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AUTOMATIC FUZZY MODELING OF CIRCUIT FUNCTIONS WITH NOISE CANCELLATION

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ABSTRACT

The design of complex analog circuits requests higher level models of circuit functions. To solve the problem of model generation we develop an automatic method that implies Takagi-Sugeno fuzzy systems that emulate the behaviour of the circuit functions. These fuzzy models are built starting from a set of parameters-function data pairs and use an automatic procedure to eliminate noisy data to obtain very accurate models. The interaction between the user and the computer program is facilited by a friendly graphical user interface.

Our method is applied to model two functions (a linear and a nonlinear one). The results confirm our espectations, the noisy data pairs being eliminated so that the final models have great accuracy.

Keywords: fuzzy system model, anfis, noise cancellation, data set

1. INTRODUCTION

In the domain of mixed signal circuit design the need has arisen for higher level of abstraction to describe and simulate analog circuits.

Gielen and Rutenbar [1] take into consideration three reasons for this. In a top-down design methodology at higher levels of the design hierarchy, where the detailed lower-level circuit implementations are yet unknown, there is a need for higher-levels models describing the pin-to-pin behavior of the circuits rather than the (yet unknown) internal structural implementation. Second, the verification of integrated mixed-signal systems also requires higher description levels for the analog sections, since such integrated systems are computationally to complex to allow a full simulation of the entire mixed-signal design in practical terms. Third, when providing or using analog IP macrocells in a SoC context, the virtual component has to be accompanied by an executable model that efficiently models pin-to-pin behavior of the virtual component. This model can then be used in system-level design and verification, even without knowing the detailed circuit implementation of the macrocell.

Also in the optimization based analog design, the iterative process requires a large number of circuit performances evaluations. A very efficient way to reduce the time spent with these simulations is to build models of circuit functions [2]. Two factors determine the utility of the circuit function model. First, the model should be computationally efficient to construct and evaluate so that substantial computational savings can be achieved. Second, the model should be accurate [3].

The automatic generation of such higher level-models is a quite difficult problem. In this paper we developed an automatic method to build fuzzy models based on a set of numerical data. Besides of its automatic features, our method has another advantage; we can model any nonlinear, multivariable function since the fuzzy systems are universal aproximators [4], [5]. Also we incorporated a strategy to automatically find and eliminate the data points affected by noise and rebuild the model. This way we can obtain fuzzy models of the circuit functions with a great accuracy.

The remainder of the paper is organized as follows. Section 2 presents the overview of the method. Section 3 shows the implementation of the method and some experimental results. Finally we conclude this paper in Section 4.

2. OVERVIEW OF THE METHOD

Due to the fact that Takagi-Sugeno fuzzy systems can accurately approximate any complex multivariable functions, we have selected this class of models to automatically construct computationally inexpensive models for analog circuits functions.

According to [7], [8], [2] for building fuzzy models we need a set of numerical data. To obtain accurate models for the analog circuit functions, a large number of data pairs is requested, that should uniformly cover the function domain and include the function characteristics, as much as possible. In Figure 1 the bloc diagram of the proposed automatic fuzzy modeling method is shown.

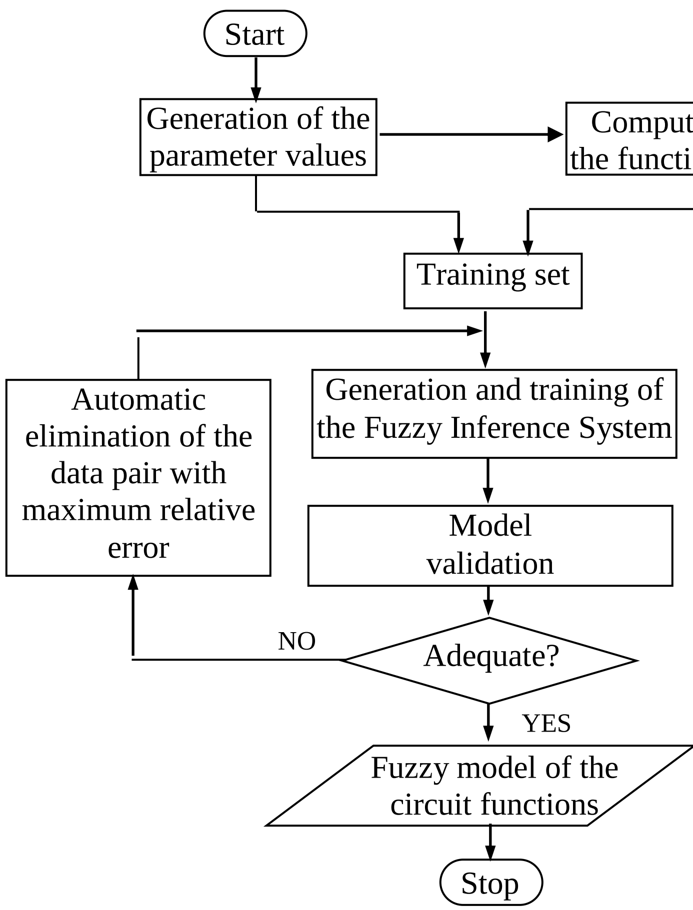

Figure 1. Bloc diagram

In order to obtain uniformly distributed data pairs we used the Latin Hypercube Sample (LHS) technique [3]. The user sets the parameters number, the range of each parameter, and the number of data pairs. For each parameter all portions of its distribution are represented by sample values. If N is the desired number of data pairs the range of each parameter is divided into N non-overlapping interval of 1/N length. From each interval we obtain a random value and so we will obtain N values for each parameter. Next, the N values for one parameter are randomly paired with the N values for another parameter, and so on. In this way we obtain sets of parameter values that will uniformly cover the parameters space. Note that LHS will provide a more uniform coverage of the parameters space than other experimental design techniques.

Using the parameters set, the correspondent values of circuit functions are to be computed. Due to the LHS technique, the function values will cover the behavior of the analog circuits in all possible situations.

With the sets of parameters-function data pairs we will generate and train a Fuzzy Inference System as a model for our function. The generation of initial fuzzy model uses a fuzzy subtractive clustering, the resulting clusters being used to extract the set of fuzzy sets and rules. The number of clusters (the same with the number of rules) is determine by a variable "radii" which specifies a cluster center's range of influence in each of the data dimensions. This initial fuzzy model is than trained with Adaptive-Network-based Fuzzy Inference Systems (anfis), which is the major training routine for Sugeno-type fuzzy inference systems. Anfis uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descend method for training membership function parameters to emulate a given training data set. The fuzzy inference system is trained during a number of epochs specified by the user. More details about anfis can be found for example in [8], [9].

Then we perform a model validation. In order to see the model accuracy and to see if the function values provided by user were affected by noise, we calculate the relative error between the initial function values and the function values computed with the fuzzy model, resulting an error vector. The user sets a maximum acceptable value for the relative error. If this value is bigger than the maximum value in the error vector, than the model is considered adequate. Otherwise the algorithm eliminates the noisy data. In each iteration we eliminate a data pair corresponding to the maximum relative error. With the new set of training data we generate, train and validate a new fuzzy model. The process stops if all the error vector values are smaller than the maximum accepted value, which means that the algorithm has eliminated successfully the noisy data and we achieved our goal to obtain an accurate model. The process also stops if the number of data pairs is 25% smaller than the initial number of pairs; in this case we consider that the training data is inconsistent meaning that the provided data are very noisy or do not capture enough characteristics of the function.

3. IMPLEMENTATION AND RESULTS

We implemented our algorithm in Matlab and build a friendly graphical user interface as a communication bridge between the software and the user (Figure 2).

In order to see how our method works, we use it to model two functions: a linear mathematical function f(x,y)=x+y and a nonlinear two variables electronic circuit function, voltage gain (avo) for a simple operational transconductance amplifier[10]. For the circuit function we chosed I_b and $(W/L)_{1,2}$ as parameters. For the mathematical function we used 1200 data pairs to build the fuzzy model and for the circuit function we used 850 data pairs obtained from Pspice simulation. In order to see if our algorithm cancel the noisy data we intentionally altered the value of the mathematical function in 7 data pairs and the value of the circuit function in 5 data pairs circuit , as one can see in Table 1 and Tabel 2.

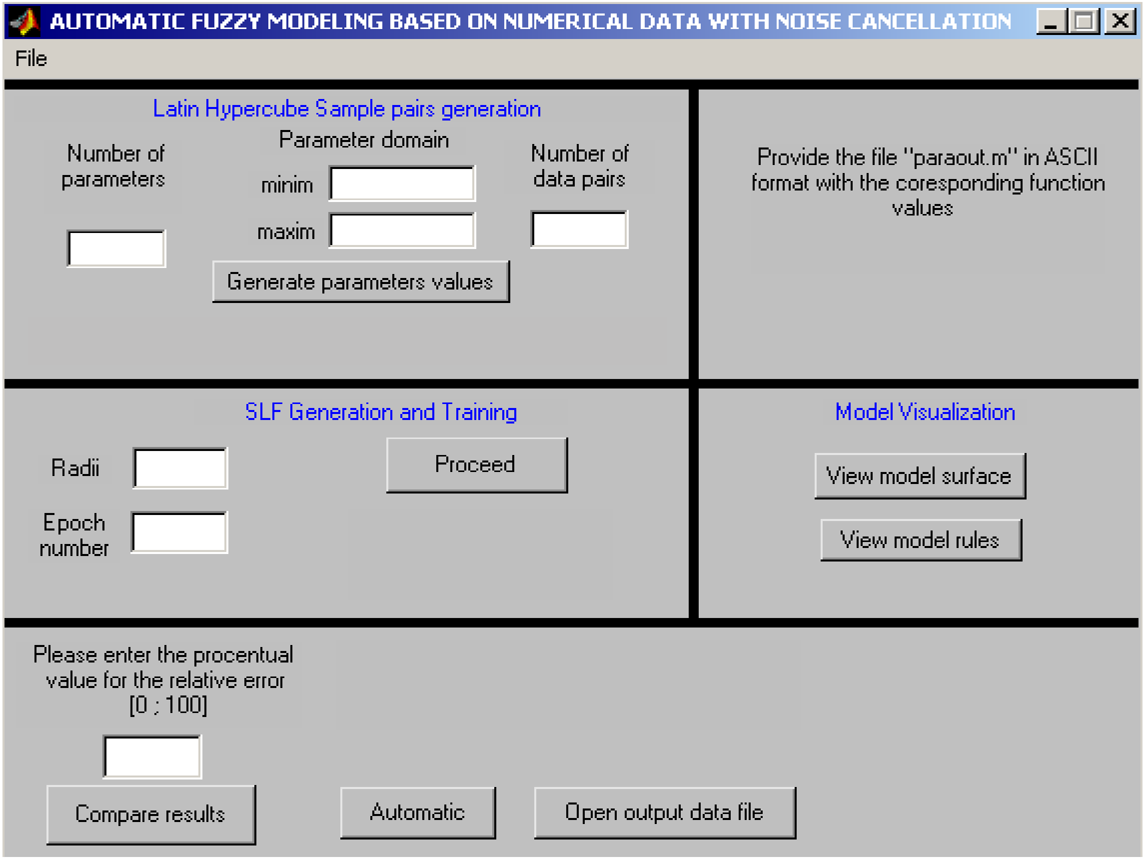

Figure 2. Graphical user interface

Table1

Data Point		Correct Value	Noise Affected	Computed with fuzzy model	
				With noise	After noise cancellation
1.	Function value	70.9	200	76	70.89
	Error [%]		182	7.1	0.014
2.	Function value	77	17	40.12	76.91
	Error [%]		77.92	47.89	0.116
3.	Function value	77.7	37.7	73.82	77.7
	Error [%]		51	4.99	0
4.	Function value	110	810	56.7	110.02
	Error [%]		636	48.45	0.018
5.	Function value	125	825	148.5	125
	Error [%]		560	18.4	0
6.	Function value	98.6	18.6	73.65	98.61
	Error [%]		80.5	25.3	0.010
7.	Function value	36.6	66.6	38.62	36.6
	Error [%]		81.96	5.51	0

We can see that even the initial fuzzy modes, built with noisy data, generates function values closed to the correct ones, relative errors being in the range: (4.99%; 47.89%) while the relative errors in the noisy pairs were (51%; 636%) for the mathematical function and for analog circuit function the relative errors in the noisy pairs were in the range of (44.8%; 193%) and after obtaining the initial fuzzy model the range of the relative errors was (6.33%; 22.72%). This is due to the interpolation capabilities of the fuzzy models.

Table 2

Data Point		Correct Value	Noise Affected	Computed with fuzzy model	
				With noise	After noise cancellation
1.	Function value	31.04	91.04	33.6	30.10
	Error [%]		193	8.24	2.93
2.	Function value	38.54	18.54	36.1	37.41
	Error [%]		51.8	6.33	2.93
3.	Function value	28.32	88.32	31.9	29.05
	Error [%]		211	12.64	2.57
4.	Function value	44.57	24.57	54.7	46.03
	Error [%]		44.8	22.72	3.27
5.	Function value	31.17	71.17	34.2	32.01
	Error [%]		128	9.72	2.69

After 8 respective 12 iterations the algorithm has eliminated all the noisy data pairs from the training set. The finals fuzzy models provide more precise values of the functions, the relative errors being reduced with at least two magnitude orders. The maximum relative error for the final fuzzy model is decreased to 0.116% compared with 47.89% in the initial fuzzy model for the mathematical function and to 3.27% from 22.72% for the analog circuit function.

In Figure 3 and Figure 4 the functions values obtained with fuzzy models affected by noise and after noise cancellation are shown. It can be easily observed that after the noise cancellation (Figure 3b and 4b) the fuzzy model surface is fixed.

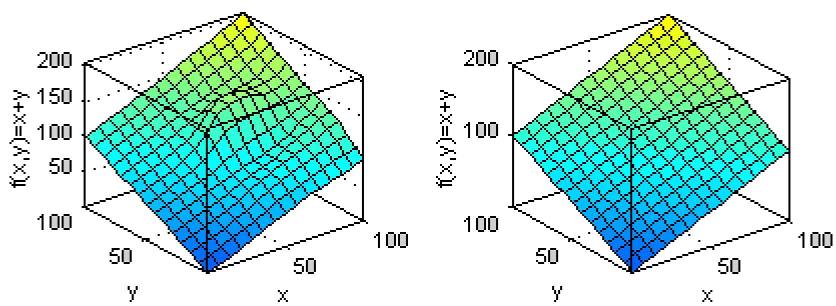

Figure 3. Fuzzy model for the mathematical function
a) with noisy data; b)after noise cancellation

A small disadvantage of our method is that the automatic elimination of noisy data pairs have a collateral effect. Other good data points are also eliminated (2 good pairs for the linear function and 7 good pairs for the nonlinear one), as it shown in Table 3.

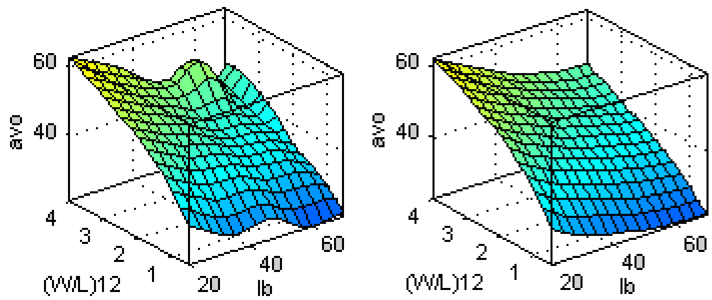

Figure 4. The fuzzy model for the analog circuit function
a) with noisy data; b)after noise cancellation

Table 3

Function	Noisy data pairs	Eliminated data pairs
Mathematical two variables linear function f = x + y	1, 3, 5, 8, 10, 13, 15	**3**, **5**, **8**, **1**, 43, **13**, 87, **15**
Nonlinear analog circuit function avo=f(Ib,WL12)	1, 5, 13, 15, 16	14, **1**, 110, 437, **15**, 338, 31, **16**, 823, **13**, 165, **5**

4. CONCLUSION

An automatic method to build fuzzy models of circuit functions, with noise cancellation was presented. The results obtained in modeling two kind of function (a linear one and a nonlinear one) prove the efficiency and utility of the proposed method. The noisy data were successfully eliminated and the final fuzzy models have a high accuracy degree, the maximum relative error in the final fuzzy models being 0.116% for the linear function and 3.27% for the nonlinear one.

In the noise cancellation process a collateral effect was noticed. A small number of good data points were also eliminated besides the noisy ones.

The applicability domain of the proposed method is practically unlimited; it can be used to model any kind of multivariable, complex function. The only requirement is to provide enough data pairs to capture all the relevant characteristics of the function.

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