnosed, although sometimes it doesn't appear alone. For example, the case R1+50% is detected in 100% of the cases. Actually, this percentage corresponds to R1 in 98.7% of cases and 1.3% to the set R1, R6.

Table 16 shows that in the majority of cases, the successes percentage is good. In the nominal one, it has a lower value because of the overlapping with other sets. For instance, it diagnosis R5 in 11.25% of the cases, and the set R2, R3, C1 in 9% of them. It has to be mentioned as well, that the cases R2-20%, R3-20% and C1-20% are never detected. This is due to that rules 7 (concerning to R2-20%), 11(concerning to R3-20%), 18 (concerning to R5+20%) and 27 (concerning to C1-20%) are fired at the same time due to overlapping. Evaluating the output using the centroid method, the final conclusion is R5 faulty. The same happens with the other non detected cases.

Temporal method

Now, the parameters *overshoot*, *rise time*, *delay time* and *steady state* will be taken as the fuzzy system inputs. As in the frequencial method, each input attribute is divided into 33 *membership function* triangular shaped. For example, for R2+20% the final diagnosis is R2, R3 and C1. Doing the same for the other faults, it can be concluded that the fact of applying fuzzy does not make worse any of the results obtained with the ramp method, and it is able to improve the huge overlapping. Taking into account that real circuits have tolerances, the system is tested making a randomly gaussian distributed sweep in the component values. 2000 runs were made for each considered fault, and the percentage of successes is given in table 17

The conclusions are not made worse testing the method with non predicted cases, so the fuzzy system

Fault	Diag. success	Fault	Diag. success
Nom	55.15%	R5+20%	81.6%
R1+20%	88.05%	R5-20%	24%
R1-20%	80.70%	R5+50%	99.1%
R1+50%	99%	R5-50%	96.1%
R1-50%	99.05%	R6+20%	85.25%
R2+20%	85.15%	R6-20%	81.7%
R2-20%	0.1%	R6+50%	98.7%
R2+50%	97.1%	R6-50%	99.15%
R2-50%	94.35%	C1+20%	83.7%
R3+20%	84.7%	C1-20%	0.1%
R3-20%	0.05%	C1+50%	96.6%
R3+50%	97.1%	C1-50%	95.4%
R3-50%	94.9%	C2+20%	86.2%
R4+20%	86.25%	C2-20%	82.25%
R4-20%	82.95%	C2+50%	98.65%
R4+50%	98.95%	C2-50%	98.85%
R4-50%	97.35%		

Table 17: Diagnosis success for 2000 runs. Ramp method

is able to interpolate and predict unlearned cases. But, the cases C1+30%, R2+20% and R3+20%, among others, remain impossible to distinguish, because the responses are almost identical.

Conclusions

Two fault dictionary techniques has been shown. One of them based in frequencial measures and the other temporal. Both of them are simple to apply but they show a great overlapping in the final diagnosis due to tolerances. The first step in order to cope with tolerances has been to store intervals instead of just one value in the dictionary. The decision is taken simply if the measures belongs to the interval or not.

Then, qualitative reasoning is introduced over the previous intervals by means of fuzzy logic. So, a degree of membership is introduced on the intervals. Triangular membership function shapes have been tried first, because their simplicity. The authors can state that there are no great differences using the real measures distribution shape observed at the circuit output.

After applying fuzzy to the temporal and frequencial methods, a great improvement in the diagnostic is obtained, because the overlapping is drastically reduced. Furthermore, from the set of faults used to generate the dictionary, the system is able to interpolate an identify a fault that was not on the original set.

The system including fuzzy sets has been tested taking into account that real circuits are affected by tolerances. In particular, when testing the fault isolation capability of the system, 2000 cases were generated for each fault considered. The results resumed in tables and , depicts that good diagnosis are made despite of tolerances.

Finally the diagnosis system should be applied to other electronic circuits in order to check if the proposed method is easily extrapolable.

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