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Indirect Measurement Method Using Reconfigurable Non-intrusive Sensors for Integrated Sensory Electronics

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Summary:
This paper presents a new approach for indirect measurement methods (IMs) by using reconfigurable non-intrusive sensors (NS) for the infield optimization of the reconfigurable integrated circuit with self-x properties. The typical IMs approach of using the regression model for the device under test (DUT) performance prediction is integrated with a metaheuristic optimization algorithm for the reconfigurable non-intrusive sensors. The novelty of this work comes from running the optimization algorithm on the NS by copying the same tuning knobs of the DUT, which allows for indirectly optimizing the DUT performance without interrupting its operation. Additionally, the infield optimization will be based on low-cost measurement of the embedded sensors. The achieved correlation performance metrics for the regression task is 90.13%. The DUT circuit is designed using XFAB 0.35 µm technology.

Keywords: Indirect measurements, Non-intrusive sensors, Infield optimization, Self-x properties, Metaheuristic optimization algorithm, Reconfigurable integrated circuit.

Background, Motivation and Objective

The integration of machine learning (ML) and artificial intelligence (AI) with other emerging technologies, such as cyber-physical systems and edge computing, is initiating the most profound transformation in the industrial domain known as industry 4.0 [1,2]. The smart sensory electronics systems (SSES) perform the essential part of the data generation in this domain. However, the performance of SSES is normally deviated with time [3]. To tackle the aging and process variations effects, analog ICs are commonly overdesigned, leading to more power and or larger chip area. Nevertheless, with the introduction of ML and AI, the reconfigurable hardware structure of the SSES enables the self-X (self-healing, self-calibration, self-learning, etc.) properties [4][5]. In order to support self-X properties, the analog ICs is designed with controllable tuning knobs and performance evaluation set-up [6] for chip performance monitoring. The primary objective of this work is to replace and reduce the number of real expensive chip measurements with a simple and cost-effective indirect performance evaluation method (RIMs) for SSE

Description of the Proposed Methodology

The block diagram of the proposed methodology is shown in Fig. 1. The reconfigurable non-intrusive sensors (NS) are integrated in close proximity to the main design under test (DUT) to face the same operating conditions imposed on the DUT, that is, PVT variations (process, voltage, temperature). In this work, the reconfigurability is introduced in the NS for the first time and the whole optimization is performed by utilizing the tuning knobs of NS rather than tuning knobs of the DUT with the help of the pre-trained regression model (RM). A wide tunable range low pass filter (LPF) is used to present this concept. The DUT and NS share similar TK values to reduce the search space complexity and ease the ML regression task. This feature also allows the online performance optimization of the DUT without interrupting its operation.

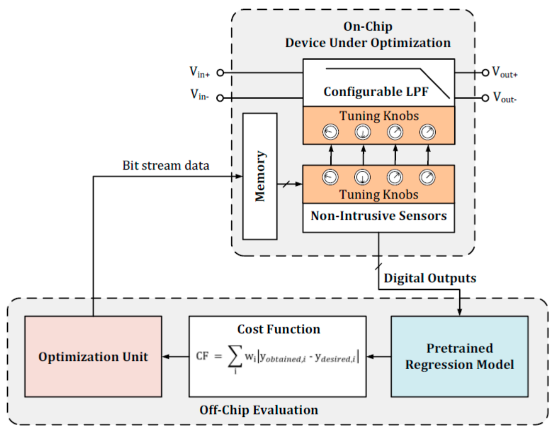

Fig. 1. Block diagram of the proposed IMs method.

The TK values are copied to the main DUT after the completion of the optimization process. Random forest regressor (RFR) is used to create an accurate regression model between the

NS outputs, TK, and DUT performance. The RFR helps to simplify the estimation of the DUT performance indirectly based on the low-cost measurement of the quasi-digital output frequency of the NS. The flow diagram of the proposed approach is depicted in Fig. 2.

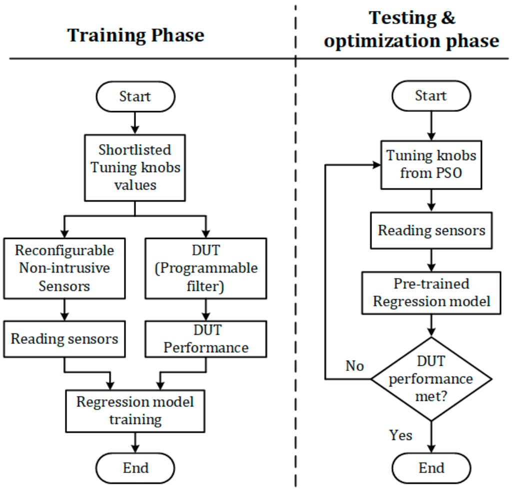

Fig. 2. Flow chart of the proposed IMs approach

First, different TK values are shortlisted for the training phase from the optimization search space to minimize the training data set and evaluation time. In the next step, the output of the NS and performance of the DUT are simulated and subjected to similar PVT conditions. 80% of data set are randomly used for the training of the RFR while the residual 20% are selected to assess its performance. During the testing phase, the particle swarm optimizer (PSO) determines the TK values which will be applied to the NS. The output response of the NS is provided as input to the pre-trained RFR along with the current TK values to indirectly predict the DUT performance. Based on the output response of the RFR the PSO decides the respective TK values for the next iteration.

Results

For this experiment, a fully differential fourth-order tunable continuous-time active low pass filter based on the Sallen–Key structure with Butterworth approximation is used as a test vehicle [7]. The digitized MOS resistor is used as a TK of the filter to determine the cutoff frequency. We used a total of 1000 estimators with mean squared error as a criterion for the RFR. The performance of the RFR is graphically illustrated Fig. 3. The adjusted R squared value (ARS) of the RFR is 90.13%. The details about the metaheuristic parameters of the PSO can be found in our previous work [8]. This experiment is performed using 10 particles and 100 iterations. The experiment is repeated five different times, and the averaged optimization results are summarized in Table 1. The maximum estimation error of the optimization result is roughly 9% for the 1 kHz but can be minimized by increasing the training data set around this region. Our institute already submitted the chip prototyping for fabrication to prove the concept practically with real measurements.

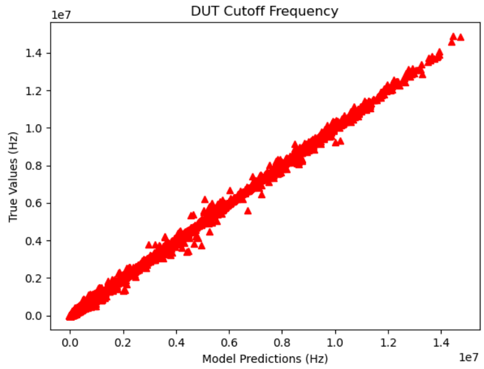

Fig. 3. Scatter plot of the predicted and true values.

Tab. 1. Optimization results of the DUT.

DUT Characteristic	Targetted	Achieved
3 dB cutt off frequency	5 MHz	4.95 MHz
	1 MHz	1.03 MHz
	100 kHz	94.37 kHz
	10 kHz	9.56 kHz
	1 kHz	1.09 kHz

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