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HAL Id: lirmm-03000910

https://hal-lirmm.ccsd.cnrs.fr/lirmm-03000910v1

Submitted on 12 Nov 2020

Implementing indirect test of RF circuits without compromising test quality: a practical case study

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Abstract — **Cost reduction is a crucial step in testing AMS/RF circuits, and one way of achieving this is to implement an indirect test strategy. Although this strategy relaxes the requirements on test equipment, it still raises some accuracy concerns, which might compromise the test quality. In this work, we explore the benefit that can be brought by a two-tier adaptive test flow, in which only circuits with a sufficient prediction confidence level are evaluated by the indirect test while others are re-evaluated by specification-based test. A methodology is presented that permits to explore different tradeoffs between test quality and test cost and to make pertinent choices for the efficient implementation of such a test flow. The results are illustrated on a front-end RF circuit designed for WLAN applications and show that substantial test cost reduction can be achieved without compromising the test quality.**

Keywords: Indirect test, RF integrated circuits, machine-learning algorithms, quality metrics, test efficiency, test confidence

I. INTRODUCTION

Testing Integrated Circuits (ICs) is a crucial step in the production process since it ensures the quality of manufactured devices. However, test costs represent a significant part of the production costs, especially for RF circuits that require very expensive specific test equipment and long test procedures in order to measure the RF performances and verify that they comply with their specifications. An attractive solution is to adopt an indirect test approach, in which the device RF performances will be predicted from Indirect Measurements (IMs) that do not require specific equipment [1]. Such approach could therefore significantly reduce the testing costs, provided that sufficient confidence can be placed in the accuracy and robustness of the predictions. Many research works have been conducted over the past twenty years to investigate the influence of different elements on the quality achieved by indirect test: composition of the learning population [2], use of embedded sensors or multi-Vdd conditions [3,4], selection of relevant indirect measurements [5,6] etc. A comprehensive review of works related to indirect test can be found in [7].

In this paper, we explore on a practical case study how it is possible to combine indirect test and standard specification test in a two-tier adaptive test flow. The objective is to benefit from the test cost reduction offered by indirect test without compromising the test quality brought by specification test. A complete methodology is presented that permits to guide the test engineer in the different choices he has to make for an efficient implementation of the test flow. The paper is organized as follows. Section II recalls the principle of indirect test and introduces the two-tier adaptive test flow together with its specific proposed implementation. The methodology for the

practical elaboration of the test flow is then detailed in Section III. Finally, the case study is presented in Section IV, and results are presented and analyzed in section V.

II. BASICS OF INDIRECT TEST

The indirect test principle relies on the fact that manufacturing process variations induce not only variations on specification parameters but also variations on some indirect parameters. Using measurements of indirect parameters to test integrated circuits (ICs) entails to establish the link between both parameter spaces. The complexity of the relationship between these two spaces makes necessary to use machine-learning. As a consequence, the indirect test synopsis combines two distinct phases, named training and production testing phases, as illustrated in Figure 1. During the training phase, both conventional performance measurements and indirect measurements (IMs) are performed on a set of training devices and a machine-learning algorithm is trained to build regression models that map the IM space to the performance space. Then during the production testing phase, only the low-cost indirect measurements are performed and the performances of every new device are predicted using the mapping learned in the initial training phase; device is then binned as a good or bad circuit by comparing predicted performances with specification limits.
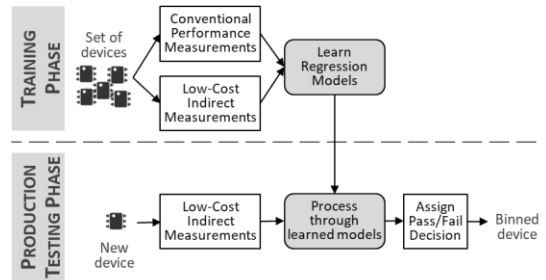
Fig.1. Indirect test synopsis.

A drawback of this strategy is that machine-learning algorithms used to build regression models are perceived as a black box and often induce a lack of confidence. A solution to increase confidence and guarantee test quality is an extension called the two-tier adaptive test flow. The principle is illustrated in Figure 2. The idea is that during production testing, every device is first processed by the indirect test; if the confidence in the decision proposed by this first tier is high enough, the device is labeled according to the indirect test decision; otherwise it goes to the second tier where it is retested through the standard specification test. Assuming that only a small number of circuits will be retested through the standard specification test, this

approach remains cost efficient as the majority of devices will be sorted using only the low-cost indirect test.
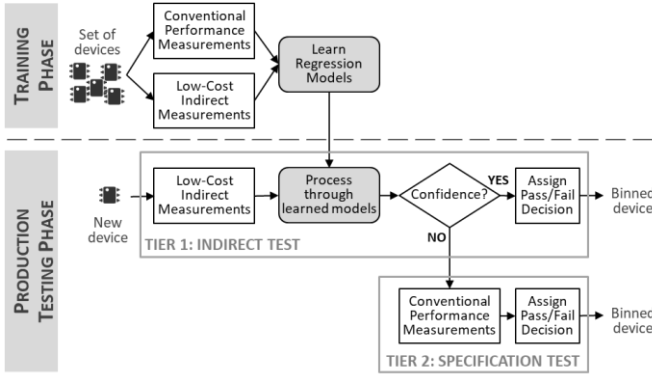

Fig.2. Two-tier adaptive test flow synopsis.

The two-tier approach was first proposed in the context of classification-oriented indirect test, where the machine-learning algorithm is not used to predict the device performances but is trained to define a pass/fail boundary directly in the IM space [8,9]. In this case, confidence is established by looking at the location of a device with respect to guard-bands allocated around the pass/fail boundary in the IM space. The two-tier approach has also been explored in the context of prediction-oriented test, based on the use of model redundancy [10]. In this case, confidence is established by checking the consistency between the values predicted by the different redundant models.

In this work, we investigate a novel implementation of the two-tier adaptive test flow in the context of prediction-oriented indirect test. The idea is to evaluate confidence based on a tolerance zone around test limits. Indeed, previous works have shown that almost all of misclassified circuits are circuits with a predicted value close to a test limit, while correct decisions are taken for circuits with a predicted value far from test limits [11]. Therefore, the proposal is to establish confidence by looking at the location of the predicted value with respect to a tolerance zone defined around a test limit, as illustrated in Figure 3. More precisely, any device with a performance prediction that falls outside the tolerance zone will be directly classified as a good/bad device for this performance according to the indirect test tier, while any device with a prediction that falls within the tolerance zone will be directed to the second tier in order to be evaluated through conventional specification test.
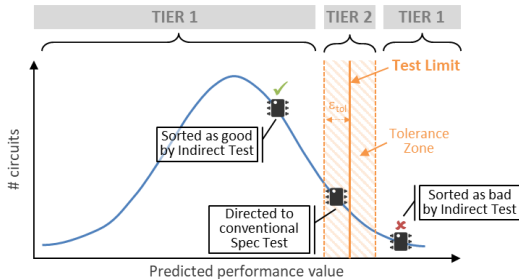

Fig.3. Principle of confidence estimation in the proposed two-tier adaptive test flow.

The size of the tolerance zone is a crucial parameter that will determine the tradeoff between test quality and test cost. Indeed, with a tolerance zone set to zero, 100% of the devices are evaluated with the indirect test tier and the test costs are minimal; however, the test quality might not be sufficient to meet the industrial constraints. By creating and expanding the tolerance zone, we expect an improvement of the test quality but at the expense of a number of devices that need to be evaluated with the conventional specification test. It is therefore essential to have an appropriate setting of this parameter during the initial learning phase in order to really benefit from the two-tier adaptive test approach.

III. METHODOLOGY

In the previous section, we have introduced the principle of the indirect test strategy and the two-tier adaptive test approach. The practical implementation implies several choices, such as the selection of pertinent IMs, the choice of the regression algorithm or the size of the tolerance zone. Obviously the achieved test quality depends on these choices. In this section, we describe the methodology that has been defined in order to assist the test engineer in the elaboration of the test flow. The general overview of this methodology is depicted in Figure 4.
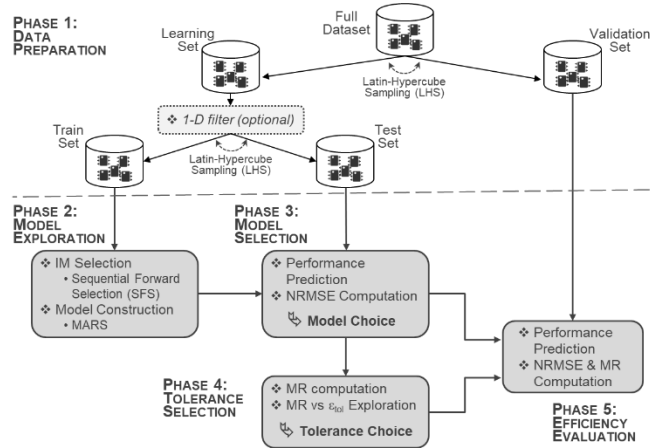

Fig.4. General overview of the test flow elaboration methodology.

The first phase concerns data preparation. The initial dataset should contain the conventional performance measurements and a large variety of indirect measurements on a sufficient number of circuits (typically several thousands). This full dataset is first partitioned into two datasets, called learning and validation sets. The learning set will be used to explore the different possibilities regarding the test flow implementation and to identify the best options. The second set is dedicated to the validation of the retained options using an independent set of devices; it is intended to represent the production testing phase. Note that, although both sets are independent, it is essential that they present similar characteristics to ascertain the validity of results. Therefore, the partitioning is realized using Latin-Hypercube Sampling (LHS), which is a sampling approach that preserves the statistical characteristics of the initial distribution in the sampled sub-datasets. The learning set is in turn partitioned into two subsets, i.e. the train set and the test set. The first one will be used to train the prediction models and the second one to evaluate the accuracy of the constructed models. It is important to perform this evaluation on different instances than the ones used for training in order to verify model generalization ability and avoid issues related to overfitting. Finally, note that it is

often recommended in the literature to work with a dataset that does not contain outliers. Indeed, data outliers can spoil and mislead the training process resulting in longer training times, less accurate models and ultimately poorer results. Consequently, we have also considered the possibility of cleaning the learning set by applying a simple filter. The filter is applied on both the RF performances and the indirect measurements; it simply removes all instances that have a measured value outside $\pm k\sigma$ of the regular distribution, where k is a positive integer number and σ is the standard deviation of the population [12].

The second phase of the methodology is the model exploration. In this phase, a number of regression models will be built using different subsets of IMs. The problem of selecting a pertinent subset of IMs within a large set of candidates is a recurrent problem in the field of machine-learning, known as feature selection. In the context of indirect test, the common approach is a wrapper method called Sequential Forward Selection (SFS) [5]. For this study, we have implemented such a procedure, limiting the number of selected IMs to 15. The next step is then to train regression models using the selected IMs. Many different algorithms exist to perform this task. Classical algorithms include Multiple Linear Regression (MLR), Multi-Adaptive Regression Splines (MARS), Support Vector Machine (SVM), or more elaborated algorithms that combine several models in an approach called ensemble learning [11]. For this study, we have implemented one of the most commonly used algorithms in the context of indirect test, i.e. MARS.

The third phase of the methodology concerns model selection. In this phase, all models learned in the previous phase are used to perform prediction of devices of the test set. The accuracy of these models is evaluated in terms of Normalized Root Mean Square Error (NRMSE), which is a normalized measure of the rms prediction error expressed in percentage. Models with the lowest NRMSE are then retained as the best solutions for each RF performance.

The following phase is specific to the implementation of a two-tier adaptive test flow. It is related to the exploration of the tradeoff that can be achieved between test quality expressed in terms of Misclassification Rate (MR), and test cost expressed in terms of percentage of devices that need to be retested with a conventional specification test. Practically for each selected model, the misclassification rate is first computed with a tolerance zone set to zero (only indirect test). The size of the tolerance zone is then progressively enlarged in order to study the evolution of the misclassification rate versus the number of devices directed to the second tier. The appropriate size of the tolerance zone can be chosen for each RF performance with respect to a targeted test quality, i.e. the smallest size that does not overcome a predefined maximum MR.

Finally, the last phase of the methodology is dedicated to the evaluation of the two-tier adaptive test flow efficiency. All the options retained in the learning phase are evaluated on devices of the validation set. Indeed, it is important to verify that the efficiency established on the test set during the learning phase is preserved on the validation set, which is intended to be representative of the realistic conditions encountered during the industrial testing phase.

IV. CASE STUDY

The case study is a front-end integrated circuit designed for WLAN applications. The three main specifications to be verified are the gain of the receiver chain (Rx-gain), the gain of the transmitter chain (Tx-gain) and the Error Vector Magnitude of the transmitter chain (Tx-EVM). The low-cost indirect measurements investigated for this product include standard DC measurements performed on external nodes of the device together with internal DC measurements (the device is equipped with an internal DC bus and internal probes that give access to the voltage at some specific nodes and signatures delivered by built-in process monitors). Overall, we have a total of 131 possible indirect measurements.

An extensive campaign of measurements has been carried out in the production test environment and test data have been collected on more than 26,700 circuits coming from different wafers fabricated under various extreme process conditions. The test data, which include both the conventional measurements of the three RF specification performances and the 131 indirect measurements, constitute the full dataset. This full dataset has been partitioned into two sets of 13,350 devices using Latin Hypercube Sampling (LHS), i.e. the learning and validation sets. The main characteristics of these two sets are summarized in Table I.

TABLE I. CHARACTERICTICS OF LEARNING AND VALIDATION SETS FOR THE 3 RF PERFORMANCES

		RF Performance		
		Tx-EVM	*Tx-gain*	*Rx-gain*
Learning Set *13,354 instances*	Coef. of Variation	11.0%	3.0%	3.7%
	% of good circuits	77.2%	97.9%	100%
	% of bad circuits	22.8%	2.1%	0%
Validation Set *13,352 instances*	Coef. of Variation	11.3%	3.0%	3.7%
	% of good circuits	75.5%	97.6%	100%
	% of bad circuits	24.5%	2.4%	0%

From this table, it clearly appears that the learning and validation sets exhibit similar characteristics in terms of distribution dispersion and proportion of good or bad circuits for each RF performance, confirming that the use of Latin-hypercube sampling permits to obtain several sets with the same distribution characteristics as the initial population. However, it can be noticed that the characteristics of the population significantly differ depending on the considered RF performance. For the Tx-EVM, we observe a quite large distribution with a dispersion around 11%; a bit more than 75% of circuits satisfy the targeted EVM requirement. For the Tx-gain, the distribution is tighter with a dispersion of only 3%; more than 97% of circuits satisfy the targeted gain requirement. Finally, for the Rx-gain, we also observe a tight distribution with a dispersion around 3.7%; in this case the targeted requirement is sufficiently far away from the distribution so that 100% of circuits satisfy the requirement. At this point, it is important to underline that circuits coming from wafers fabricated with corner process conditions have been included in the population on purpose. Therefore, the proportion of bad circuits is not representative of what would be the actual production yield under normal process conditions.

The influence of the use of a filter during the learning phase has also been examined. Two different filters have been

investigated, i.e. a relaxed filter with a limit at 10σ and a stricter one with a limit at 6σ. The relaxed filter eliminates about 10% of the learning population, whereas the strict filter eliminates more than 35% of the learning population. The main characteristics of the filtered learning sets are summarized in Table II. It can be observed that the use of the filter does not significantly modify the characteristics of the learning population. Indeed, for each RF performance, the filtered learning sets exhibit a similar dispersion than the original learning set (maximum difference of 0.4%) and proportion of good or bad circuits is globally preserved (maximum difference of 1.2%). Although this might seem unexpected, it can be explained by analyzing which circuits are eliminated by the filter. Actually, there is no circuit with an RF performance value outside the regular distribution but only circuits that have outlying values for indirect measurements. Moreover, there is no direct relation between the fact that a circuit exhibits outlying values for indirect measurements and the fact that it is a good or bad circuit with respect to its RF performances. Indeed, the set of eliminated circuits contains good and bad circuits in the same proportion than the original learning set.

TABLE II. CHARACTERICTICS OF THE FILTERED LEARNING SETS FOR THE 3 RF PERFORMANCES

		RF Performance		
		Tx-EVM	*Tx-gain*	*Rx-gain*
10σ-filtered Learning Set *12,067 instances*	Coef. of Variation	11.0%	2.9%	3.7%
	% of good circuits	77.4%	98.5%	100%
	% of bad circuits	22.6%	1.5%	0%
6σ-filtered Learning Set *8,295 instances*	Coef. of Variation	11.1%	2.6%	3.7%
	% of good circuits	77.8%	99.1%	100%
	% of bad circuits	22.2%	1.5%	0%

From these observations, it is consistent that the use of the filter does not affect the main characteristics of the learning population with respect to the RF performances, but only modify the composition of the population with respect to the indirect measurements. This remark is noteworthy because it indicates that the use of such filter would be totally ineffective during production testing since it does not help to discriminate between good and bad circuits.

V. RESULTS

The methodology presented in Section III has been applied on our case study. Results are commented in this section, first regarding the selection of pertinent models, then regarding the efficiency of a classical indirect test implementation, and finally regarding the efficiency of a two-tier adaptive test flow solution.

A. Model selection

Results regarding the accuracy that can be achieved in the prediction of the three RF performances are summarized in Figure 5. This figure reports, for each RF performance, the evolution of the NRMSE score with respect to the number of IMs used in the construction of the model, considering either the original learning set or the filtered learning sets.

Several comments arise from the analysis of these graphs. A first general comment is that there is no phenomenon of overfitting since there is no discrepancy between the NRMSE scores evaluated on train and test sets. Then, it can be observed that the level of accuracy significantly differs over the different

performances, with an NRMSE score that can be below 1% for the Tx-gain and Rx-gain performances but that remains between 2.5% and 3% for the Tx-EVM in the best cases of the different scenarios. Finally, regarding the influence of the learning population, the impact is mostly visible on the prediction of the Tx performances. We observe that the use of a filter leads to an improvement in the accuracy of the constructed models, especially with the strict filter.
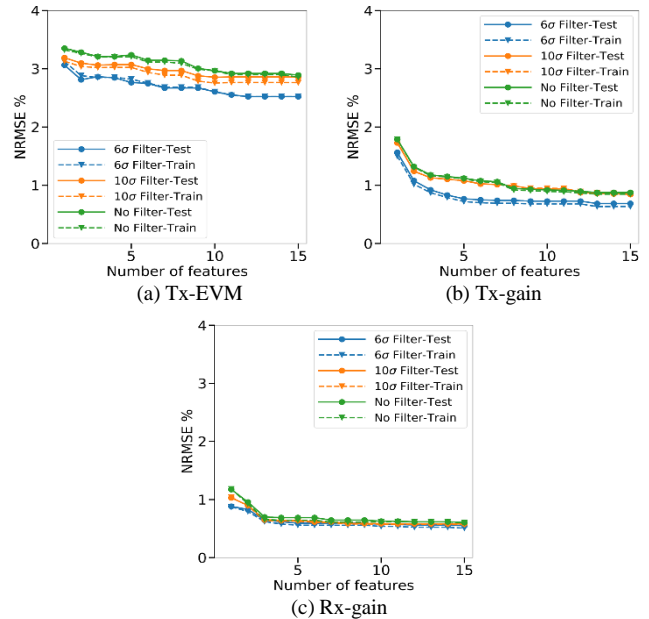

(a) Tx-EVM

(b) Tx-gain

(c) Rx-gain

Fig.5. NRMSE score achieved on train and test sets for the different scenarios of learning population

From this exploratory phase, the best model (i.e. the one with the lowest NRMSE score on the test set) can be selected for each RF performance and for the different scenarios. Results are summarized in Table III, which reports for each model the number of selected IMs together with the NRMSE scores computed on train and test sets.

TABLE III. SUMMARY OF BEST RESULTS ACHIEVED UNDER DIFFERENT SCENARIOS OF LEARNING POPULATION FOR THE 3 RF PERFORMANCES

		# IMs	*NRMSE-Train Set*	*NRMSE-Test Set*
Original Learning Set	Tx-EVM	15	2.86%	2.89%
	Tx-gain	13	0.85%	0.87%
	Rx-gain	15	0.60%	0.60%
10σ-filtered Learning Set	Tx-EVM	10	2.76%	2.86%
	Tx-gain	15	0.85%	0.84%
	Rx-gain	14	0.57%	0.58%
6σ-filtered Learning Set	Tx-EVM	12	2.52%	2.52%
	Tx-gain	13	0.63%	0.68%
	Rx-gain	15	0.51%	0.55%

These results confirm the general trends previously commented on the graphs. Indeed, we observe that whatever the learning set, the difference between the NRMSE scores computed on train and test sets never exceeds 0.2%, clearly indicating that there is no overfitting. Regarding the improvement brought by the use of a filter, it is negligible in case of the relaxed filter with a reduction of the NRSME score that remains inferior to 0.1% over the 3 RF performances. In case of the strict filter, the improvement is also negligible for the Rx-gain (NRMSE reduction less than 0.1%), quite small for the

Tx-gain (NRMSE reduction around 0.2%), and more significant for the Tx-EVM (NRMSE reduction around 0.35%).

Globally, these results are positive for the implementation of the indirect test strategy since they show that it is possible to build quite accurate models for the three RF performances. The best solution is obtained using models constructed on a learning population filtered with a strict filter. In this case, we obtain an accuracy of 0.55% for Rx-gain prediction, 0.68% for Tx-gain prediction and 2.52% for Tx-EVM prediction.

B. Efficiency of classical indirect test implementation

In this part, we explore the efficiency that can be achieved with a classical indirect test implementation, i.e. all circuits are evaluated using only the indirect test flow and there is no circuit directed to a regular specification test flow (tolerance zone set to zero). We also explore how this efficiency is influenced by the use (or not) of a filter during the initial learning phase. Results are summarized in Figure 6, which compares the NRMSE and MR scores achieved on test and validation sets for the different scenarios of learning population and the three RF performances.

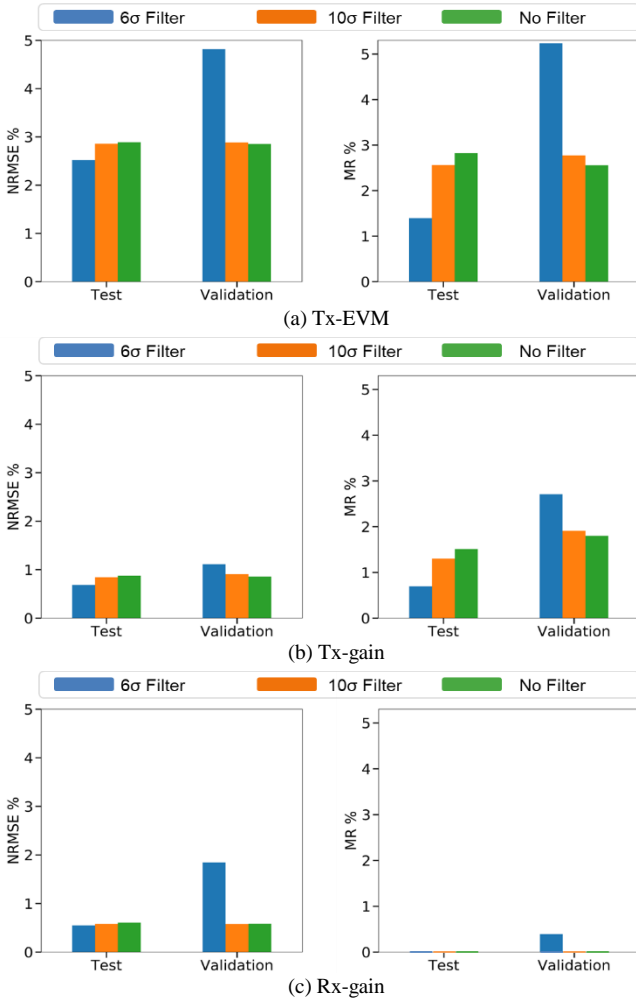(a) Tx-EVM

(b) Tx-gain

(c) Rx-gain

Fig.6. NRMSE and MR scores achieved on test and validation sets for the different scenarios of learning population

A first evident comment arises: although working with a filtered population during the initial learning phase permits to improve the quality of constructed models, these models are nevertheless not able to correctly handle all circuits that can be encountered during the production testing phase. Indeed, there is a significant degradation between NRMSE and MR scores determined on the test set and the ones achieved on the validation set when the strict filter is used. The strongest difference is observed for the Tx-EVM, with an increase of the NRMSE and MR scores by +2.3% and +3.8% respectively. For the Tx-gain, we observe a small increase of the NRMSE score by +0.4% and a more significant increase of the MR score by + 2.0%. For the Rx-gain, the impact is mostly visible on the NRMSE score with an increase of +1.3%. The difference between NRMSE and MR scores determined on test and validation sets lessens by using the relaxed filter (maximum difference of 0.3% in NRMSE and 0.7% in MR over the three RF performances), and becomes negligible when the learning is performed on the original population (maximum difference of 0.06% in NRMSE and 0.3% in MR over the three RF performances). These results indicate that it is not pertinent to work with a filtered population since it can entail a strong discrepancy between the test quality estimated during the learning phase and the one that will be encountered during the production phase. Moreover, it can be observed that the best results achieved on the validation set are obtained when the learning is done on the original learning set. It is therefore recommended to include circuits with possible outlying values in the indirect measurements in the learning population.

For the practical case study investigated in this paper, a fairly good efficiency can be attained by the classical indirect test implementation, with a low MR of 2.5% and 1.8% for the Tx-EVM and Tx-gain respectively, and the ideal MR of 0% for the Rx-gain. However, despite the drastic testing costs reduction offered by this solution where all circuits are evaluated based only on low-cost indirect measurements, a misclassification rate around 2% might not be sufficient to comply with industrial test quality constraints.

C. Efficiency of two-tier adpative test flow

In this part, we present results regarding the benefit that can be brought by the implementation of a two-tier adaptive test flow, in particular regarding the tradeoff between test quality and test cost. As mentioned in Section II, this tradeoff depends on the size of the tolerance zone around the test limits.

Results are summarized in Figure 7, which reports the tradeoff curves between MR score and percentage of retested circuits obtained by varying the size of the tolerance zone. Note that these curves are presented only for the Tx-EVM and Tx-gain performances since the ideal MR of 0% is achieved for the Rx-gain without the need of retesting any devices. These results indicate again that the use of a filter during the learning phase (especially the strict one) is not recommended since there is a huge difference between the tradeoff curve evaluated on the test set and the one observed on the validation set. Moreover, the decrease in the MR score observed on the validation set is much slower than the one obtained when the learning is performed on the original population. These results also clearly demonstrate that it is possible to significantly improve the test quality compared to a classical indirect test implementation. Indeed, with a learning performed on the original population, there is a rapid decrease of the MR score observed on the validation set, which means that the test quality improvement can be obtained

with only a limited number of devices that need to be retested through a conventional specification test. In particular, it is possible to attain a very low MR score below few tenths of percent with a majority of devices that are tested using only the low-cost indirect measurements.
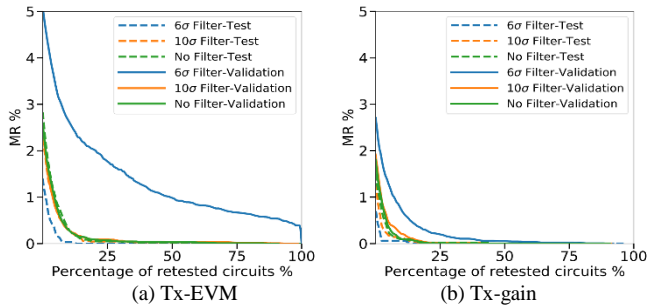

Fig.7. Tradeoff curves between MR and percentage of retested devices

For the sake of a concrete illustration, an arbitrary target of a MR score below 0.1% for each RF performance has been fixed. Based on devices of the test set, the size of the tolerance zone necessary to fulfil this constraint has been determined for each RF performance; the efficiency of the two-tier adaptive test flow has then been evaluated on the validation set. Results are summarized in Table IV (results obtained under the best learning scenario with no filter applied on the learning population).

TABLE IV. SUMMARY OF RESULTS ACHIEVED BY THE TWO-TIER ADAPTIVE TEST FLOW WITH A MR TARGET OF 0.1% FOR EACH RF PERFROMANCE

	MR		Percentage of retested devices	
	Test Set	*Valid Set*	*Test Set*	*Valid Set*
Tx-EVM	0.10%	0.14%	15.3%	15.7%
Tx-gain	0.10%	0.09%	9.4%	12.0%
Rx-gain	0%	0%	0%	0%
Global	**0.19%**	**0.23%**	**22.2%**	**23.8%**

These results confirm that the two-tier adaptive test flow permits to reach a substantial reduction of the test costs while preserving a very good test quality. Indeed, the targeted MR score of 0.1% can be attained for each RF performance; the difference between the MR score forecasted on the test set and the one evaluated on the validation set remains inferior to 0.04%. Only a limited number of devices need to be retested to ensure this quality, i.e. around 16% for the Tx-EVM, around 12% for the Tx-gain, and 0% for the Rx-gain.

Globally for this practical case study, a very good test quality is achieved with only about 0.2% misclassified devices over the three RF performances while more than 76% devices are processed using only the low-cost indirect measurements, leading to substantial saving in the test costs. Note that the global misclassification rate achieved over the three RF performances is a bit higher than the targeted one on each individual RF performance because misclassified devices with respect to a given performance are not necessarily the same than misclassified devices with respect to another performance. In the same way, the global percentage of circuits that need to be retested is higher than the one established for each individual RF performance. Also note that all these numbers correspond to worst-case results because they are established on a population fabricated with corner process conditions. We can expect lower numbers, especially the percentage of circuits that need to be

retested, in the regular context of production testing where circuits are manufactured under normal process conditions.

VI. CONCLUSION

In this paper, we have investigated on a practical case study whether it is possible to benefit of the potential test cost reduction offered by the indirect test strategy without compromising the test quality. We have proposed an original implementation of a two-tier adaptive test flow that relies on the use of a tolerance zone around test limits in order to establish the confidence in the decision proposed by the indirect test; only devices with sufficient confidence are processed by the indirect test while others are directed to a second tier where they are evaluated by a standard specification test. A methodology has been defined in order to make the pertinent choices for the efficient implementation of this test flow.

Results have shown that a very good test quality can be preserved while achieving a substantial test cost reduction, i.e. a low misclassification rate of few tenths of percent (the classical indirect test implementation remains above the percent) and less than 25% of devices that need to go through a standard specification test.

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