The use of ensemble methods for indirect test of RF circuits

Hassan El Badawi, Florence Azaïs, Serge Bernard, Mariane Comte, Vincent Kerzérho, François Lefevre

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H. El Badawi (1,2), F. Azais (1), S. Bernard (1), M. Comte (1), V. Kerzérho (1), F. Lefevre (2)

(1) LIRMM, University of Montpellier, CNRS, 161 rue Ada, 34095 Montpellier Cedex, France

(2) NXP Semiconductors, 2 Esplanade Anton Philips, 14000 Caen, France

***Abstract* — Indirect testing of analog and RF integrated circuits is a widely studied approach, which has the benefits of relaxing requirements on test equipment and reducing industrial test cost. It is based on machine-learning algorithms to train a regression model that maps an indirect and low-cost measurement space to the performance parameter space. In this work, we explore the benefit of using ensemble learning. Rather than using one single model to estimate targeted parameters, ensemble learning consists of training multiple individual regression models and combining their outputs in order to improve the predictive power. Different ensemble methods based on bagging, boosting or stacking are investigated and compared to classical individual models. Results are illustrated and discussed on three RF performances of a LNA for which we have production test data.**

Keywords: indirect testing, RF integrated circuits, machine-learning algorithms, ensemble methods, test efficiency

I. INTRODUCTION

Process variation and manufacturing imperfections could lead to faulty devices, thus integrated circuit manufacturers should ensure the quality of their products and guarantee their behavior and functionality by testing these circuits. Nonetheless, testing many circuits will result in an increase of the total cost of the finished product. Moreover, in the case of analog and RF circuits, the manufacturer would be obliged to test each specification which requires the use of expensive and sophisticated test equipment. To reduce the cost of testing, researchers have investigated one of the possible solutions in implementing the concept of indirect test. Basically, the aim will be to replace specification-based testing with low-cost test resources, and build a predictive model to correlate these measurements, called Indirect Measurements (IM) with the device specifications. These kinds of predictive models are generally established using regression and statistical machine learning algorithms.

Initially, the concept was introduced for analog circuits [1], extended then to RF circuits [2]. Furthermore, different aspects have been analyzed to enhance the performance, such as the choice of the prediction model, the various test stimuli and the processing of complex signatures, the use of embedded sensors [2,3] to gather pertinent information, examining multi-Vdd [4] test conditions, and the selection of appropriate IM.

The objective of this paper is to highlight the advantages of using novel prediction models like ensemble learning, which have been previously implemented in various domains, to achieve more generalized prediction models.

This paper is organized as follows. Section II summarizes the basics of the indirect test approach. Section III gives an overview on the used algorithms and the necessary metrics to evaluate the performance of the various prediction models. Finally, before the conclusion, the case studies and the results are presented and discussed in Section IV.

II. INDIRECT TEST PRINCIPLE

The underlying idea of indirect testing is that process variations that affect the device performance also affect indirect parameters. If the correlation between the indirect parameter space and the specification space can be established, then specifications may be verified using only the low-cost indirect signatures. Unfortunately, the relation between these two sets of parameters is complex and cannot be simply identified with an analytic function. The solution commonly implemented uses machine-learning algorithms. The indirect test synopsis is split into two distinct phases, namely training and production testing, as illustrated in Figure 1.

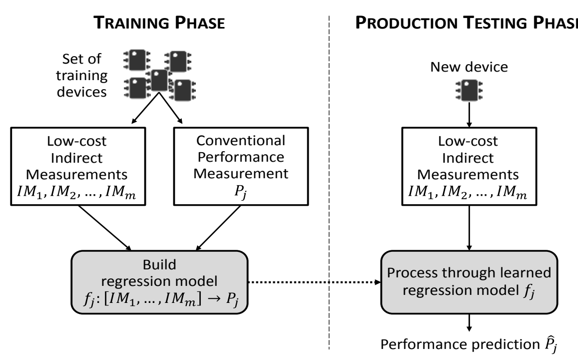

Fig.1. Indirect test synopsis.

The idea is to learn during the training phase the unknown dependency between the low-cost indirect measurements (IM_i) and the conventional performance measurements (P_j). To achieve this, both the specification tests and the low-cost measurements are performed on a set of training devices and a machine-learning algorithm is trained to build regression models that map the indirect parameters space to the performance parameters space. During the production testing phase, only the low-cost indirect measurements are performed, and the specifications of every new device are predicted using the mapping learned in the initial training phase.

III. PREDITCION MODELS AND MODEL EVALUATION

The classical approach to predict the value of a target feature on unseen instances is to build a single regression model. The most popular algorithms used in the context of indirect test are Multiple Linear Regression (MLR), Multi-Adaptive Regression Splines (MARS), and Support Vector Machine (SVM). However, the performances achieved with these algorithms can significantly differ depending on the case study and there is no obvious winner when it comes to choosing a single prediction model.

To cope with the model performance dependency on the size and the structure of the training data, researchers have started to use multiple regression models and aggregate their outcomes to get the final prediction results. The idea is that with an appropriate combination of diverse individual models, it should be possible to exploit the strengths and overcome the weaknesses of the individual models and obtain better overall predictive performance. This approach is called ensemble learning, which refers to the procedures used to train multiple individual regression models (base learners) and combine their outputs in order to improve the stability and the predictive power of the ensemble model. Numerous methods for constructing ensemble models have been proposed in the literature [5], which includes parallel and sequential methods, based either on a single type of base learners (homogenous ensemble model) or learners of different types (heterogeneous ensemble model). The three most used methods are Bagging, Boosting, and Stacking.

Finally, to be able to evaluate the different prediction models, we should base our judgment on certain evaluation metrics. The most commonly-used metric is the coefficient of determination R^2, which describes the quality of the model fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

where y_i is the actual performance value of the i^{th} instance, $\hat{y}_i$ is the predicted performance value of the i^{th} instance, and n is the number of instances in the validation set.

Another metric has been suggested in [6], which permits to quantify the prediction reliability of a model. This metric, called Failing Prediction Rate (FPR), expresses the percentage of circuits with a prediction error that exceeds the conventional measurement uncertainty ε_{meas}:

$$FPR = \frac{1}{n} \sum_{i=1}^{n}(|y_i - \hat{y}_i| > \varepsilon_{meas}) \quad (3)$$

with $(|y_i - \hat{y}_i| > \varepsilon_{meas}) = 1$ if true
$(|y_i - \hat{y}_i| > \varepsilon_{meas}) = 0$ otherwise

Lastly, if the test limits are available, we can compute another metric called the Misclassification Rate (*MR*). This metric simply expresses the ratio of misclassified circuits with respect to the total number of circuits.

IV. CASE STUDIES

The test vehicle is a Low-Noise Amplifier (LNA) for which we have production test data on 3,850 devices. More precisely, test data include the conventional measurements of three RF specification performances, namely the gain, the output power at 1dB compression point (P1dB) and the third-order intercept point (IP3). Test data also include 79 low-cost indirect measurements which correspond to DC voltages on internal nodes (the device is equipped with an internal DC bus and internal DC probes) and DC signatures delivered by built-in process monitors. To perform the training phase, we have sampled 2000 of the initial test data by using Latin Hypercube Sampling (LHS), and the remaining circuits (1850) were used for result evaluation. Eight models have been trained and evaluated. Three models are single ones based on classical methods. Five models have been trained on an ensemble method. The results are highlighted in Table I, were we show the best performing model for each specification

TABLE I. COMPARISON BETWEEN CLASSICAL AND ENSEMBLE METHODS: SUMMARY OF BEST RESULTS FOR THE THREE RF PERFORMANCES

	Best solution selected from max(R^2) on validation set					
	RF Perf	***Model***	***$R^{2\ (*)}$***	***FPR (*)***	***MR (*)***	***# feat.***
Classical method	Gain	MARS	0.65	2.86%	0%	9
	P1dB	SVM	0.85	12.32%	0.1%	8
	IP3	SVM	0.93	0.59%	4.2%	14
Ensemble method	Gain	Stack+RF	0.72	1.51%	0%	9
	P1dB	Stack+RF	0.87	11.24%	0.1%	12
	IP3	Stack+RF	0.94	0.70%	4.2%	14

(*) Score computed on validation set

V. CONCLUSION

In this paper, we have explored the use of ensemble methods for indirect test of RF circuits. Different ensemble methods based on bagging, boosting and stacking have been investigated and compared to classical individual models. Results have demonstrated the superiority of ensemble models built with stacking compared to ensemble models. Results have also shown that such models can outperform the classical individual models, both in terms of accuracy and reliability, and that they offer a superior predictive power over a variety of different situations.

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