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Multi-objective optimization and analysis for the design space exploration of analog circuits and solar cells

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ABSTRACT

This paper introduces PareDA (ParetoDesignAutomation), a composite automated methodology for the optimization of analog circuits and solar cell devices. The PareDA framework combines randomized algorithms, domain and constraints sensitivity analysis, epsilon-dominance and global robustness analysis in order to perform simulation-based, multi-scenario and multi-objective optimization. PareDA is evaluated on the problems of designing a three-stage operational amplifier, a yield-aware optimization of a folded-cascode operational amplifier (requiring multiple operating conditions) and a model for selective emitter solar cells.

Comparisons with a selection of state-of-the-art techniques (such as NSGA-II and YdIRCO) highlight the effectiveness of PareDA both in terms of Pareto optimality of the solutions found and time-to-converge. The solutions obtained by PareDA dominate those of comparative techniques, in particular, the proposed technique shows a significant average performance improvement (ranging from 35% to 49%) with respect to such techniques. Moreover, the CPU time required by PareDA to converge is smaller of at least 75% if compared with the other methodologies here analyzed (e.g. significantly improved designs for folded-cascode operational amplifier are found in just 320 s). Finally, the PareDA algorithm can also benefit from parallelization, which leads to a significant speed-up with respect to the nonparallel version.

1. Introduction

Analog circuits find application in a large variety of different fields (Roychowdhury et al., 2007). The technological advancement has led to development of highly complex integrated circuits (IC) in order to meet increasingly demanding design requirements. In addition, the short product life and the tight time-to-market constraints, that are characteristics of the electronic industry, increase the difficulty of designing circuits (Gielen and Rutenbar, 2000). A suitable approach to tackle such strict requirements might be through a combination of design automation methodologies (Anile et al., 2005).

Another major issue of the development of circuits and solar cells concerns the scaling down of their designs. For instance, if the thickness of the oxide layer reduces to a few atoms, the combination of quantum effect, random dopant fluctuations and manufacturing imperfections might cause significant differences between different devices and, more generally, performance degradation. Hence, robust designs of the model, with additional attention to the physical parameters, are crucial in order to cope with the uncertainty that occurs at small-scales (Nuzzo and Sangiovanni-Vincentelli, 2011). Analogous considerations can be made for solar cell devices, in which even very small fluctuations of the doping levels of the different layers can lead to significant degradation of the cell efficiency. Moreover, design problems can also be characterized by large disjoint *design* spaces, due to an overly abundant number of design variables, and/or non-linear physical constraints on the model parameters and outputs (Ciccazzo et al., 2008a). In this context, efficient and device-independent methodologies can aid the design of circuits and solar cells.

We propose a simulation-based, multi-scenario and multi-objective optimization algorithm that can afford the simultaneous optimization of yield and performance of different types of devices. The Pareto Design Automation algorithm (PareDA) is based on the paradigm of Immune Algorithms. It performs, in the case here studied, notably better than several academic tools largely employed in this field. Moreover, we extend our algorithm with *global* domain-space *sensitivity analysis* (SA), which leads to

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considerable computational complexity reduction; *epsilon-dominance analysis*, which allows a rigorous exploration of *approximately non-dominated* designs (i.e. designs satisfying a non-dominated condition relaxed by a small $\epsilon > 0$ value); *constraints sensitivity analysis*, which gives an insight on the behavior of a model's constraints; *global robustness analysis*, which we use to evaluate a device resistance against perturbations.

Indeed, heuristics for multi-objective optimization enable easier global design space exploration and can be used to design robust devices (Tiwary et al., 2006; Biondi et al., 2006). A vast amount of work can be found in this field (Cutello, 2006; Ciccazzo et al., 2008b). In Graeb et al. (2009), the authors proposed a multi-objective optimization problem formulation operating on the process parameters, while in Stracquadanio and Romano (2013), a multi-objective optimization has been used for designing semiconductor devices. In Tiwary et al. (2006), *yield-aware* Pareto fronts are generated using two stochastic algorithms and Monte Carlo analysis. However, both methods are sequential, which can lead to a waste of computational resources. Following this consideration, the authors in Liu et al. (2010) extend the NSGA algorithm to optimize simultaneously yield and device performance. NSGA-II, whereas, is used in the MOJITO (McConaghy et al., 2007) system for multi-topology and multi-objective design of analog circuits, while in Conca et al. (2009) an immune-oriented approach has been used.

In Li and Stojanović (2009) the authors proposed an iterative yield-driven robust optimization algorithm. However, it has the drawback of being inaccurate (20% mismatch with HSPICE). In Bermel et al. (2010) the authors show that heuristic global optimization of thermophotovoltaic solar cell devices can lead to significant efficiency improvement. Also in this case (Sheng et al., 2009), NSGA-II is adopted as the core of the heuristic approach. Notice that each of these methodologies either does not consider yield in the optimization phase or base the optimization on heuristic methods, which are therefore of *paramount* importance for the optimality of the designs obtained. We remark that an heuristic approach is not the only possible alternative for multi-objective optimization. Works in the field of multi-objective optimization are also focused on finding mathematical conditions, which would allow the exact determination of a problem Pareto fronts, rather than approximations of the latter. For example, a rank-deficient condition on a problem-dependent Jacobian matrix is used in Brown et al. (2013) in order to identify the problem boundaries on the objective space, and hence the Pareto Front as a subset of the latter.

We would like to remark that immune-system optimization algorithms are recently receiving an ever-increasing attention on various engineering fields that require heuristic optimization as a step of the design process. For example, in Omkar et al. (2008) the authors develop an artificial immune system based multi-objective optimization algorithm for the optimization of laminated composite components design. An immunity-based hybrid evolutionary algorithm for constrained and unconstrained multi-objective optimization has been proposed in Wong et al. (2009), and it has been validated against state-of-the-art optimization algorithms. Multimodal function optimization is the subject of Xu et al. (2010), in which an artificial immune system based algorithm proves its efficiency on various benchmark problems. Finally notice that the immune system paradigm finds applications in other research fields related to that of artificial intelligence. For what it concern data mining, the author in Aydin et al. (2010) combines swarm learning and the artificial immune system paradigm, in order to develop an efficient classification algorithm. A clustering algorithm is whereas presented in Zhang et al. (2014). The regression problem is whereas tackled in Diao and Passino (2002), where an immunity-based learning approach is used to adjust the form and the parameters of specific spatially localized models.

The specific contributions of this paper are (i) we formulate the yield-aware optimization of analog circuit as a multi-scenario and multi-objective problem; (ii) we propose an immune optimization algorithm which is able to tackle the latter class of problems; (iii) we validate our algorithm against the problem of designing analog circuits and solar cell devices; (iv) we enhance our algorithm with sensitivity, epsilon-dominance and robustness analysis.

2. The design space exploration by PareDA

In this section, we introduce PAREDA, a new methodology for designing electronic circuits and solar cells. The proposed method relies on a stochastic *black-box* optimization algorithm inspired by the clonal selection principle of the immune system of vertebrates. Given a large space of solutions, PAREDA provides an in-depth search of its promising zones (Pavone and Narzisi, 2012). PAREDA is composed of four different models, (i) sensitivity analysis, which evaluates the importance of each parameter with respect to the problem considered, this information can be used to reduce the size of the domain space considered; (ii) optimization, which is the core method of PAREDA, which can be both single-objective and multi-objective; (iii) identifiability analysis, through which we study the functional relationship between the model parameters; (iv) robustness analysis, a perturbation-based index that evaluates how robust a given design is against random variations of its design parameters.

The optimization algorithm of PAREDA is based on an abstraction of the immune system: the analyzed problem corresponds to the antigen, namely the threat to neutralize, while candidate solutions correspond to B-cells, namely the cells responsible for the adaptivity of the immune system. The *affinity* between the antigen and a B-cell depends on the objective function(s) of the problem. Each B-cell is a vector of k real values (k is the dimension of design space). Each candidate solution has an age τ, which is the number of iterations since the last successful mutation (initially $\tau = 0$).

At the onset of the algorithm, an initial population $P^{(0)}$ of cardinality d is randomly generated. Then the population of candidate solutions is evolved by applying iteratively a set of operators. In particular, each iteration consists of a cloning phase, a mutation phase and a selection phase. The pseudo-code of PAREDA is summarized in Algorithm 1. In the cloning phase, each member of the population is cloned *dup* times (where *dup* is a user-defined parameter), thus generating a population P_{clo}. Each cloned candidate solution gets the same age of its “parent”, whereas the age of the latter is increased by one. Mutations are then applied to the new population, with the intent of generating better (in terms of affinity) B-cells. Firstly, the hyper-mutation operator (Cutello et al., 2006) mutates a randomly chosen variable x_i of a given candidate solution using a *self-adaptive Gaussian mutation* (Beyer and Schwefel, 2002). Successively, the hyper-macromutation applies a convex perturbation to a given B-cell, by setting $x_i^{new} = (1-\gamma)x_i + \gamma x_k$, where x_i and x_k are randomly chosen components of the candidate solutions such that $i \neq k$ and γ is uniformly distributed in $[0, 1]$. The mutation rates of these operators are controlled by the parameter α: for the hyper-mutation operator, we define $\alpha = e^{-\rho f}$; while for the hyper-macromutation we use $\alpha = \frac{1}{\beta}e^{-f}$, where f is affinity of the B-Cell, normalized in the interval $[0, 1]$. The hyper-mutation operator acts on the population P_{clo} thus producing a new population P_{hyp}, which is in turn hyper-

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