# Application of Multiobjective Optimizer Algorithms to the Design of SiC devices

Marco Bellini* and Lars Knoll
ABB Switzerland Ltd. Corporate Research Center,Dättwil, Switzerland
*Email: marco.bellini@ch.abb.com

***Abstract*—This work evaluates the feasibility of optimizing SiC power MOSFETs through multiobjective optimizers (MOOs) based on modern elitist genetic algorithms. This technique is validated on a 0D problem of high practical interest – the optimization of the epitaxial drift layer, using the ionization coefficients from [1] and [2] in addition to those from [3], extensively used in literature. Then the results are confirmed with 1D TCAD, removing approximations introduced by [4] and [5]. Finally MOOs are used with 2D TCAD simulations to evaluate the tradeoff of breakdown voltage ($V_B$), threshold voltage ($V_T$), saturation current ($I_{dsat}$) and on-state resistance ($r_{on}$) as the channel profile is varied.**

## I. Introduction

Optimization of semiconductor devices through TCAD simulation are routinely used to shorten time to market and to reduce the number of prototype lots. Most design optimizations are a trade-off between conflicting objectives such as the conduction losses and the switching losses in an IGBT, and are often performed by empirical approaches such as sweeping sequentially the values of design parameters.

Algorithm-based design optimization is also in use in the semiconductor industry but it is limited to the more traditional approach of combining the optimization objectives into a single cost function, typically through the use of weighted sum and using a single objective optimizer (SOO)[6][7]. However, only a portion of the trade-off between the objectives is explored, depending on the convexity properties of the optimal trade-off between the objectives. Also, the quality of the solution depends on the choice of the weights, since small perturbations in the choice of the weights can lead to quite different solutions. Modern MOOs are better at fully exploring the design space and at identifying the set of optimal solutions, known as the Pareto front. The solutions on the Pareto front are such that the value of one of the objectives cannot be improved without degrading at least one other objective. Identifying the Pareto front enables the designers to understand the nature of the problem and to pick the most advantageous trade-offs. MOOs are typically realized through Evolutionary Algorithms (EA) that evolve a population of candidate solutions by evaluating their fitness, retaining the best performing candidates, breeding and mutating them in an attempt to improve the fitness of the new population. MOOs require more simulations than SOOs, therefore they typically used for simulations that are not extremely computationally intensive, such as interconnect circuit simulation [8] or electromagnetic antenna design [9].

Extending this approach to the needs of the power semiconductor industry is not straightforward, as simulations require significant computational time because of the device size or the numerical problems due to widebandgap semiconductors.

This work explores the applicability of MOOs to practical aspects of the design and optimization of SiC power semiconductor devices in increasing order of complexity and of computational requirements.

## II. TCAD Simulations of SiC devices

Silicon Carbide has shown in the past years tremendous potential for high voltage power semiconductor devices: the widebandgap allows MOSFET devices to operate at the blocking voltage typical of bipolar devices, with even lower conduction losses [10]. Additionally the unipolar devices switch at higher frequency with lower losses, thereby reducing the size, weight and cost of passive components [11]. Simulating SiC devices involves additional challenges with respect to Silicon devices: the material has been less thoroughly characterized and there are still uncertainties in the precise values of the parameters of some physical models [6]. Furthermore, the wide bandgap of SiC causes significant numerical problems. The intrinsinc carrier concentration in SiC is 18 orders of magnitude lower than in Si, leading to extremely small carrier concentrations in depleted regions, in the absence of generation centers or optical illumination. These very small carrier densities coupled with very high doping levels challenge the numerical precision of 64 bit computation. In order to capture device breakdown, it is necessary to solve the numerical problem with at least 80 bit precision [6]. Arithmetic at 128 bit, 256 bit, or even at arbitrary precision are feasible on the x86_64 architecture but the computation time needed increases exponentially, limiting practical applicability.

## III. Multiobjective Optimization of SiC unipolar devices

In the case of unipolar devices such as JBS diodes, JFETs and MOSFETs both $r_{on}$ and $V_B$ are determined by the doping and the thickness of the epitaxial layer. Deviating from the optimal thickness and doping combination results in excessive resistance or insufficient margin over the required breakdown voltage.

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Many analyzes and optimizations of non-punch through SiC devices, such as [12], are based on the well-known dependance of the critical field from the doping concentration from [3].

### *A. Multiobjective Optimization for the 0D test case: SiC drift layer*

Since TCAD simulations of SiC devices are computationally intensive, it is advantageous to approach the problem starting from a 0D model, i.e. from an analytical model.

Design rules for the design of the drift layer of punch-through devices are derived with several approximations in [4] and then refined in [5], by finding iteratively the distribution of the electric field for which the ionization integral for either holes (eq. 1) or electrons reaches unity [13].

The Pareto front for the optimal trade-off is found in [5] by brute force by varying alternatively the thickness and the doping. This inefficient approach is shown in Fig. 1 by the thin dotted lines for a thickness of 11 and 13 $\mu m$, using the impact ionization coefficients for holes and electrons $\alpha_{n,p}$ from [3]. By choosing a set of thicknesses for the epitaxial layer and, for each of those, a large corresponding set of doping concentrations, [5] identifies the locus of optimal design.

$$\int_0^{x_D} \alpha_N(x)\, exp\left[\int_0^x \left(\alpha_P(x') - \alpha_N(x')\right) dx'\right] dx \to 1 \quad (1)$$

The optimization problem can be efficiently solved by the elitist genetic algorithm [14], setting boundaries on $V_B$ to focus on the voltage classes of interest, as indicated by the dot symbols in Fig. 1. To simplify the problem, only the Poisson equation is considered and epitaxial layer is discretized in 1D with a non-uniform step, to increase the resolution of the grid near the peak of the electric field. The breakdown voltage is found by a bisection algorithm, by evaluating the electric field distribution as a function of doping, thickness, and applied electric field, and solving for either the ionization integral for holes or electrons approaching unity. An efficient implementation in Python enables to identify the Pareto front in a few minutes for a given voltage class.

The optimal solutions have been calculated for $\alpha_{p,n}$ from [1], [2], and [3], as shown in Fig. 1. The impact of the choice of impact ionization model is discussed in Section III-C with the support of TCAD simulations.

### *B. Performance of MOOs for the 0D test case*

The optimization of the drift layer for $V_B = 3.3\ kV$ is chosen as a 0D test case, to compare the performance of different MOOs. The 0D test case is extremely efficient since the physics of the optimization problem is quite correctly captured and the computation cost is extremely low compared to a TCAD optimization problem. In fact, the performance of MOOs can only be evaluated on a series of runs of optimizations for the same problem, so that the influence of the initial function evaluation and of the random seeds of the MOOs is averaged out. Furthermore it's important to compare optimization runs with varying numbers of function evaluations to assess the speed of convergence to the Pareto front.

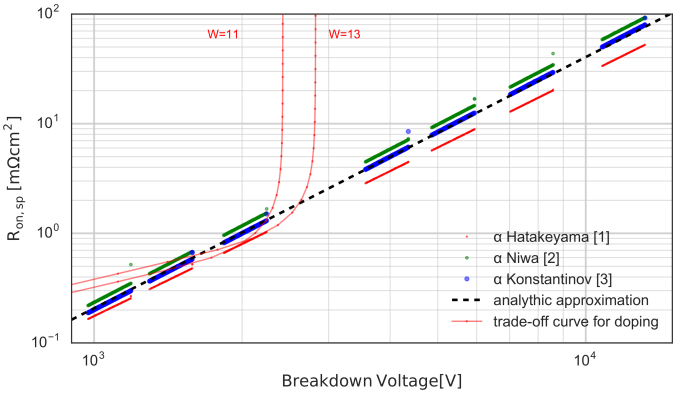


Fig. 1. Trade-off curve between $r_{on}$ and $B_V$. The dots are obtained through MOO optimization[14] of a 0D model with $\alpha_{n,p}$ from [1][2][3]. The dashed line represents the approximate design rule from [5], obtained though a brute force approach (illustrated by the thin dotted lines).

To illustrate the complexity of comparing the performance of MOOs, Fig. 2 depicts the Pareto fronts obtained by the well-known NSGAII[14] and NSGAIII[15] MOOs after 10 runs of optimizations with a limit of 500 and 2000 function evaluations.

NSGA-II[14] and NSGA-III[15] are EA with surrogates for evolutionary operators including selection, genetic crossover, and genetic mutation that select and rank a hierarchy of sub-populations based on the ordering of Pareto dominance. They aim at promoting a diverse front of non-dominated solutions.

In this particular case, NSGA-III clearly obtains a much closer and more stable approximation of the Pareto front after 500 evaluations than NSGA-II. A quantitative evaluation of the approximation of the Pareto front for different MOOs can be performed introducing the concept of hypervolume, as indicated on the left side of Fig. 2.

The hypervolume $hv_0$ of a particular Pareto front is the area subtended by the front and delimited by the worst acceptable combination of objectives, represented by the point $P$ in Fig. 2 [16].

Fig. 3 compares the hypervolume indicators for the NSGA-II[14], NSGA-III[15], MOEA/D[17], and SMPSO[18] MOOs. The decreased performance of NSGA-III compared to NSGA-II for a larger number of function evaluations may result because NSGA-III attempts to improve the variance of the candidate sub-populations adaptively, to avoid local minima. MOEA/D is a EA that decomposes the MOO problem into a number of SOO sub-problems and then optimizes them simultaneously by applying search heuristic criteria [17]. Despite its wide and successful use in electromagnetic applications, it can encounter issues depending on the shape of the Pareto front and the specific optimization problem. SMPSO is a particle swarm MOO inspired by the social behavior of bird flock that reduces the exploration the velocity of the particles to improve the quality of the solutions [18].

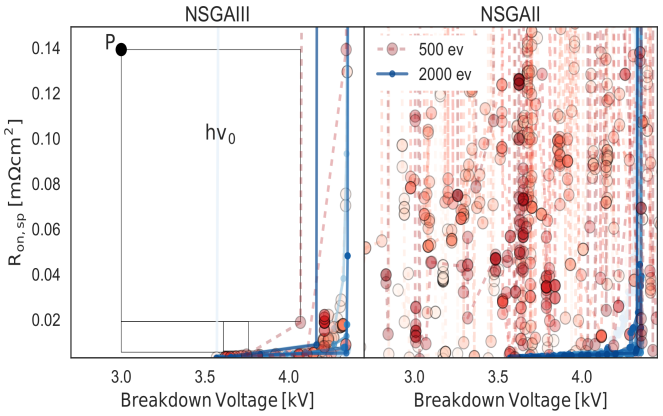


Fig. 2. Comparison of the Pareto fronts found by the NSGA-II[14] (on the right) and NSGA-III[15] (on the left) MOOs for 10 runs of optimization of 0D model for with a limit of 500 evaluations (red dashed lines with circle marker) and 2000 evaluations (blue solid lines with dot marker). Each of the 10 runs is shown with a different shade of color. On the left side, the procedure for the evaluation of the hypervolume for a particular Pareto front is shown.

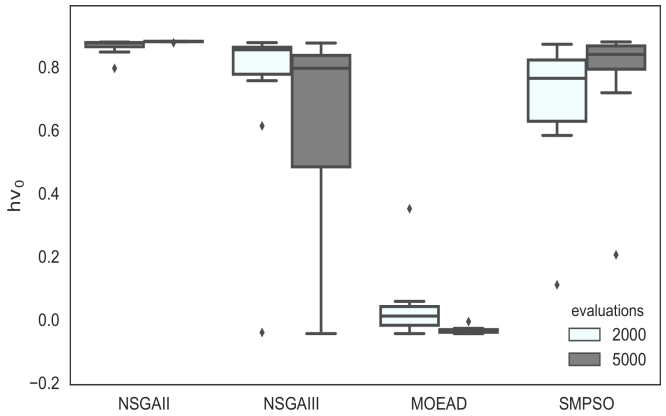


Fig. 3. Comparison of the hypervolume metrics for 10 runs of 2000 and 5000 evaluations using the NSGA-II[14], NSGA-III[15], MOEA/D[17], and SMPSO[18] MOOs.

Finally, the performance of NSGA-II[14], NSGA-III[15], MOEA/D[17] is compared in detail in Fig. 4, showing that [14] results in a more even exploration of the design space and in a more consistent approximation of the Pareto front.

### *C. Multiobjective Optimization for the 1D TCAD test case: SiC drift layer*

To understand the implications of the choice of the model for impact ionization, 1D TCAD simulations are compared with measurements of experimental sample SiC structures in Table I. Considering that the efficiency of the termination in the samples is unknown and can only be roughly estimated at 90%, the simulations give some indication that [1] may potentially overestimate $V_B$ and that [2] might underestimate $V_B$ for the 4000 V structure. In particular, [2] presents a very comprehensive and rigorous extraction of the impact ionization coefficients. A possible explanation of the discrepancies may be that the extraction of the ionization coefficient for holes $\alpha_p$, shown in Fig. 8 in [2] focuses on the range of values of

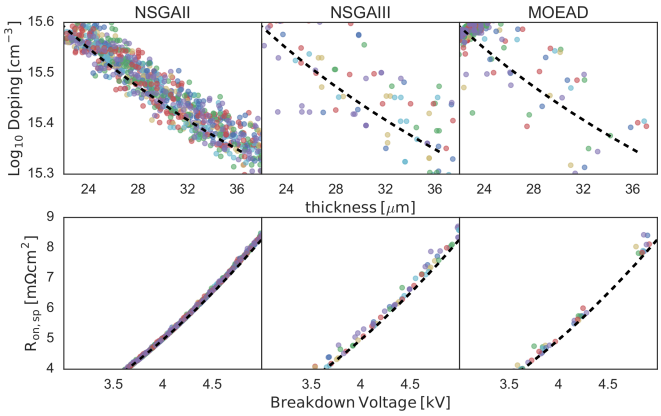


Fig. 4. Comparison of the performance of the MOOs [14],[15],[17] for 10 runs of 5000 evaluations of 0D model. The dashed line represent the approximate design rules from [5]. While [14],[15] obtain a reasonable approximation of the Pareto front, [17] does not fully explore the design space.

TABLE I
1D TCAD SIMULATED $V_B$ FOR TWO SAMPLE SIC STRUCTURES

| Model | 2400 V sample | 4000 V sample |
|---|---|---|
| Konstantinov | 2682 | 4211 |
| Hatakeyama | 2906 | 4793 |
| Niwa | 2572 | 4028 |

the electric field between 1 and 2 $MV/cm$. Furthermore, the fitting of $\alpha_p$ slightly favors the lower end of the range of the electric field. Considering that SiC devices are often optimized for minimum on-state resistance, the typical maximum electric field can be moderately in excess of 2 $MV/cm$, which could explain the discrepancies observed. Obviously, a much more refined study is necessary to provide solid and extensive conclusions.

Then, NSGA-II[14] is used with 1D TCAD simulations with $\alpha_{n,p}$ from [3] to introduce the self-consistency between electric field and carriers, neglected by 0D models such as those previously presented and those in [4] and in [5] . The Pareto front shown in Fig. 5 is obtained with 1000 TCAD simulations (requiring about 4 hours) and is in good agreement with the 0D models.

### *D. Multiobjective Optimization for the 2D TCAD test case: SiC MOSFET*

Finally, NSGA-II[14] is applied to a much more challenging problem: the optimization of a SiC MOSFET with 2D TCAD simulations of $V_B$, $V_T$, $I_{dsat}$ and $r_{on}$. Given that SiC simulations require computation times in the range of tens of minutes to hours for breakdown, it possible to explore only a few hundreds candidate solutions in the objective space in a reasonable time. However, with educated guesses on the parameter ranges it is possible to obtain valuable information on the trade-off curves of the objectives and sensitivities to design parameters.

In Fig. 6 the doping profile of the channel of MOSFET is optimized, showing that the designer can trade a limited

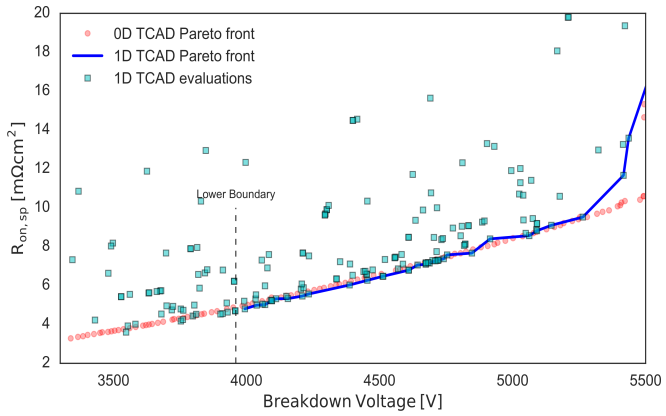


Fig. 5. Trade-off curve between $r_{on}$ and $B_V$. The squares are obtained through MOO optimization[14] of a 1D TCAD model with $\alpha_{n,p}$ from [3]. The circles indicate the Pareto front shown in Fig. 1 for $\alpha_{n,p}$ from[3].

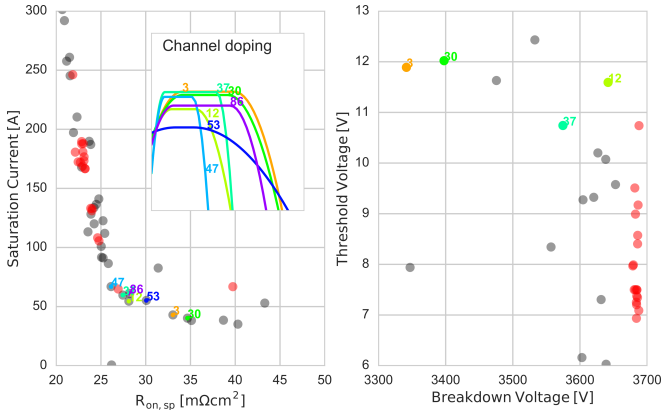


Fig. 6. Trade-off curves between $r_{on}$ and $I_{dsat}$ (left) and $B_V$ and $V_T$ (right) as the channel of a SiC MOSFET (inset) is varied in a 2D TCAD simulation.

increase in $r_{on}$ to effectively limit $I_{dsat}$ without compromising $V_B$. The optimization with 4 objectives, 5 design variables and 4 constraints requires approximately 2 days.

## IV. Conclusion

This work demonstrates the applicability of MOOs to facilitate semiconductor device design. The well-know design rule from [5] is cross-checked by using several models for impact ionization coefficient and both analytical models and 1D TCAD simulations. Finally, a realistic example of 2D TCAD multiobjective optimization is presented.

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