Implementation Issues in the Hierarchical Composition of Performance Models of Analog Circuits

M. Velasco-Jiménez, R. Castro-López, E. Roca and F. V. Fernández
Email: {velasco,castro,eli,pacov}@imse-cnm.csic.es
Instituto de Microelectrónica de Sevilla, IMSE-CNM, CSIC and Universidad de Sevilla

***Abstract*—Emerging hierarchical design methodologies based on the use of Pareto-optimal fronts (PoFs) are promising candidates to reduce the bottleneck in the design of analog circuits. However, little work has been reported about how to transmit the information provided by the PoFs of low hierarchical level blocks through the hierarchy to compose the performance models of higher-level blocks. This composition actually poses several problems such as the dependence of the PoF performances on the surrounding circuitry and the complexity of dealing with multi-dimensional PoFs in order to explore more efficiently the design space. To deal with these problems, this paper proposes new mechanisms to represent and select candidate solutions from multi-dimensional PoFs that are transformed to the changing operating conditions enforced by the surrounding circuitry. These mechanisms are demonstrated with the generation of the performance model of an active filter by composing previously generated PoFs of operational amplifiers.**

Keywords*—*Hierarchical design methodologies, Pareto-optimal fronts, evolutionary algorithms.

I. Introduction

Analog components constitute a major bottleneck in the design of analog and mixed-signal circuits and systems. Electronic design automation (EDA) tools for analog circuits are far behind the level of automation of the digital domain. To bridge this gap, the knowledge of experienced analog designers should be adequately systematized into more efficient design methodologies that overcome the limitations of traditional approaches. For instance, using a hierarchical decomposition followed by a traditional top-down design flow [1] (which maps top-level requirements into lower-level block specifications), has three serious drawbacks. First, specifications of some blocks may be impossible to achieve. Second, when the whole system is verified it may not fulfill the specifications. And finally, the design may be globally suboptimal due to inappropriate specification transmission. These problems may incur several iterations of the whole design flow. To palliate these problems, emerging design methodologies facing the design in a bottom-up style have been proposed [2]-[4]. In these, the feasibility information of each block in the hierarchy, beginning at the lowest level (bottom-level) and ending at the system level (top-level), is transmitted. Feasibility information can be given in the form of performance models that can be generated and stored a priori so that they can be reused later for the design of a different system. In [5], the feasibility information of each block is given in the form of Pareto-optimal Fronts (PoFs). The PoF of a circuit is the set of all its possible designs that, altogether, characterizes the best trade-offs between usually conflicting performances. The generation of a PoF involves the resolution of a multi-objective optimization problem (MOOP), which can be defined as follows:

$$\text{maximize/minimize } \mathbf{y} = f_i(\mathbf{x}) \ , \ i = 1, 2, ..., b \tag{1}$$

$$\text{subject to } g_j(\mathbf{x}) \geq 0 \ , \ j = 1, 2, ..., k \tag{2}$$

where $\mathbf{x}$ is a vector whose components are the variables involved in the design (such as transistors sizes or bias currents), b is the number of design objectives (circuit performances) and k is the number of constraints (requirements the circuit has to fulfill). An efficient and extensively adopted mechanism to solve MOOPs is based on the use of a multi-objective evolutionary algorithm (EA) [6]. EAs are based on the evolution of a set of the best designs solutions (known as population of individuals) found during a number of optimization iterations (known as generations). To attain the final PoF, individuals are constantly mutated and crossed over (i.e., their design variables are slightly changed and swapped with other individuals' variables, emulating the rules of natural evolution).

For the sake of illustration, let us consider the generation of the PoF of an operational amplifier (opamp). The design objectives are a set of conflicting performances, like the dc-gain, the unity-gain frequency, the power consumption and the area. The design variables are those that define the performances of the opamp, such as transistor sizes and bias currents and voltages. Some constraints must be considered to guarantee the correct operation of the circuits: to impose all transistors to operate in saturation regime or to have a phase margin greater than a given value. At the end of the process, the PoF of the opamp will be composed of a set of different designs that are fully sized and non-dominated. The non-dominance characteristic means that there is not any design better than other in all design objectives. The advantage of using PoFs is that, once generated, they can be stored to be used later as performance models of the circuits in the design of a more complex system. For example, if the block at level $i+1$ is an active filter that uses two opamps, we can use the PoFs of the opamps from level i that have been previously generated to compose them and generate the PoF of the active filter.

In a bottom-up flow, the PoFs of the blocks at each level are composed to form the PoFs of higher-level blocks. This hierarchical composition, although it is an essential aspect

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of the bottom-up flow, has deserved little attention in the literature. Actually, it poses two key issues. The first one is related to the context for which a PoF was generated. In the example of the opamp, this context is defined by the loading conditions. If these conditions change when the opamps of the PoF are used in the filter, the PoF must be re-generated as their performances will be different or not valid any more. In [7] a solution is proposed to transform PoFs of opamps to different loading conditions using a hybrid-2 parameter characterization.

The second problem is related to how low-level PoFs are used in the exploration of the design space for the generation of higher-level blocks. For low-level PoFs, the design space is a uniformly distributed set of values of transistor widths, lengths, resistance values, etc. Searching over this design space using the EA mutation operator is straightforward, as a slight movement in the space means a small change of width, length, resistance, etc. For higher-level PoF generation, the design space is composed of the finite set of design solutions of each lower-level PoF. Searching over this space is not as straightforward as before as we need a representation of such a complex space that allows the mutation operator (and, thus, the exploration mechanisms of the EA) to adequately move from one low-level design solution to a slightly different one (following thus the correct use of the mutation operator). A possible representation is to assign to each individual of the PoF of lower-level blocks (e.g., opamps) an integer value, an **indexing variable**, in such a way that each value of this variable represents a different individual of the lower-level PoF. This variable can be used as design variable during the generation of the PoF of the higher-level block (e.g., the active filter). However simple, this representation does not guarantee that mutation provides slightly different design solutions of the higher-level block, as the two close values of the indexing variables does not necessarily represent two slightly similar individuals of a lower-level PoF. For instance, when applied to the generation of the PoF of the filter, a slight change of the indexing variables representing the PoFs of the opamps does not guarantee a slight change of the filter performances because the index value assigned to each opamp solution is totally independent of its performances.

A direct solution is to sort the individuals of the PoF. A simple approach is to use the euclidean distance in the performance space to sort the population with respect the individual being mutated (the reference individual). In [8] a similar solution is proposed that assigns a relative position to each individual for each design objective. These positions are used to sort the population with respect to the reference individual. The main advantage of this approach with respect to the euclidean distance calculation is that the sorting process is performed in two steps, one previous to the composition of fronts (pre-sorting) and one that is performed during the composition. This requires that the lower-level PoF to compose is always the same. However, as discussed above, in a real situation the PoF must be transformed and this transformation affects the sorting. Therefore the pre-sorting process cannot be performed a priori in many situations.

Both approaches represent the design space of the lower-level PoFs with a single indexing variable, which does not resemble to what is done at lower-levels (where there are as many design variables as parameters can be changed). This, as it will be shown later, strongly affects the efficiency of the generation of the higher-level PoF.

In this work, we propose a different sorting approach that performs a representation of the PoF that uses $(n-1)$ indexing variables for each individual (where n is the number of design objectives of each lower-level PoF). These indexes can be used later as design variables.

The paper is structured as follows. Section II describes different approaches that can be considered for the implementation of the hierarchical generation of PoFs. Section III describes the problem that has been used to make the comparisons between the different approaches. Finally in section IV the results are shown.

II. Representation Approaches

A. Using a Unique Indexing Variable

This approach is based on the use of a unique indexing variable to codify the information of the individuals of a PoF. The mutation of this variable, whose value points to a reference individual, is carried out by assigning a position to each other individual according to the value of a distance to the reference individual. This distance can be the normalized euclidean distance in the performance space between individuals, which is calculated as in 3:

$$d_i = \sqrt{\sum_j \frac{\left|obj_i^j - obj_0^j\right|}{r_j}} \tag{3}$$

where r_j is the range covered by the population in design objective *j*.

An example is shown in Fig.1 where individual 0 is the reference individual. It can be seen that the position assigned to each individual does not always coincide with the value of the indexing variable.

In [8] the Manhattan distance is used to sort the individuals to a reference individual. It is calculated using positions assigned to each individual according to its performance values. Individuals with lower number of differing performances are preferred.

Whether using the euclidean or the Manhattan distance, the mutation process of the indexing variable is done as follows:

1) Calculate the normalized euclidean/Manhattan distance in the performance space between each individual and the reference individual.

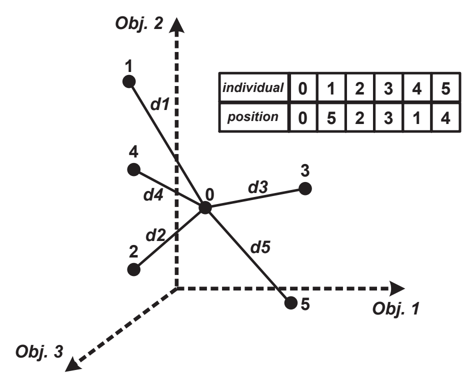


Fig. 1: Calculation of the distance of each individual to the reference individual.

2) Sort the individuals in increasing order of this distance, assigning to each individual its position in the arrangement.
3) Perform a mutation on the position of the arrangement. The resulted value points to the individual that will be selected.

An example is depicted in Fig.2 where the set of design variables is form by an indexing variable called ***cont*** and other regular variables. The population is sorted in increasing order of euclidean/Manhattan distance to the performances of the reference individual. A slight variation of the position of the arrange gives as result position **X**, which points to the new individual ***cont'***.

B. Our Approach

The approach proposed in this work assigns a set of coordinates to the individuals of the PoF that represent their position in each design objective. Since a PoF is a hyper surface of $(n-1)$ dimensions, where n is the number of design objectives, the individuals can be characterized using $(n-1)$ coordinates. The process is done as described below:

- Individuals of the PoF are grouped according to their value of the first design objective and the first coordinate is assigned to them.
- Individuals in each one of these groups is sub-grouped according to their value of the second design objective and the second coordinate is assigned to them.

The process is repeated for $(M-1)$ design objectives until each individual of the PoF has a unique set of coordinates.

An example is represented in Fig.3, where a PoF that has been generated for 3 design objectives is mapped using two coordinates.

The coordinates can later be used as design variables during the generation of the PoF of a higher-level block. No special treatment is necessary for these variables since individuals with similar performances will have near coordinates. Moreover, as each coordinate will mutate independently of the others, the mutation operator can decide the direction of the change. Furthermore, the crossover operator also contributes to the

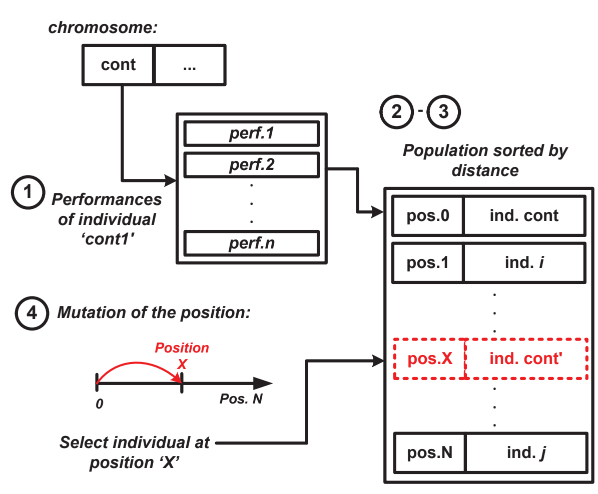


Fig. 2: Mutation of the indexing variable using the euclidean/Manhattan distance.

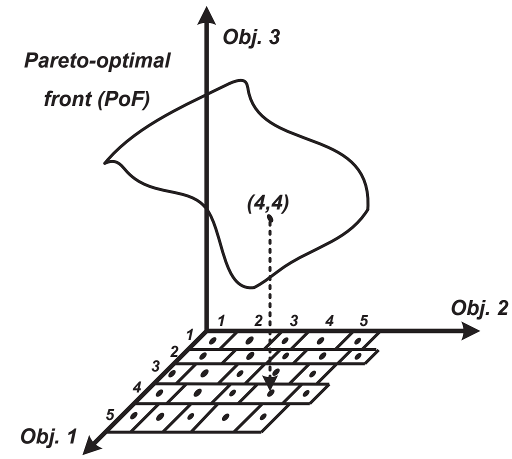


Fig. 3: Mapping of a PoF in a 3D space using two coordinates.

design space exploration when the opamps of the PoF are represented by several indexing variables.

III. Demonstration Vehicle

To demonstrate the validity of the mechanism proposed in this work we will focus on the generation of the PoF of one component of an IQ Digital-to-Analog (IQ DA) transmit interface system [9]: a continuous-time low-pass filter (CT LP filter) whose schematic is shown in Fig.4. The function of the filter can be summarized in three points:

- To attenuate the image components of the baseband spectrum at multiples of the clock frequency.
- To smooth the output signals generated by the preceding segmented current-steering Digital-to-Analog converter.
- To provide the required current-to-voltage conversion.

The transfer function of the filter, assuming ideal opamps (with infinite gain and bandwidth) is that in 4:

$$F(s) = \frac{V_{out}}{I_{in}}(s) = \frac{G_{FF}}{G_{FB}G_{FF} + G_1C_1s + C_1C_2s^2} \tag{4}$$

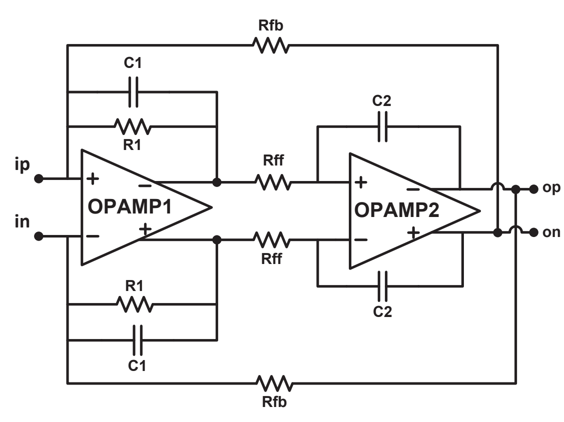


Fig. 4: Schematic of the CT-LP filter.

The DC-Gain of the filter is determined by the value of the overall feedback resistance, R_{FB}. Thus, if the full-scale output current of the preceding DA converter takes a fixed value I_{FS} and the resistance must guarantee a full-scale output voltage V_{FS}, its value is given by 5:

$$R_{FB} = \frac{V_{FS}}{I_{FS}} \tag{5}$$

The quality factor and the natural frequency are given by 6 and 7.

$$Q = \frac{1}{G_1}\sqrt{\frac{C_1 G_{FB} G_{FF}}{C_2}} \tag{6}$$

$$\omega_n = \sqrt{\frac{G_{FB} G_{FF}}{C_1 C_2}} \tag{7}$$

The quality factor must be equal to $1/\sqrt{2}$ to ensure a maximally-flat transfer of the baseband signal to the filter output. Besides, the cut-off frequency $f_{p,CTF}$ of the filter must be set in accordance to the minimum image rejection imposed by the standard, which defines the filter natural frequency as:

$$\omega_n = 2\pi f_{p,CTF} \tag{8}$$

The CT-LP filter is composed of two opamps whose finite DC gain and bandwidth will have a major impact on its performances. The folded-cascode with Miller compensation opamp shown in Fig.5 will be used to implement both opamps of the filter (although they may be differently sized). The design variables that will be used to generate the PoF of opamps are also shown in the figure.

To generate the PoF of the LP-CT filter, the elements defining the design space are:

(a) The design variables characterizing all the passive devices and
(b) a previously generated, load-independent PoF of the opamp (following the methodology explained in [7]).

At each iteration of the optimization process, the following critical steps are taken:

1) During the mutation of the indexing variables/coordinates, the PoFs of the opamps must be transformed to the load conditions imposed by the passive elements of the filter, which are also variables. This is done by using the approach presented in [7].
2) Once transformed, the indexing variables/coordinates can be established according to the new performances of the opamps.

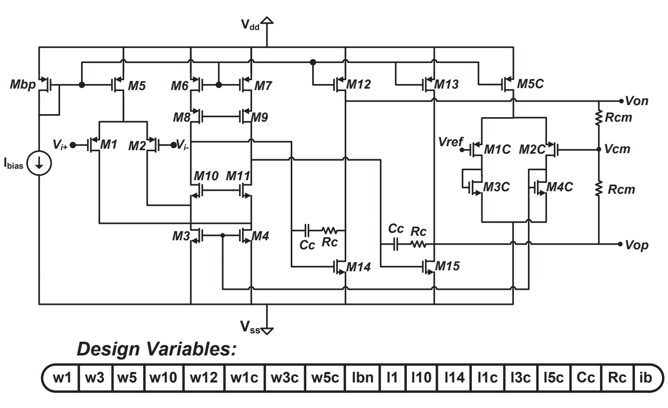


Fig. 5: Folded-cascode, Miller-compensated Operational Amplifier.

To better illustrate the effect of the contribution of this paper, the values of the passive devices will not be considered as design variables in this work and they will be determined a priori. As the loading conditions will be thus fixed, a PoF of opamps previously generated will be transformed to these loading conditions only once at the beginning of the process. This allows isolating the sorting issue to study the effects that each approach produces in the generation of the PoF of the filter.

IV. Results

The values of the passive devices are determined by the design considerations of the filter detailed in section III and the specifications of the GSM standard. The results are shown in Table I. These values define the load seen by OPAMP1 and OPAMP2. The loads are both resistive and capacitive and they can be easily obtained by simulation. The results are shown in Table II.

The PoFs of the opamps are obtained by transforming a previously generated PoF to these loading conditions using the technique described in [7]. This PoF was generated considering as design variables the widths and lengths of the transistors, the values of the compensation capacitor and resistor and the value of the bias current. This makes a total of 17 design variables. The design objectives and contraints were those shown in Table III. Constraints dm_i are the drain-source voltage over the effective voltage of each transistor. It ensures the transistors to operate in saturation regime. It is important to emphasize here the fact that the same PoF of the opamps can be used in any other design problem and no extra time is required for its generation.

Figure 6 shows the projections onto the DC Gain - unity gain frequency plane of the PoFs of opamps transformed to loading conditions 1 and 2. The PoF of the filter, for the design objectives and constraints shown in Table IV, will be generated by selecting the opamps from these PoFs.

The constraints are imposed by the analog back-end specifications and are shown in Fig.7. $At.1$ to $At.3$ are measurements of the attenuation at multiples of the sampling clock frequency of the preceding current-steering DAC used in the GSM standard. Parameters $dimar1$ and $dimar2$ ensure

TABLE I: Elements of the Passive Network.

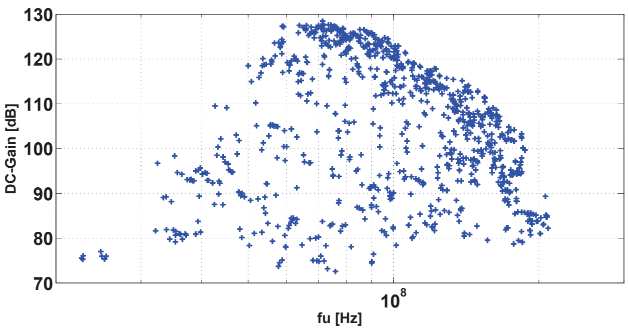
Element	Value
R_1	30kΩ
R_{ff}	10kΩ
R_{fb}	2.85kΩ
C_1, C_2	23pF

TABLE II: Load conditions of each opamp in the filter.

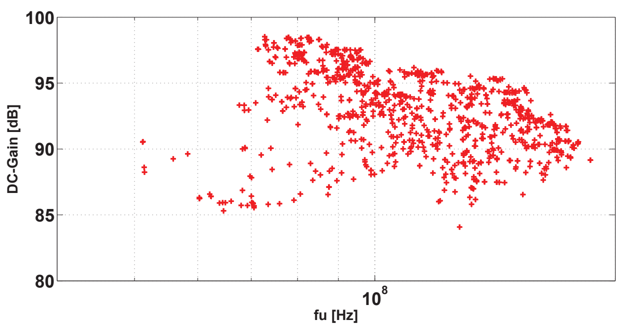
Element	Value
R_{LOAD1}	30kΩ
C_{LOAD1}	4.08pF
R_{LOAD2}	2.3075kΩ
C_{LOAD2}	1.0052pF

TABLE III: Design Objectives and Constraints for the Optimization of the OPAMP.

	Name	Treatment
Design Objectives	DC-Gain	maximize
	fu	maximize
	Power Consumption	minimize
	Area	minimize
Constraints	dm_i	> 1.1
	Phase Margin (PM)	$> 60°$
	Output Swing (OS)	$> 3.6V$



(a)



(b)

Fig. 6: Projections onto the DC Gain - fu plane of the PoFs of opamps transformed to load conditions 1 (a) and 2 (b).

that these attenuations increase with frequency. This helps to reduce the bump that appears in the filter stop-band characteristics as a result of the effect of the output impedance of the opamps.

To compare the different approaches described in Section II, the PoF of the filter will be generated using the following approaches:

1) **NO SORT method**. Two indexing variables are used to represent the combination of the two opamps that are being used by each filter in the population. We call these variables ***cont1*** and ***cont2***. These indexing variables will be treated as regular variables.
2) **EUCLIDEAN method**. The indexing variables ***cont1*** and ***cont2*** are also used, but for their mutation the approach based on the euclidean distance in the performance space described in section II is used.
3) **METHOD IN [8]**. The indexing variables ***cont1*** and ***cont2*** are also used, but for their mutation the approach described in [8] is used.

TABLE IV: Design Objectives and Constraints for the Optimization of the Filter.

	Name	Treatment
Design Objectives	Area	minimize
	Power	minimize
Constraints	At.1	> 30 dB
	At.2	> 30 dB
	At.3	> 30 dB
	dimar 1	< 1
	dimar 2	< 1
	DC-Gain	> 50 dB
	fcut	< 6.0 MHz

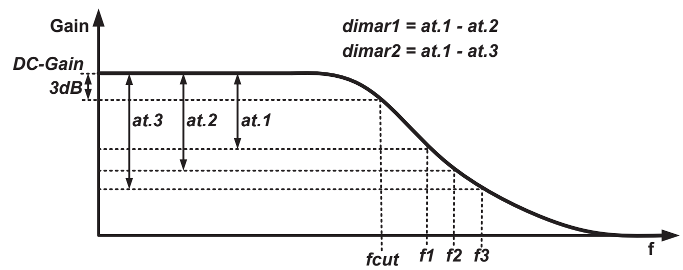


Fig. 7: Constraints imposed by the analog back-end specifications.

4) **OUR APPROACH**. As the PoFs of the opamps have four dimensions, in our approach three integer coordinates are assigned to each individual in these PoFs according to the values of its performances. These coordinates will be used as design variables and can be mutated as regular variables.

With a sufficient number of generations, all approaches will converge to the same region of the performance space, that is, the performance model with best trade-offs that could be achieved. However, for a real design problem, where design time is important, the critical aspect is the convergence rate to that region. In Fig.8 the PoFs generated by each approach at generation 10 in a typical run are shown. As it can be seen, the PoF generated by our approach dominates the rest in terms of convergence rate. In other words, it has converged faster to the region with better trade-offs between the area and power consumption.

Due to the stochastic nature of the optimization algorithms, it is necessary to perform a statistical study to find if some approach is consistently advantageous over the other ones. The convergence of the PoFs resulting from the different approaches will be compared by using the two-set coverage metric (CS) [10]. This metric is defined as:

$$C(B,A) = \frac{|\{a \in A | \exists b \in B, b \prec= a\}|}{|A|} \quad (9)$$

where $b \prec= a$ means a is dominated by b. It calculates the number of individuals in PoF A that are dominated by individuals in PoF B. If all individuals in PoF A are dominated by individuals in PoF B, then $CS(B,A) = 1$.

A set of 17 runs is carried out for each approach using a population of 100 individuals during 200 generations. In Table V the average value of the coverage metric between the PoFs generated in those runs are shown. Each cell has the result of $CS(Column, Row)$. The PoF generated using our

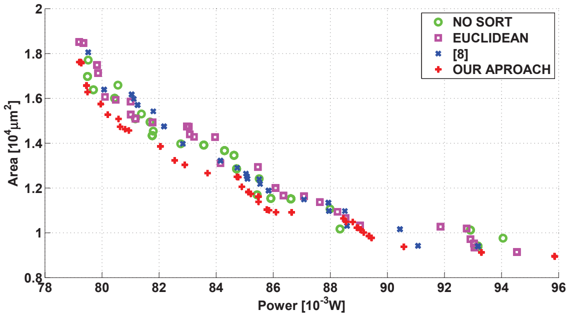


Fig. 8: Pareto-optimal front of the filter generated by each approach at generation 10.

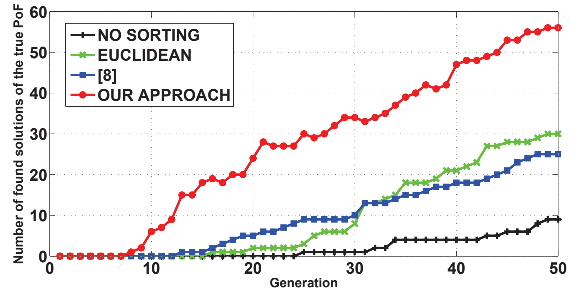


Fig. 9: Number of solutions of the true PoF that each approach has found until generation 50.

TABLE V: Coverage metric between the PoFs generated by each approach.

	NO SORTING	EUCLIDEAN	[8]	OURS
NO SORTING		0.5294	0.4506	0.7718
EUCLIDEAN	0.3471		0.3988	0.7241
[8]	0.3706	0.4524		0.7571
OURS	0.0653	0.1153	0.1159	

approach dominates more than 70% of the individuals of the PoFs generated using the rest of approaches. This demonstrates that our approach consistently produces a faster convergence to the non-dominated region.

The convergence to the true PoF can also be studied in this particular experiment. The true PoF is composed of those filter designs with best power consumption vs. area occupation trade-off values. Getting the true PoF is not always feasible in a reasonable amount of CPU time, due to the complexity of the optimization problem. In this case, where the only variables were the opamp designs (having the passive network fixed beforehand), the true PoF was found by exhaustively simulating each combination of opamp1 and opamp2, taking all possible opamp designs from the PoFs of the opamps in Fig.6. To that end, 10^6 simulations were carried out. In Fig.9 the number of solutions of the true PoF found by each approach vs. the number of generations is depicted. Taking into account that the CPU Time per generation is similar for our approach and for the Euclidean or [8] approaches (approx. 15 seconds), the convergence of our approach is better since at generation 50 the double of solutions of the true POF have been found compared to the other approaches.

V. Conclusions

This work presents a new mechanism that improves the hierarchical composition of PoFs of analog circuits. Unlike other approaches using a simpler representation of the lower-level design spaces, the mechanism presented here performs a mapping of the individuals of PoFs assigning $(n-1)$ coordinates (with n being the dimensionality of each lower-level PoF) depending on their relative position in the performance space. This mechanism is compared to other methods in the generation of the PoF of a continuous-time low-pass active filter by composing PoFs of operational amplifiers. Results show that our approach strongly improves the convergence rate to better regions of the performance space.

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