A Novel Multi-objective Optimization Framework for Analog Circuit Customization

Mutian Zhu, Mohsen Hassanpourghadi, Qiaochu Zhang, Mike Shuo-Wei Chen, A. F. J. Levi, and Sandeep Gupta
Department of Electrical and Computer Engineering, University of Southern California
Los Angeles, CA 90007 USA
Email: {mutianzh, mhassanp, qiaochuz, shuoweic, alevi, sandeep}@usc.edu

Abstract—**Prior research has developed an approach called Analog Mixed-signal Parameter Search Engine (AMPSE) [1] to reduce the cost of design of analog/mixed-signal (AMS) circuits. In this paper, we propose an adaptive sampling method (AS) to identify a range of Pareto-optimal versions of a given AMS circuit with different combinations of metric values to enable parameter-search based methods like AMPSE to efficiently serve multiple users with diverse requirements.**

As AMS circuit simulation has high run-time complexity, our method uses a surrogate model to estimate the values of metrics for the circuit, given the values of its parameters. In each iteration, we use a mix of uniform and adaptive sampling to identify parameter value combinations, use the surrogate model to identify a subset of these samples to simulate, and use the simulation results to retrain the model. Our method is more effective and has lower complexity compared with prior methods [2] [3] [4] because it works with any surrogate model, uses a low-complexity yet effective strategy to identify samples for simulation, and uses an adaptive annealing strategy to balance exploration vs. exploitation.

Experimental results demonstrate that, at lower complexity, our method discovers better Pareto-optimal designs compared to prior methods. The benefits of our method, relative to prior methods, increase as we move from AMS circuits with low simulation complexities to those with higher simulation complexities. For an AMS circuit with very high simulation complexity, our method identifies designs that are superior to the version of the circuit optimized by experienced designers.

Index Terms—**analog circuit, surrogate model, multi-objective optimization**

I. Introduction

Searching for key parameter values of an AMS circuit is a time-consuming process due to the high dimensional parameter space and long simulation times. Often, improving one metric may require sacrificing another, hence designers with different requirements favor design versions with different trade-offs.

Recently an approach called Analog Mixed-signal Parameter Search Engine (AMPSE) [1] has been developed to accelerate the process of generating, from a single circuit netlist topology, multiple versions of an AMS intellectual property (IP) block to efficiently meet a wide range of user requirements. Given a new user's requirement, AMPSE performs the search for optimal parameter values by solving a *scalar-valued optimization problem* (SOP). However, since the designs identified by solving a SOP are highly customized for a single set of requirements, satisfying multiple user requirements requires solving multiple SOPs independently, which can be time-consuming and inefficient.

In this paper, given a fixed circuit topology netlist, we aim to improve the efficiency of satisfying multiple user requirements by discovering a library of diverse designs in a single search. The library will contain the designs that optimally meet any user's requirement in the future, avoiding the need for multiple independent searches. We propose an Adaptive Sampling (AS) method to solve a *multi-objective optimization problem* (MOP) by searching for *Pareto-optimal* [2] designs efficiently within a given run-time budget. Pareto-optimal designs are the ones that make the most efficient trade-offs, therefore should include the optimal designs for any designer, independent of their requirements. The set that contains the metric values of Pareto-optimal designs is called *Pareto front* (PF).

II. Proposed Adaptive Sampling Method

To improve sample efficiency, our method utilizes a *surrogate model*, which is a regression model that approximates the mapping from the parameter space to the metric space. Since inferencing from the surrogate model has much lower complexity compared to circuit simulations, model predictions, together with other information are used to estimate the effectiveness of a sample and high complexity simulations are used only for samples deemed the most effective.

At the top level, our method is an evolutionary algorithm which starts with an initial set of samples and uses simulators to compute their metric values. New samples are iteratively selected for simulation based on all previously simulated samples.

The set of all samples that have been simulated since the start of the algorithm is denoted as X, and the corresponding metric values are collected in the set Y. The parameters for the Pareto-optimal simulated samples is denoted as X_{Pareto}. Next, we introduce our key steps.

A. Initialization

At initialization, we aim to obtain a more complete understanding of the mapping from parameter space to metric space. Therefore, we initialize X with uniformly distributed samples and simulate all of them to obtain Y. An initial surrogate model is then trained using X and Y.

B. Hybrid Sample Creation

The purpose of this step is to create a diverse set of samples that are either effective for **exploration** or **exploitation**.

We assume that samples with larger Euclidean distance in the parameter space, d_X, to the simulated samples are more effective for exploration, and samples with more optimal predicted metrics, $\hat{\mathbf{y}}$, are more effective for exploitation. Then we run two sampling procedures respectively: uniform search and adaptive search.

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TABLE I: Comparison for equal runtimes

	Two-stage Differential Amplifier (5 repetitions)				Comparator (5 repetitions)				TI SAR ADC (1 repetition)			
Method	Budget	HV	R_{sv}	M_{v}	Budget	HV	R_{sv}	M_{v}	Budget	HV	R_{sv}	M_{v}
AS	66 hours	**0.57**	**0.83**	**0.006**	8 hours	**0.991**	**1.0**	$\mathbf{3.63 \times 10^{-6}}$	7 days	**0.999**	**1**	$\mathbf{4 \times 10^{-5}}$
BNNBO		0.08	0.0	0.179		0.860	0.0	9.0×10^{-6}		0.87	0	3×10^{-4}
MOBO		0.24	0.0	0.171		0.964	0.04	9.0×10^{-6}		0.985	0	3×10^{-4}
MOEA/D-DE		0.54	0.48	0.010		0.968	0.09	8.2×10^{-6}		0.8	0	3×10^{-4}

Uniform search has lower complexity. It creates random uniformly distributed samples that are more likely to have larger d_X, effective for exploration. Adaptive search has higher complexity. It searches for samples with $\hat{\mathbf{y}}$ that are superior to the Pareto-optimal simulated samples, which are more likely to have more optimal $\hat{\mathbf{y}}$, effective for exploitation.

Note that in order to control the sample creation complexity, we do not search for sample with optimized d_X or $\hat{\mathbf{y}}$. This is because $\hat{\mathbf{y}}$ may not be entirely accurate, and our assumptions regarding the effectiveness may not be entirely correct. Therefore, optimization can introduce unnecessary computational complexity with little benefits.

C. Sample Selection

In this step, we propose a strategy to select a subset of newly created samples for simulation with an adaptive balance between exploration and exploitation.

We filter out samples with less optimal $\hat{\mathbf{y}}$, and then select a subset from remaining samples that fill the parameter space as evenly as possible for simulation. The balance between exploration and exploitation is controlled by the tolerance for samples with less optimal $\hat{\mathbf{y}}$ during the filtering.

When the tolerance is high, the filter allows more samples to pass, which increase the probability of filling the parameter space more uniformly, favoring exploration. On the other hand, when the tolerance is low, the filter mostly allows samples with the best $\hat{\mathbf{y}}$ to pass, which reduces the size of the search space and increases the number of samples in promising regions, favoring exploitation.

The magnitude of tolerance is determined by the validation errors of the surrogate model as well as the remaining run-time budget. Smaller validation errors leads to lower tolerance as the model predictions are more reliable. Less remaining budget also leads to lower tolerance to fine-tune the results.

D. Evaluation and Evolution

Once the selected samples are simulated, the validation errors of the surrogate model are calculated. Then X and Y are augmented with new samples and the model is retrained. Then the tolerance for sample selection is updated with the most recent validation errors and the remaining run-time budget.

III. Experimental Results

We compared our method with two other surrogate model-based methods MOBO [3] and BNNBO [4], which are based on Bayesian optimization, and one classical method MOEA/D-DE [2], which is based on genetic algorithm. While our method can work with any regression model, to emphasize the comparison of sampling strategies rather than model quality, we employ Gaussian process regression, used by MOBO, as our surrogate model.

We tested on three AMS circuit blocks: a two-stage differential amplifier, a comparator in a SAR ADC, and a 8-bit 4 Channel Time-Interleaved (TI) SAR ADC.

We propose three evaluation metrics. **Hypervolume (HV)** [5] calculates the hypervolume of the region in the metric space excluded by Pareto-optimal designs. **Survival Rate** R_{sv} calculates the percentage of Pareto-optimal designs discovered that are non-inferior compared to the results from other methods. **Mesh volume measure** M_{v} estimates the diversity of the Pareto-optimal designs discovered. Smaller M_{v} indicates larger diversity. The results are shown in Table I. For TI SAR ADC, as shown in Table II, we also select one of Pareto-optimal designs discovered by AS and compared it to a design optimized by an experienced designer.

The results clearly demonstrate than our method can discover better Pareto-optimal designs compared to prior methods, even identifying designs that improve the expert design within limited run-time.

TABLE II: TI SAR ADC: Comparison of design identified by AS with expert optimized design

Method	Power (mW)	ENOB	SFDR
AS	**133**	**7.84**	**66.58**
Expert designer	208.573	7.446	60.559

IV. Conclusions

We propose an adaptive sampling (AS) method which effectively and efficiently identifies the PF of an AMS circuit. AS adaptively balances between exploration and exploitation, and has much lower complexity than other surrogate model-based methods. Compared with other state-of-the-art methods, AS shows superiority in runtime efficiency, and identifies PFs that are strongly superior to the PFs identified by other methods.

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