FLAMES : A Fuzzy Logic ATMS and Model-based Expert System for Analog Diagnosis

F. MOHAMED, M. MARZOUKI, M.H. TOUATI

TIMA/INPG, 46 avenue Félix Viallet, 38031 GRENOBLE Cedex FRANCE

Tel. (+33) 76574837 - Fax. (+33) 76473814

E-mail :

firas@verdon.imag.fr, Meryem.Marzouki@imag.fr,

Hedi.Touati@imag.fr

Abstract

Diagnosing analog circuits with their numerous known difficulties is a very hard problem. Digital approaches have proven to be inappropriate, and AI-based ones suffer from many problems. In this paper we present a new system, FLAMES, which uses fuzzy logic, model-based reasoning, ATMS extension, and the human expertise in an appropriate combination to go far in the treatment of this problem.

1 Introduction

when trying to overcome the challenging problem of testing and diagnosing analog circuits, the continuous nature of signals, the inherent interactions between various circuit parameters [1], the inaccuracy of measurements, and the non-directional nature of their behavior, which means that any component can be responsible for any symptom, constitute the core of the problem. It is necessary to model parameters with tolerances and to compute with intervals, to use qualitative values, or to use fuzzy sets as we suggest in this paper. Classical approaches are inappropriate, which has driven the research towards AI to try to get it out from this bottleneck. In section 2, we briefly present the contribution of AI in this domain. Section 3 presents fuzzy logic which constitutes the mathematical basis of our approach. In section 4, we discuss the main ideas among the reasons of our research directions, and the general diagram of our system is presented in section 5. Section 6 details the fuzzy ATMS (Assumption Truth Maintenance System), which is the kernel of this system, while sections 7 and 8 describe two other units of FLAMES, respectively dealing with learning from experience and best test strategy finding based on fuzzy entropy

ED&TC '96

and fuzzy estimations. Some experimental results are provided in section 9, and finally conclusion and future work directions are given in section 10.

2 The contribution of AI in the Diagnosis of Analog circuits

The contribution of AI in this domain is not recent. Fault dictionaries, diagnostics, rule-based methods, model-based reasoning, or qualitative reasoning have been used with more or less of success.

Here, we will discuss model-based reasoning and qualitative reasoning approaches which to our view are the most important ones.

2.1 Model-based Reasoning

Model-based reasoning considers the model which is built from the structure of the device and the correct behavior of its components. A fault is defined by excluding "anything other than expected behavior", so it covers a wide class of faults [2]. Numerous systems used this approach : DART [3], GDE [4], DIANA [5]. All these systems partially fail when they deal with dynamic systems and more difficulties arise when dealing with analog circuits.

2.2 Qualitative Reasoning

In the area of AI, the qualitative reasoning has become a very productive domain. But the loss of quantitative information by the qualitative description involves the prediction of invalid behavior or the neglect of valid ones which can cause a loss of candidates in analog circuits diagnosis.

3 Fuzzy Logic

The principal objective of fuzzy logic is to cope with the inaccuracy and the uncertainty of information.

3.1 Fuzzy Sets and Membership Degree

A fuzzy set A is defined on a domain T by a function μ_A:T —>[0,1], such that μ_A(t) is the membership degree of t $\in$ T to the set A. The **support** of a fuzzy set A is the set of elements with a membership degree greater than 0. The **core** of A is the set of elements with a membership equal to 1.

3.2 Fuzzy Intervals

A fuzzy interval is a convex fuzzy set. In practice, it will be defined by a 4-tuple [m1,m2,α, β] (figure 1), where [m1,m2] is its core. A real number m can be defined by

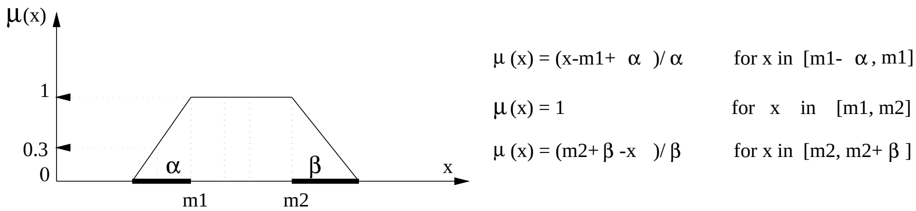


Figure 1: Fuzzy interval

[m,m,0,0], a crisp interval [a,b] by [a,b,0,0], a fuzzy number m by M=[m,m,α, β]. Hence, this representation allows a crisp number, a crisp interval, a fuzzy number, and a fuzzy interval to be uniformly described.

For two fuzzy intervals M=[m1,m2,α, β] and N=[n1,n2,γ, δ], we can accept the arithmetic operations defined in [6] from which we give as an example :

- $M \oplus N = [m1 + n1, m2 + n2, \alpha + \gamma, \beta + \delta]$;

- $M \ominus N = [m1 - n2, m2 - n1, \alpha + \delta, \beta + \gamma]$;

4 Towards Fuzzy Logic

4.1 Some Famous Systems

Some systems have been developed for analog circuit fault diagnosis. The most representative ones are briefly described in the following.

DEDALE [7] is based on *order-of-magnitude* reasoning. Its main weakness appears when dealing with components which operate at the limit of their designed behavior. because it assumes that defects lead to significant changes in behavior of the circuit which is a hard assumption. In DIANA [5] imprecision is processed by means of numerical (crisp) intervals. The management of intervals is done by an ATMS extension. FIS [8] uses *qualitative causal models* to describe the unit-under test.

Fuzzy logic, which we suggest here, was not previously used in this domain to our knowledge, except in [9], where the authors are up to now restricting its utilization to the decision-making problem, for the purpose of functional verification of analog circuits.

4.2 Discussion of Currently Used Ideas

Fuzzy sets allow to define the order-of-magnitude operators in an accurate manner [10].

Crisp intervals contain all sorts of inaccuracy without any distinction which can cause an explosion in the value propagation through the circuit. The following example (figure 2) [11], shows the problem : If we consider the three amplifiers as fuzzy numbers :

amp1[1,1,0.05,0.05], amp2[2,2,0.05,0.05], amp3[3,3,0.05,0.05], and Va in input :

(1) Va[2.95,3.05,0,0] as crisp interval (boundaries equal to 0) in the first case and

(2) Va[3,3,0.05,0.05] as fuzzy number in the second one.

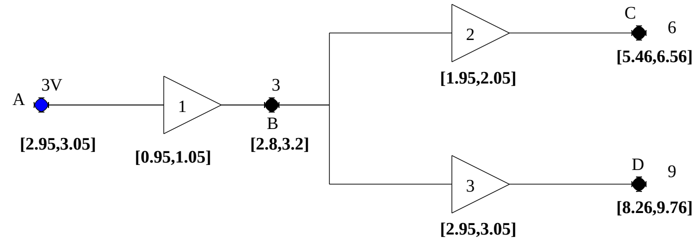


Figure 2: Crisp intervals propagation

The propagation will give in the two cases :

(1)	(2)
Vb[2.95, 3.05, 0.15, 0.15]	Vb[3, 3, 0.20, 0.20]
Vc[5.90, 6.10, 0.44, 0.46]	Vc[6, 6, 0.54, 0.57]
Vd[8.85, 9.15, 0.58, 0.62]	Vd[9, 9, 0.73, 0.77]

Note that in (1) we divided the imprecision into two parts. In (2) the imprecision does not have the same importance as in crisp intervals.

Now, let us look how these approaches behave when we take amp2 as faulty with a slight difference from its nominal value : 1- with crisp intervals let amp2[1.8,1.8] for example, and the output Vc is measured to be [5.6,5.6]. In this case we will have Vb=[3.11,3.11], and Va=[2.96,3.27], which masks the faulty value of amp2 (in comparison with the results in figure 2), 2- with fuzzy numbers and for the same values for amp2 and Vc, we will have : Vb=[3.11,3.11,0.027,0.027] and Va=[3.11,3.11,0.17,0.17], which shows that there is a problem. Then, a value which oversteps the boundaries of the interval will be considered as faulty, but possibly true in order-of-magnitude [10]. In fuzzy intervals it will be a fault with a membership degree.

We suggest replacing crisp intervals by fuzzy intervals. This representation is more general, since it can represent the knowledge embedded in the soft boundaries of the interval and there is no exclusivity of values. Also, it allows to distinguish between different types of imprecision : this of the human expert, these of the components, or that of the measuring equipment. Each value from the fuzzy interval has a membership degree which, for us, gives *its acceptance degree*. In fact, what crisp intervals mean can be discussed [12]. The psychological plausibility prefers the fuzzy ones. In any case, the fuzzy approach is the most general one and a much better approximation of the reality.

Considering this discussion, our idea is to build a fuzzy-logic-based expert system which is the subject of the following sections.

5 FLAMES : An Overview

FLAMES (A Fuzzy Logic ATMS and Model-based Expert System) is a system principally aiming at diagnosis faulty analog devices (especially in the case of soft faults). Its main components are (figure 3) : A fuzzy ATMS (FLAMES's kernel) which propagates fuzzy intervals and assumptions ; A database of models which will be used for diagnosis based on structure and correct models of components on one hand, and assumptions governing the validity of models and observations on the other hand ; A knowledge base made up of fuzzy qualitative rules and component fault models (which can help the diagnosis process) ; a search strategy unit that helps finding best test points to probe in case that the diagnosis process needs more information ; A learning module in which the system could use its previous diagnosis to learn from its experience. Finally, since we want to keep FLAMES as an open system, an expert can interact with each of its main units. It

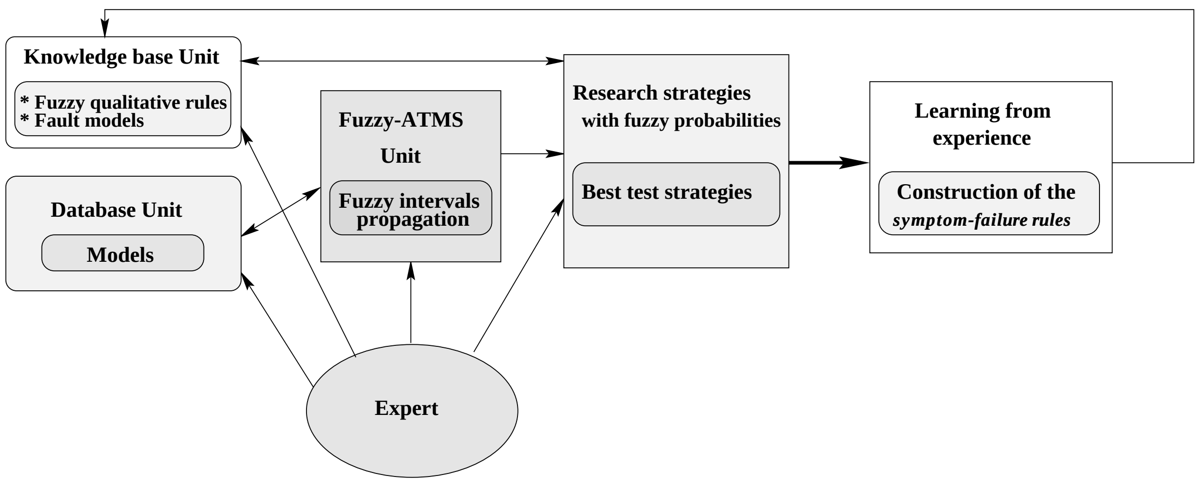


Figure 3: FLAMES : The Fuzzy-Logic-ATMS-based Expert System

is clear that FLAMES is mainly based on fuzzy logic principles, and this has many advantages (apart from those mentioned previously) : it allows an accurate representation of the Unit-Under Test, and a simple while accurate (said semi-qualitative) representation of the human expertise either about a priori fault estimations or about how to update these estimations after tests. This knowledge representation problem, is a crucial one in AI applications. which is closely related to the knowledge acquisition problem, Choosing the qualitative one is not advised for analog circuits. The quantitative one is also not advised. Thus fuzzy sets which are able to represent the two kinds are chosen in FLAMES.

6 Fuzzy ATMS Unit

This section presents an extension of the ATMS concept, called fuzzy-ATMS, which incorporates in its mechanisms a processing of inaccuracy by propagating fuzzy intervals and uncertainty based on intersection between different fuzzy intervals which express either nominal values, or measured values through propagation. Thus this fuzzy-ATMS looks like the possibilistic ATMS of [13] where clauses are uncertain. Moreover, it does not neglect the expert preference in the decision-making process. An ATMS is a truth maintenance system based on manipulating assumption sets. It is able to work effectively and efficiently with inconsistent information. Reasoning on assumptions is very general. In electronics, for example, an assumption might be the correct functioning of each component [14]. Note that the ATMS is necessary because we entertain the possibility of *multiple faults* where the space of potential candidates grows exponentially with the number of faults under consideration.

In our approach, result of the diagnosis (sets of candidates) will have degrees giving how serious the corresponding faults are. An expert can use this supplementary information and his experience to choose between candidates. When it is possible, the diagnosis can be helped by some rules describing the unit under test, its qualitative correct behavior and its faulty one.

6.1 The Conflict Recognition Engine

The central task of diagnosis is to detect discrepancies between predicted values and measurements and to build the sets of candidates which support these discrepancies ; the important step of fault detection is better realized by using fuzzy intervals (section 4). Discrepancies are detected and the corresponding minimal nogoods (a nogood is the set of assumptions which supports the fault) and minimal candidates, are built.

6.1.1 Fuzzy Interval Propagation

Here, we concentrate on fuzzy interval labelling (label for a quantity refers to the set of its possible values and should not be confused with the assumption label attached to each particular value). Quantities values take two possible forms : predicted values (from the model), and measured ones. A fuzzy quantity will be propagated each time a new value is entered. The propagation takes place through constraints which constitute the model of the circuit (fuzzy operations are considered). The discovery of a known value for a point for which we already know a predicted propagated value is called a coincidence. Figure 4 summarizes the possible cases either in propagation of crisp or fuzzy intervals. The

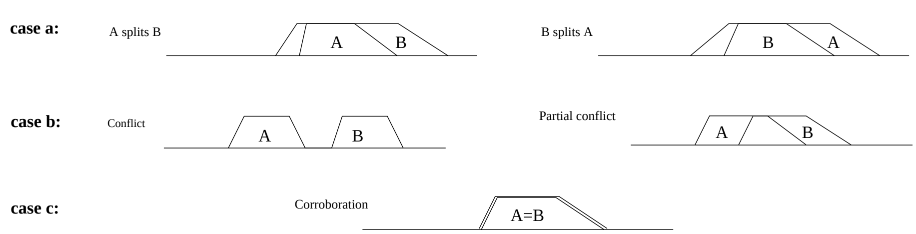


Figure 4: Possible cases of coincidence

case of coincidence (figure 4) between two propagated values is the most complicated one since we have to take the assumptions of both propagations into account. Our *coincidence* *resolution* process consists in considering that a coincidence between two propagated values is a coincidence between either of them with the predicted value. Consequently, it reasons on a degree of consistency Dc (see section 6.1.2), and a particular attention should be given to the path which led to the worst one. Reasoning on Dc eliminates most of the problems mentioned above especially.

6.1.2 Fuzzy ATMS

Here, the different cases of figure 4 will be summarized by a degree of consistency between the nominal value and the measured one. The idea is that if we have decided that Vn is the nominal value of a quantity X and a measurement gave Vm for X then in order to clearly see the situation we should evaluate the proposition X $\in$ Vn. In general, if Vm $\subseteq$Vn then the proposition is necessarily true ; otherwise , if Vn$\sqcap$Vm $\neq$ $\emptyset$ then it is only possibly true. We define Dc $\in$ [0,1], as the degree of consistency between Vm and Vn by :

$$\mathbf{Dc = area(Vm \sqcap Vn) \ / \ area(Vm)}$$

which equals 1 if Vm $\subseteq$ Vn, equals 0 if the intersection is empty, and is inferior to 1 when this intersection is not empty. As Vm and Vn are defined in terms of fuzzy intervals which gives their definition as a possibilistic distribution (possibilistic logic) then the justification of this choice is that the degree of certainty that the quantity takes a value in Vn is this intersection between its propagated value (actual possible values) and its nominal value (possible nominal values). at the right or at the left of Vn, respectively.

Dealing with analog circuits is very difficult : a component can be faulty without manifesting a symptom, for example. Corroborations (case c : figure 4) do not always imply that the components involved are unfaulted. A conflict (case b) indicates a nogood (the set of assumptions which supports the value) with a degree 1, and a partial conflict indicates a nogood with a degree $<$ 1.

The resolution takes place through two steps : the propagation which gives as result a conjunction of assumptions with their consistency degrees in [0,1], and a second step which searches the contradictory environments. In this fuzzy-ATMS clauses are not reduced to Horn's clauses (as in [13]). Thus it allows the expert to add rules of faulty estimations or to build component's fault models with certainty degrees. Another advantage of this method is the possibility to give to the user a list of "nogoods" sorted according to their consistency degrees which allows to restrict the effect of explosion.

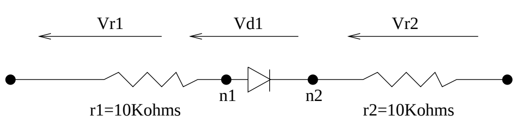
6.2 Database Unit (Models)

The model-based reasoning approach is suitable to this type of circuits. Models of correct behavior, assumptions governing the validity of models, and measurements (observation) constitute the principal elements of this approach. Kirchhoff's laws and Ohm's law are applied and constraints which govern the behavior of components are used. Qualitative models are also applied whenever they are more suitable. A resistor is governed by Ir = Vr / r and Vr = Ir * r, for example, but the correctness of the resistor will be the assumption of applying these rules. Then one or more propositional assumptions govern the validity of models. For us, a propositional assumption belongs to fuzzy logic which means that it will have a membership degree indicating its degree of validity. Let us take a detailed example to clarify this :

If the transistor T is correct and Vbe(T) ≤ 0.4, *Then* it should be in an *Off* state. Since the $\leq$ operation is fuzzy (as all the other arithmetic and logic operations) and Correct(T) is also fuzzy then Off(T) will be defined as a fuzzy set. Defining assumptions, quantities, and fault modes (as shown later) in terms of fuzzy sets give this system its flexibility, and both slight changes and significant ones are discovered.

6.3 Illustrating Example

DIANA propagates of crisp intervals in order to detect inconsistency between values and to form the sets of candidates. The following example (figure 5) [15] could explain our view to this problem in compatibility with fuzzy logic.



Measurement	Model	Prediction	Assumption
Vd1=0.2 V	Diode's model	Id1 =< 100 microA	{d1}
	Kirchhoff's law in n1	Ir1 =< 100 microA	{d1, r1}
	Kirchhoff's law in n2	Ir2 =< 100 microA	{d1, r2}
Vr1=1.05 V	Ohm's law	Ir1 = 105 microA	{r1}
	conflict on Ir1 -----> Nogood{r1,d1}		
Vr2=2 V	Ohm's law	Ir2 =200 microA	{r2}
	conflict on Ir2 -----> Nogood{r2,d1}		

The candidates calculation will finally give → **CANDIDATES : [d1] or [r1,r2]**

Figure 5: Candidates with crisp intervals

To be able to capture the slight changes in values, we will define all the arithmetic and logic operations in fuzzy manner. Thus, the ≤ 100 condition will be the fuzzy set [-∞,100,0,10], for example, and in this case if measurements give : Vr1 = 1.05 V then Ir1 = 105 microA and Nogood{r1,d1} will have a membership degree equal to 1-0.5 = 0.5 (it is good with 0.5 degree). In the same manner, for Vr2 = 2 V, we will have Nogood{r2,d1} with degree 1 (good with 0 degree). The candidates in this case will be $[r1, d1]_{0.5}, [r2, d1]_1$ which indicates a certain order between them. The expert can use this order to give more concentration on [r2,d1]. or he can use the a priori estimations of faults to decide if the diode or one of the resistances is faulty. In any case, considering the fault modes of the diode (open or shorted), drives us to strongly suspect the resistance r2 which has to be very low. In the case of crisp intervals and crisp operations we can only suspect the three components with the same weight.

7 Learning From Experience and Building the Knowledge Base

Adding this unit has the goal to make our model-based reasoning able to learn from its experience to improve its performance incrementally. As regards to fault modes, our intention is not to define a fault dictionary, but we believe that defining some common fault modes for components can be useful in many cases. This unit should be applied only as last step in order to refine candidates sets.

Common fault modes (such as open, short, high, or low for resistors) in our approach are defined as fuzzy sets. This will avoid us to use special heuristics to find slight deviations.

When the system succeeds to locate a faulty component, a *symptom-failure* rule which summarizes the work would be formed and an estimation will be given to this component. This rule is given with a degree of certainty which is compatible with fuzzy logic from one side, and with the complex nature of analog circuits from the other side. This information, learned from experience would be added to the knowledge-base unit. Thus, in future diagnosis, FLAMES will give the expert the rules which are attached to some candidates to help him in making his decision.

8 Best Test Strategies

We want FLAMES to be able to recommend at any point the next best test to make. from a set of predefined available tests, and to estimate the faultiness degree for a given component, given some test results. Achieving this goal is not very simple. Many systems, such as FIS and GDE, used the probabilistic approach, which is a numerical approach. To move away from this approach with its heavy calculus and hard assumptions (a priori probabilities, mutual exclusiveness of hypotheses, etc.), we have considered an approach based on fuzzy logic. This approach reduces the calculation needed, and replaces numbers by qualitative linguistic terms.

8.1 Fuzzy Data

The idea is to decompose the [0,1] interval into linguistic terms (fuzzy estimations of faultiness) defined by *fuzzy intervals* (as Correct=[0,.05,0,.05], Likely_correct=[.18,.34,.02,.06], etc.). The degree of granularity of this decomposition depends on the application and on what the expert assumes suitable.

8.2 Fuzzy Entropy and Best Test point finding

To discriminate between candidates, the entropy of a system of fuzzy probabilities which measures how random this fuzzy system is, can be useful. The module under test is considered as a system of components for which we give estimations of their states in terms of fuzzy probability, so we adapted the definition of Shannon entropy to calculate the fuzzy entropy. Let S be a set of n components characterized by their fuzzy estimations. Its fuzzy entropy is defined by :

$$Ent(S) = \oplus_{i=1}^{n} Fi \otimes Log_2(1 \oslash Fi)$$

where Fi is the fuzzy estimation of the faulty component i. The arithmetic operations are the fuzzy ones defined in [6]. Considering the result of the fuzzy-ATMS, the "best test ", which is the test minimizing the expected total cost of the tests required to achieve some specified degree of certainty about which modules in the circuit are faulty and which ones are not, can be evaluated by the expected entropy, assuming that the measurement has been done. This expected entropy is calculated by using the fuzzy entropy mentioned above.

9 Experimental Results

Some parts of FLAMES have been implemented in C++ on Sun sparc 20 workstation, and have been tried on different kinds and sizes of circuits, either in dynamic mode or in static one. One of these circuits and its corresponding results are shown in figures 6 and 7, respectively. This is a single path circuit so measuring Vs to be faulty (figure 6) suspects all the modules with the same degree. The table of results (figure 7) shows how Dc plays the principal role in reducing the candidates especially in slightly soft faults cases. Finally, we have to mention that the chosen values of ' the components ensure the linear region of transistors.

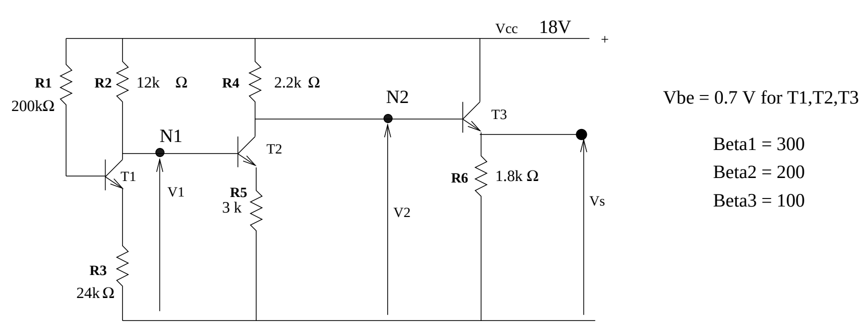


Figure 6: 3 stages circuit amplification

DEFECT	DIAGNOSIS	COMMENTS
Short circuit on R2	$\{R1,R2,R3,T1\}_1 \Longrightarrow \{R1\}_1\ \{R2\}_1\ \{R3\}_1$	Propagating the measured value of V1 and V2 reduces the candidates to {R2}
R2 is slightly high R2 = 12.18k	$\{R1,R2,R3,T1\}_{0.11} \Longrightarrow \{R2\}_{0.11}\ \{T1\}_{0.11}$	Thanks to Dc because Dc(Vsm,Vsn)=0.89, Dc(V2m,V2n)=0.89,and Dc(V1m,V1n)=0.89
Beta2 is slightly low Beta2 = 194	$\{R2,R4,R5,T2\}_{0.04} \Longrightarrow \{T2\}_{0.04}\ \{R4\}_{0.04}$	Dc(Vsm,Vsn)=0.96, Dc(V2m,V2n)=0.96, and Dc(V1m,V1n)= 1
Open circuit on R3	$\{R1,R2,R3,T1\} \Longrightarrow \{R2\}_1\ \{R3\}_1$	Thanks to the sign of Dc: Dc(Vsm,Vsn)=1, Dc(V2m,V2n)=1, and Dc(V1m,V1n)= -1, R2 is very low or R3 is very high
Open circuit in N1	$\{T2\}_1\ \{R4\}_1$	Thanks to transistor model, measuring V1 is decisive

Figure 7: Experimental Results with FLAMES

10 Conclusion

The present work is a step towards the complete implementation of FLAMES. This new approach of analog device fault diagnosis based on fuzzy logic is very general, realistic, and reliable to represent the human expertise (e.g. a priori estimations of faultiness in components, qualitative rules, etc.). In any case, it is the only one which is able to be qualitative and quantitative at the same time. Best test strategies have been successfully tried on digital circuits, they appear even more suitable for analog ones. The fuzzy ATMS using fuzzy intervals in its practical form allows to treat uncertainty and inaccuracy in analog circuits. Moreover, propagation of fuzzy intervals avoids possible explosions either in treating tolerances or in sets of candidates resulting from the ATMS.

Finally, FLAMES idea tries to make profit of other approaches whenever possible.

References

[1] F. Novak, I. Mozetic, M. Santo-Zarnik, and A. Biasizzo. Enhancing Design-for-Test for Active Analog Filters by Using CLP(R). *Journal of Electronic Testing : Theory and Applications*, 4:315–329, 1993.

[2] R. Davis and W. Hamsher. Model-based Reasoning : Troubleshooting. In H.E. Shorbe and the American Association of AI, editors, *Exploring Artificial Intelligence*, chapter 8. Morgan Kaufmann, 1988.

[3] M. Genesereth. The use of descriptions in automated diagnosis. *Artificial Intelligence*, 24(1):411–436, 1984.

[4] J. DeKleer and C. Williams. Diagnosing multiple faults. *Artificial Intelligence*, 32:97–129, 1987.

[5] P. Dague, O. Jhel, and P. Taillibert. An Interval Propagation and Conflict Recognition Engine for Diagnosing Continuous Dynamic Systems. *Lecture Notes in AI*, 462, September 1990.

[6] P. P. Bonisson and K. S. Decker. Selecting uncertainty calculi and granularity : An experiment in trading-off precision and complexity. In L. N. Kanal and J. F. Lemmer, editors, *Uncertainty in AI*. Elsevier Science Publishers B.V, North-Holland, 1986.

[7] P. Dague, O. Raiman, P. Deves, and J-P Marx. DEDALE : An expert system for troubleshooting analogue circuits. In *IEEE International Test Conference*, pages 586–594, 1987.

[8] F. Pipitone, K. Dejong, and W. Spears. An AI Approach to Analog System Diagnosis. In R-W Liu, editor, *Testing and Diagnosis of Analog Circuits and Systems*, chapter 7. Van Nostrand Reihold, New York, 1987.

[9] M. Fares and B. Kaminska. A Fuzzy Decision-making for Test Space Exploration. In *European Test Conference*, pages 37–46, Rotterdam, The Netherlands, April 1993.

[10] F. Mohamed, M. Marzouki, F. Novak, and A. Biasizzo. A Fuzzy Logic Approach for Analog Circuit Diagnosis. In *Int. Mixed Signal Testing Workshop*, pages 101–106, Grenoble, France, June 1995.

[11] A. McKeon and A. Wakeling. Fault Diagnosis in Analogue Circuits Using AI Techniques. In *IEEE International Test Conference*, pages 118–123, 1989.

[12] R. Davis. Constraint propagation with interval labels. *Artificial Intelligence*, 32:281–331, 1987.

[13] D. Dubois, J. Lang, and H. Prade. Gestion d'hypothèse en logique possibiliste : un exemple d'application au diagnostic. In *10th Conf. on Expert Systems and their applications*, Avignon, France, 1990.

[14] J. DeKleer. An Assumption-based TMS. *Artificial Intelligence*, 28:127–162, 1986.

[15] P. Dague, P. Deves, P. Luciani, and P. Taillibert. Diagnostic de systèmes analogiques. In *Journées internationales sur les systèmes experts et leur applications*, Avignon, France, 1990.