A Machine-Learning Approach to Analog/RF Circuit Testing* Yiorgos Makris



TRELA

Testable and RELiable Architectures

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Research Areas

Analog/RF circuits

- Machine learning-based testing
- Correlation mining for post-fabrication tuning and yield enhancement
- Design of on-chip checkers and on-line test methods
- Hardware Trojan detection in wireless cryptographic circuits

Digital Circuits

- Workload-driven error impact analysis in modern microprocessors
- Logic transformations for improved soft-error immunity
- Concurrent error detection / correction methods for FSMs

Asynchronous circuits

- Fault simulation & test generation for speed-independent circuits
- Test methods for high-speed pipelines (e.g. Mousetrap)
- > Error detection and soft-error mitigation in burst-mode controllers

Presentation Outline

- Testing analog/RF circuits
- Machine learning-based testing
- Testing via a non-linear neural classifier
 - Construction and training
 - Selection of measurements
 - Test quality vs. test time trade-off
- Experimental results
- Analog/RF specification test compaction
- Stand-alone Built-in Self-Test (BIST)
- Performance calibration via post-fabrication tuning
- Yield enhancement
- Summary

Definition of Analog/RF Functionality

Symbol



Transistor-Level



Specifications

Symbol	Parameter	Condition	Typ (Note 5)	Limit (Note 2)	Unit
Vos	Input Offset Voltage		0.05	1.0	mV
				1.5	max
Vсм	Input common-Mode Voltage	For CMRR ≥ 50dB		0	v
	Range				min
			1.4	1.3	v
					mav
CMRR	Common Mode Rejection Ratio	0V < V _{CM} < 1.3V	100	85	dB
				70	min
PSRR	Power Supply Rejection Ratio	V* = 2.7V to 5.0V	107	85	dB
				70	min
ls	Supply Current		0.5	0.8	mA
				0.85	ma
I _{IN}	Input Current		1.5	100	pА
					max
os	Input Offset Current		0.2		pА
Avol	Voltage Gain	R _L = 10k Connect to V*/2	120	110	
		Vo = 0.2V to 2.2V		95	dB
		R _L = 2k Connect to V*/2	120	100	min
		V ₀ = 0.2V to 2.2V		85	
vo	Positive Voltage Swing	R _L = 10k Connect to V*/2	2.62	2.54	
				2.52	v
		R _L = 2k Connect to V*/2	2.62	2.54	min
				2.52	
Vo	Negative Voltage Swing	R _L = 10k Connect to V*/2	78	140	
				160	mV
		R _L = 2k Connect to V*/2	78	160	mav
				180	
6	Output Current	Sourcing, Vo = 0V	12	6.0	
	-	V_{IN} (diff) = ±0.5V		1.5	mA
		Sinking, Vo = 2.7V	11	6.0	min
		V_{IN} (diff) = ±0.5V		1.5	
e _n (10Hz)	Input Referred Voltage Noise		15.5		nV/_√

Analog/RF IC Testing - Problem Definition



Verification:

- Targets design errors
- Once per design

Testing:

- Targets manufacturing defects
- Once per chip

Analog/RF IC Test - Industrial Practice Post-silicon production flow



Current practice is specification testing



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Limitations

Test Cost:

- Expensive ATE (multi-million dollar equipment)
- Specialized circuitry for stimuli generation and response measurement

<u>Test Time:</u>

- Multiple measurements and test configurations
- Switching and settling times

<u>Alternatives?</u>

- Fault-model based test Never really caught on
- Machine learning-based (a.k.a. "alternate") testing
 - Regression (Variyam et al., TCAD'02)
 - Classification (Pan et al., TCAS-II'99, Lindermeir et al., TCAD'99)

Machine Learning-Based Testing

<u>General idea:</u>

• Determine if a chip meets its specifications without explicitly computing the performance parameters and without assuming a prescribed fault model

How does it work?

 Infer whether the specifications are violated through a few simpler/cheaper measurements and information that is "learned" from a set of fully tested chips

Underlying assumption:

 Since chips are produced by the same manufacturing process, the relation between measurements and performance parameters can be statistically learned

Regression vs. Classification <u>Problem Definition:</u>



Regression:

 Explicitly learn these functions (i.e. approximate f:x → π)

Classification:

 Implicitly learn these functions (i.e. approximate f:x→Y,Y={pass/fail})

Overview of Classification Approach



Using a Non-Linear Neural Classifier

- Allocates a single boundary of arbitrary order
- No prior knowledge of boundary order is required
- Constructed using linear perceptrons only
- The topology is not fixed, but it grows (ontogeny) until it matches the intrinsic complexity of the separation problem

Linear Perceptron





Topology of Neural Classifier



- Pyramid structure
 - First perceptron receives the pattern $\vec{X} \in R^d$
 - Successive perceptrons also receive inputs from preceding perceptrons and a parabolic pattern $x_{d+1}=\sum x_i^2$, i=1...d
- Every newly added layer assumes the role of the network output
- Non-linear boundary by training a sequence of linear perceptrons

Training and Outcome

- Weights of added layer are adjusted through the thermal perceptron training algorithm
- Weights of preceding layers do not change
- Each perceptron separates its input space linearly
- Allocated boundary is non-linear in the original space $\vec{x} \in R^d$

Theorem:

 The sequence of boundaries allocated by the neurons converges to a boundary that perfectly separates the two populations in the training set

Boundary Evolution Example (layer 0)



Boundary Evolution Example (layer 1)



Boundary Evolution Example (layer 2)



Boundary Evolution Example (output layer)



Matching the Inherent Boundary Order

Is Higher Order Always Better?

- No! The goal is to generalize
- Inflexible and over-fitting boundaries



Finding The Trade-Off Point (Early Stopping)

- Monitor classification on validation set
- Prune down network to layer that achieves the best generalization on validation set
- Evaluate generalization on test set

Are All Measurements Useful?



Non-Discriminatory

Linearly Dependent

Curse of Dimensionality



- By increasing the dimensionality we may reach a point where the distributions are very sparse
- Several possible boundaries exist choice is random
- Random label assignment to new patterns

Genetic Measurement Selection

 Encode measurements in a bit string, with the k-th bit denoting the inclusion (1) or exclusion (0) of the k-th measurement



Fitness function:

NSGA II: Genetic algorithm with multi-objective fitness function reporting pareto-front for error rate (g_r) and number of re-tested circuits (n_r)

Two-Tier Test Strategy



Guard-bands



• Introduce a trichotomy in the measurement space in order to assess the confidence of the decision

Testing Using Guard-bands



Examine measurement pattern with respect to the guard-bands

• Identify circuits that need to be re-tested via specification tests

Guard-band Allocation



- Guard-bands are allocated separately
- Identify the overlapping regions

$$D = \frac{1}{N_f} \sum_{i \in C_f} \min_{j \in C_n} \parallel \vec{x}^i - \vec{x}^j \mid$$

- Clear the overlapping regions
- $\parallel \vec{x}^i \vec{x}^j \parallel < D$
- The ontogenic classifier allocates the guard-band

Guard-band Allocation



The guard-banded region can been varied by controlling D

Experiment 1: Switch-Capacitor Filter



Specifications considered

- Ripples in stop- and pass-bands
- Gain errors
- Group delay
- Phase response
- THD

Experiment Setup

- N=2000 instances
- N/2 assigned to the training set, N/4 to the validation set and N/4 to the test set

White-Noise Test Stimulus



Test Time vs. Test Accuracy Trade-Off



Experiment 2: RFMD2411



- 541 devices (training set 341, validation set 100, test set 100)
- Considered 13 specs @850MHz (7 different test configurations)

	Gain	3 rd Order Intercept	Noise Figure	Other S Parameters		
LNA	Х	X	x	Х	Х	Х
Mixer	Х	X	x	х	-	-
LNA + Mixer (Cascade)	X	x	X	-	-	-

Test Configuration







Test Time vs. Test Accuracy Trade-Off



Analog/RF Specification Test Compaction

Non-disruptive application:

 Instead of "other, alternate measurements" use existing inexpensive specification tests to predict pass/fail for the chip and eliminate expensive ones

Case-Study:

- RFCMOS zero-IF down-converter for cell-phones
- Fabricated at IBM, in production until late 2008
- Data from 944 devices (870 pass 74 fail)
- 136 performances (65 non-RF 71 RF)
- Non-RF measurements assumed much cheaper than RF, aim at minimizing number of measurements

Setup and Questions Asked

<u>Setup:</u>

- Split 944 devices into training and test set (472 devices each, chosen uniformly at random.
- Repeat 200 times and average to obtain statistically significant results

Question #1:

- How accurately can we predict pass/fail of a device using only a subset of non-RF measurements?
 Question #2:
- How does this accuracy improve by selectively adding a few RF measurements to this subset?

Results



Only non-RF performances:

 16 measurement suffice to predict correctly over 99% of the devices (in our case 4 out of 472 are on average mispredicted



Adding RF performances:

 By adding to these 16 non-RF performances 12 RF performances, error drops to 0.38% (i.e. 1 out of 472 devices mispredicted)

Continuation of Case-Study

Larger Data Set:

 Experiment repeated for data from 4450 devices with very similar results

<u>Cost-driven compaction (TVLSI'09 – in press):</u>

 Given appropriate test cost information (test time per performance, cost per test configuration, groups of performances sharing test configuration, per second cost of non-RF vs RF ATE, etc.) select subsets of performances that minimize cost instead of cardinality

Guard-banding:

• Assess the effectiveness of our guard-banding method in enabling exploration of test-cost / test quality trade-off

Current Research Activities (TI/IBM)

Dealing with process variations, shifts, and drifts:

- Investigate whether process variations over the lifetime of production affect the accuracy of the models
- Devise a method for adapting to process variations (periodic, event-driven, or monitoring-based retraining)

Dealing with variations across ATE and across sites:

- Investigate whether variations across sites of an ATE or across ATE affect the accuracy of the models
- Devise a method for adapting to ATE/site variations (training per site or ATE, using calibration filters, etc.)

Measurement correlations:

 Use correlations between PCM, wafer sort, and final test measurements to support adaptive test

What's Next? Stand-alone Built-in Self-Test



A stand-alone BIST method for mixed-signal/RF circuits:

- On-chip generation of simple test stimulus
- On-chip acquisition of simple measurements
- On-chip implementation of trainable neural classifier (w. floating gates)

Summary

Contribution:

- A non-linear neural classifier supporting a novel paradigm for testing analog/RF circuits
 - Achieves significant reduction in test cost without sacrificing accuracy of specification test
 - Enables exploration of trade-off between test cost and test accuracy via guard-bands

Applications:

- Disruptive: Machine learning-based test
- Non-disruptive: Specification test compaction
- Futuristic: Stand-alone Built-in Self-Test

Knob-Tuning for Performance Calibration



"Healing" of failing chips:

- Low-cost machine-learning based testing
- Iterative, correlation-based knob tuning

Correlation Mining for Yield Improvement



Improve yield by:

- Guiding modifications in potential design re-spin
- Assisting in fabrication process quality control

More Information

Publications:

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Questions?

