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Sensitivity aware NSGA-II based Pareto front generation for the optimal sizing of analog circuits

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ABSTRACT

This paper deals with multiobjective analog circuit optimization taking into consideration performance sensitivity vis-a-vis parameters' variations. It mainly considers improving computation time of the inloop optimization approaches by including sensitivity considerations in the Pareto front generation process, not as a constraint, but by involving it within the used metaheuristic evolution process. Different approaches are proposed and compared. NSGA-II metaheuristic is considered. The proposed sensitivity aware approaches are showcased via two analog circuits, namely, a second generation CMOS current conveyor and a CMOS voltage follower. We show that the proposed ideas considerably alleviate the long computation time of the process and improve the quality of the generated front, as well.

1. Introduction

Analog circuit sizing/optimization problems are known as hard problems; they cannot be solved using conventional solution techniques [1–4]. It has already been shown that metaheuristics bid an efficient approach for solving such problems thanks to the fact that they rely on a stochastic way of exploring the variables' space, thus, guaranteeing the convergence to the neighbourhood of the optimal solution within a 'reasonable' computing time [2,4,5].

Analog circuit sizing/optimizing problems are multivariable and constrained problems. In addition, they are, in fact, multi-objective problems. As objectives are in most cases non-commensurable and competing ones, multi-objective metaheuristics are used [4,6].

Dealing with multi-objective analog circuit optimization problems is of paramount importance where robust designs as well as yield estimations have to be taken into consideration [7]. Actually, solving such multi-objective problems is tantamount to providing the best trade-off among those defined objectives in the form of the widely known Pareto front [8]. In other words, this is to generate the set of non dominated solutions, where the dominance criterion can be defined as follows: a design vector X dominates another vector Y if, for a minimization problem, $h_i(X) \leq h_i(Y)$, for $i \in [1,n]$, n is the number of objective functions, and there exists at least one function h_i where $h_i(X) < h_i(Y)$.

Fig. 1 depicts the Pareto front concept for a bi-objective minimization problem. In addition, it shows the dominance notion: points A, B and C are non-dominated, they belong to the Pareto front. D dominates E but is not Pareto optimal.

As detailed above, resolving analog circuit problems consists of generating a set of 'optimal' parameters (solutions) that form the Pareto front. However, as it is well known, such parameters may be subject to several effects that can force their values to change, such as temperature variation, fabrication process tolerance, etc. Consequently, sensitivity analysis is a must in every sizing process [9–13], and the Pareto front should be formed by low sensitive solutions, i.e. solutions having a sensitivity value lower than an acceptable predefined level [14,15]. Otherwise, the initial sensitivity unaware Pareto solutions will provide very bad solutions due to the dependency of the circuit performance on the parameter value variation.

According to the knowledge of the authors, up to date published papers dealing with sensitivity consideration when handling multi-objective problems consider getting low sensitive solutions a posteriori, i.e. eliminating sensitive solutions from the

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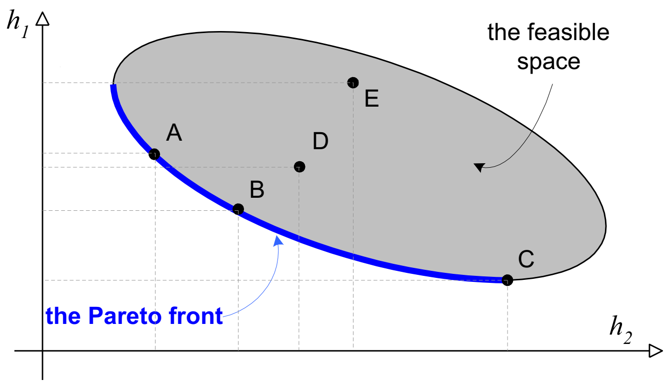

Fig. 1. Depiction of the Pareto front concept, for a bi-objective minimization problem.

non-dominated set and, thus, keeping only the low-sensitive ones in the Pareto front, see for instance [16–18]. This may lead to a reduction of the number of solutions comprising the Pareto front.

To overcome the above mentioned problem, sensitivity considerations may be included in the problem's extrinsic set of constraints to be handled. Depending on the acceptable sensitivity level, this can alleviate the aforementioned problem. However, in an inloop optimization approach, evaluation of the intermediate solutions' sensitivities is a very time consuming process, as it is shown in the following. It is to be mentioned here that the Richardson extrapolation technique is used for computing the partial derivatives necessary for deducing the sensitivity values. We refer the reader to [15,19] for further details regarding the Richardson technique.

Thus, in this work we propose some novel ideas for efficiently generating a robust Pareto front. It is to be stated that a first idea has already been proposed in [19] that, in short, consists of applying the sensitivity evaluation at the end of the non-dominated solutions' set, taking benefits from the ranking process of NSGA-II technique. Although this approach is computationally efficient, its application revealed that the lower the fixed sensitivity level, the lower the number of points forming the Pareto front, as it will be demonstrated in Section 3 via two working examples.

The rest of the paper is structured as follows. After this introduction, a concise presentation of the technique proposed in [19] is described in Section 2. In Section 3, different approaches for improving the NSGA-II based technique of [19] are described. The proposed ideas are used for optimizing two CMOS analog circuits, and a comparison of the obtained performances is provided in Section 4. Finally, in Section 5 a discussion regarding these new techniques is presented and conclusions are offered.

2. A review of the sensitivity-based optimization of exploiting NSGA-II front ranking

In this section a summary of the NSGA-II ranking process based technique proposed in [19] is presented.

First, we recall that NSGA-II is a multi-objective optimization algorithm. It is an extension of the genetic algorithm techniques for multiple objective function optimizations. It uses an evolutionary process that includes elitism, selection, crossover and mutation operators. During the algorithm evolution process, the current population is sorted by ordering the solutions into a hierarchy of Pareto fronts [20]. The flowchart represented in Fig. 2 illustrates the NSGA-II working principle. Fig. 3 depicts the NSGA-II intrinsic ranking process for a two dimensional minimization problem. It forms the elitist selection process that consists of sorting the algorithm's current population into subsets (ranked

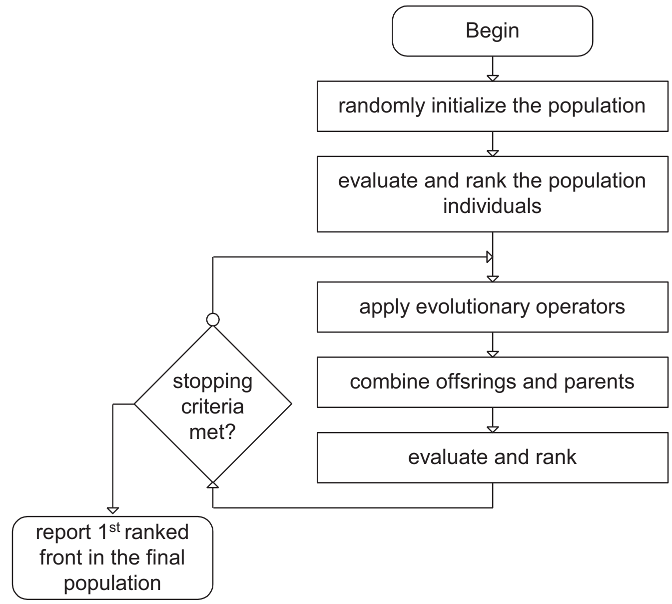

Fig. 2. NSGA-II basic flowchart illustration.

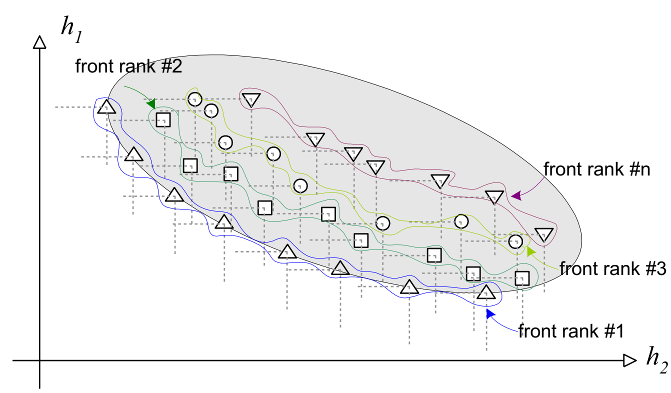

Fig. 3. Illustration of the NSGA-II ranking process for a bi-objective minimization process.

fronts) according to non-domination [20].

As introduced in Section 1, conventional approaches that take into consideration the sensitivity effect in solving multi-objective problems, proceed by simply discarding the more sensitive solutions from the generated front, at the end of the optimization process. In order to alleviate drawbacks of such an a posteriori approach, the technique described in [19] proposes taking benefits from the intrinsic ranking process of NSGA-II by creating a new archive called 'low-sensitive' Pareto front, where solutions are sorted in the following manner:

- Discard sensitive solutions from the front ranked #1, and store the remaining points in the new archive.
- While the new archive is not full, do:

Discard sensitive solutions from the front ranked #i ($i \geq 2$).

For each of the remaining (low-sensitive) solutions apply the dominance criterion and store the corresponding new solutions in case it is not dominated by any of the solutions in the archive.

Fig. 4 illustrates this approach for generating the new low-sensitive front.

As explained above, this technique overcomes problems related to the conventional a posteriori approaches (very few, or null, number of remaining solutions within the front). In the following section we propose including some modifications in the NSGA-II