Optimal Design of Monolithic ESBT® Device carried out by Multiobjective Optimization.

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Summary. This work concerns the multiobjective optimization of an monolithic ESBT® device aimed to get a characterization of the best design. The optimization will select the epitaxial specifications (thickness, doping concentration) which minimize the energy dissipation, maximize the current flow and keep a breakdown voltage of 1000V. Since these goals are in conflict with each other the best solution must be characterized with respect to all trade-offs. The search was carried out with an extension of the DIRECT algorithm to the multiobjective case.

Keywords—Multiobjective optimization, ESBT®, process simulation, device simulation, Mixed-mode simulation.

1 Introduction

On-state voltage, breakdown voltage and switching losses represent the key points in the design of power devices devoted to high voltage and high frequency applications. In order to achieve significant efficiency improvements in DC-DC converter applications, which demand high currents and high switching frequencies, both conduction and switching energy losses need to be minimized.

ESBT® (Emitter Switching Bipolar Transistors) is an innovative power device particularly suitable for high voltage and high frequency applications [1]. The epitaxial structure of the collector region is a critical parameter of the ESBT® design:

- it characterizes the highest voltage sustainable during the off-state,
- it characterizes the current which flows into the device during the on-state,
- it characterizes the energy dissipation during a on-off cycle

The above specifications consist of the pair given by the collector region *thickness* and the doping *concentration* of the region (it must be noticed that the doping concentration is strongly related to the resistivity). A multiobjective problem formulation is necessary in order to achieve an optimal design with respect to the trade-offs of the operational performances.

2 The ESBT® Device

ESBT® consists of a high-voltage power BJT and low-voltage power MOSFET that are connected in cascode connection (see figure 1). It is a monolithic solution achieved through the integration of the MOSFET inside the emitter fingers of the BJT (see figure 2). It has been created a family of devices which can reach high breakdown voltage (up to 1.7 kV) with high switching frequency, while a low forward voltage drop is maintained. The driving of the bipolar transistor in a cascode connection is realized by the switching of a MOSFET connected in series with the emitter of the BJT. As a matter of fact by switching off the MOSFET, the emitter current of the BJT is immediately cut-off and then the whole collector current is diverted to the base terminal. By this way the bipolar transistor is turned-off very quickly because the charge stored in the base and collector is fast removed. In this way the BJT can operate at very high operating frequencies (up to 200 KHz). This device is useful in many applications as lighting and power supply.

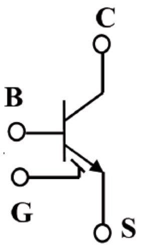

Fig. 1: The ESBT® symbol.

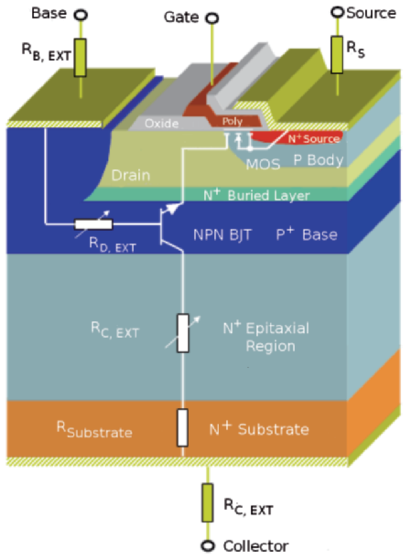

Fig. 2: Half elementary cell of the ESBT® device with superimposed the equivalent electrical circuit.

3 MultiDIRECT optimization Algorithm

A multiobjective problem is defined as

$$\min_{\mathbf{x}\in S}\{f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x})\} \quad (1)$$

where we have $k \geq 2$ *objective functions* $f_i : \mathbb{R}^N \rightarrow \mathbb{R}$. S is called *decision space* and defines an *objective space* $Z \subseteq \mathbb{R}^k$ through the objective functions [2].

Minimization process follows the *Pareto optimality* criterion:

A decision vector $\mathbf{x}^*$ is Pareto optimal if there does not exist another decision vector $\mathbf{x} \in S$ such that $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*)$ for all $i = 1, \ldots, k$ and $f_j(\mathbf{x}) < f_j(\mathbf{x}^*)$ for at least one index j.

The MODirect method is an extension to the multiobjective case [3] of the DIRECT algorithm [4]. The method is based on three operations:

- Lipschitz constant estimation,
- choice for potential optimality of domain subregions,
- domain subdivision.

The choice for potential optimality is based on the estimation of Lipschitz constant for the objective function in a partition of the domain. This partition is built by hyperrectangles which are sampled in their centers in order to evaluate the value of the objective function. Therefore the estimation of Lipschitz constant leads to a possible choice of the hyperrectangles in the partition for a further sampling which exploits the estimation to balance global and local search and reaches a quasi-global solution in a large domain. In the main loop of the algorithm 1, hyperrectangles are selected for sampling if they have a large area, an high Lipschitz constant estimation, and a good value of the function in their center. Formally it is possible to give the following definition for the single objective problem in one variable:

Definition 1. ***[Potential optimality relative to the objective** i**]*** *Let $\mathcal{S}$ be the set of hyperrectangles generated by the algorithm after k iterations, and let f^{min} and f^{max} be respectively the ideal and nadir points of the cone centered in $f(c_{\widetilde{R}})$. An hyperrectangle $\widetilde{R} \in \mathcal{S}$ with center $c_{\widetilde{R}}$ and measure $\alpha(\widetilde{R})$ is said potentially partial optimal relative to the i-th objective if there exists at least a Lipschitz constant $K_i^{lower} > 0$ such that*

$$f_i(\mathbf{c}_{\widetilde{R}}) - K_i^{lower}\alpha(\widetilde{R}) \leq f_i(\mathbf{c}_R) - K_i^{lower}\alpha(R) \tag{2}$$

$$f_i(\mathbf{c}_{\widetilde{R}}) - K_i^{lower}\alpha(\widetilde{R}) \leq f_i^{min} - \varepsilon|f_i^{min}|. \, \forall R \in \mathcal{S} \tag{3}$$

or a constant $K_i^{upper} > 0$ such that

$$f_i(\mathbf{c}_{\widetilde{R}}) + K_i^{upper}\alpha(\widetilde{R}) \leq f_i(\mathbf{c}_R) + K_i^{upper}\alpha(R) \tag{4}$$

$$f_i(\mathbf{c}_{\widetilde{R}}) + K_i^{upper}\alpha(\widetilde{R}) \leq f_i^{max} - \varepsilon|f_i^{max}|. \, \forall R \in \mathcal{S} \tag{5}$$

where $\varepsilon \sim 10^{-4}$ is a constant to control the clustering *during the search [4].*

This definition is easily extendible to the case of n variables.

Algorithm 1 DIRECT pseudocode

Require: Set of rectangles S
  $n \leftarrow 0$ {number of function calls}
  while $n < TotCalls$ **do**
    Choose $P \subseteq S$, set of potential optimal rectangles;
    Sample the rectangles in P updating the counter n;
    Subdivide the rectangles of P. Let subdivision be $D_P = \{R_1, R_2, \ldots, R_m\}$
    $S = S \setminus P \cup D_P$
  end while
  return the best minimum;

In order to obtain the heuristic which extends the above definition to the multiobjective case, let us redefine the Pareto optimality in general terms of efficiency [5].

Definition 2. ***[Efficiency criterion]*** *A decision vector $x^* \in X$ is* efficient *with respect to the convex cone D if there does not exist another decision vector $x \in X$ such that*

$$f(x^*) - f(x) \in D \tag{6}$$

The cone D is called *ordering cone* and if $D = R^n_+$ the efficiency criterion produces a partial ordering for the Pareto optimality criterion. This ordering is used by the algorithm as surrogate of linear ordering.

Remark 1. **[Multiple estimation of the Lipschitz constants]** Starting from the conditions 2 and 4 in Definition 1 it is possible to define the multiobjective optimality in terms of expected efficiency. For every objective i, from the above conditions we obtain estimates for K_i^{lower} in the form of an upper bound $\overline{K}_i^{lower} \geq 0$ and a lower bound $\underline{K}_i^{lower} \geq 0$ for K_i^{lower}. Analogously, for K_i^{upper} there will be an upper bound $\overline{K}_i^{upper} \geq 0$ and a lower bound $\underline{K}_i^{upper} \geq 0$.

The heuristic criterion leading to the choice of the optimal hyperrectangles in the multiobjective case is motivated by the potential increase of the expected efficiency.

Definition 3. ***[Multiobjective potential optimality]*** *Given the estimations of the upper bounds and the lower bounds for the Lipschitz constant of every objective i in the cone centered in $f(c_{\widetilde{R}})$, the hyperrectangle $\widetilde{R}$ is said potentially optimal if*

$$\sqrt{\sum_{i=1}^{k}[\underline{K}_i^{lower}]^2} \leq \sqrt{\sum_{i=1}^{k}[\overline{K}_i^{lower}]^2} \tag{7}$$

or

$$\sqrt{\sum_{i=1}^{k}[\underline{K}_i^{upper}]^2} \leq \sqrt{\sum_{i=1}^{k}[\overline{K}_i^{upper}]^2} \tag{8}$$

Moreover, let f^{min} and f^{max} be respectively the ideal and nadir points of the cone centered in $f(c_{\widetilde{R}})$. The choice of hyperrectangle $\widetilde{R}$ leads to a non trivial improvement of objective functions

$$\sum_{i=1}^{k}[f_i(\mathbf{c}_{\widetilde{R}}) - K_i^{lower}\alpha(\widetilde{R})]^2 \leq \sum_{i=1}^{k}[f_i^{min} - \varepsilon|f_i^{min}|]^2 \tag{9}$$

or

$$\sum_{i=1}^{k}[f_i(\mathbf{c}_{\widetilde{R}}) + K_i^{upper}\alpha(\widetilde{R})]^2 \leq \sum_{i=1}^{k}[f_i^{max} - \varepsilon|f_i^{max}|]^2 \tag{10}$$

The above definition gives a heuristic rule to choose hyperrectangles which are potentially optimal in the sense of either increasing the efficiency of the objective vector or taking into account possible trade-off (the latter arises from considering both lower and upper bounds for the Lipschitz constant). Equations 9 and 10 can be interpreted as controlling the clustering nearby the optimal points. If an hyperrectangle is potential optimal then it will be sampled in the points $\mathbf{c} \pm \delta\mathbf{e}_i$, $i = 1 \ldots N$, where $\mathbf{c}$ is the center point of the hyperrectangle, δ is one-third the side length of the hyperrectangle, and $\mathbf{e}_i$ is the ith unit vector.

Afterwards the hyperrectangle will be subdivided in thirds along its widest sides based on a dominance sorting of function values $f(\mathbf{c} \pm \delta\mathbf{e}_i)$ with respect to their efficiency. This strategy increases the attractiveness of searching near points with good function values in the large hyperrectangles.

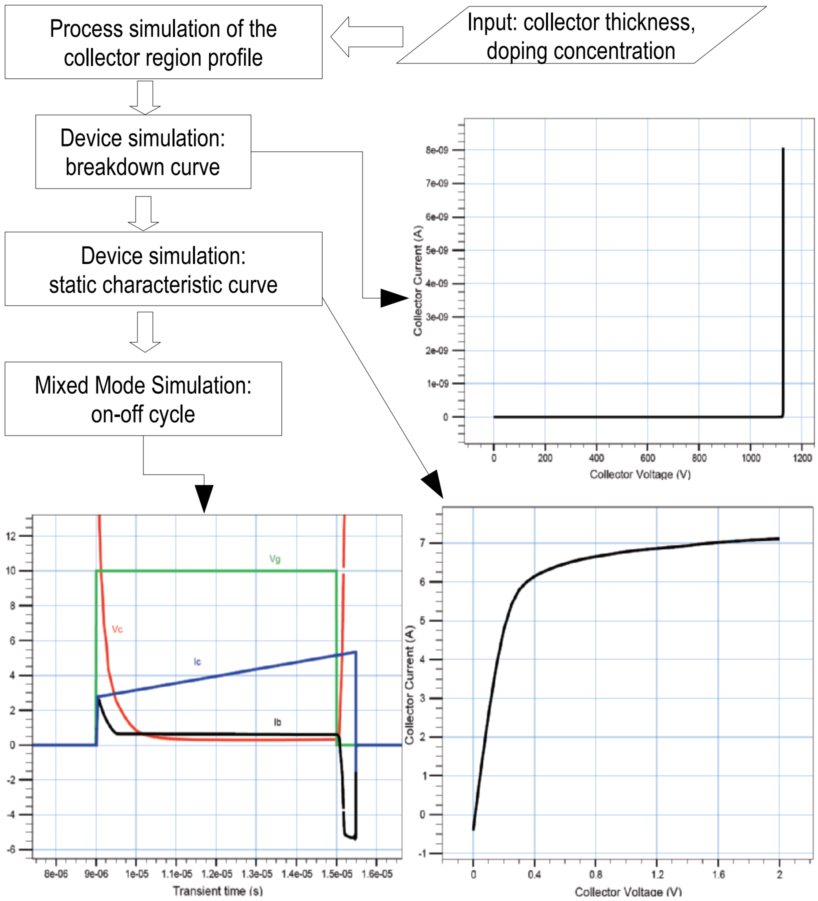

Fig. 3: The simulation flow.

4 Simulation Flow and Results

A simulation flow performed by ©SILVACO tools has been planned and it was used to evaluate the above target (see figure 3). The flow accepts as input collector thickness and doping concentration of the collector region, then a process simulation simulates the device structures. Then three device simulations extract the values of energy dissipation, current capability and breakdown voltage. Notice that the device simulations are independent and therefore can be performed in parallel.

The optimization has been carried out with respect to 3 targets:
- energy dissipation of a on-off cycle (minimizing),
- current capability (maximizing),
- breakdown voltage (to fix at 1130 Volt).

The last target constrains the optimization to functional solution which assure good process tolerances. A budget of 350 simulations has been established to perform the whole optimization.

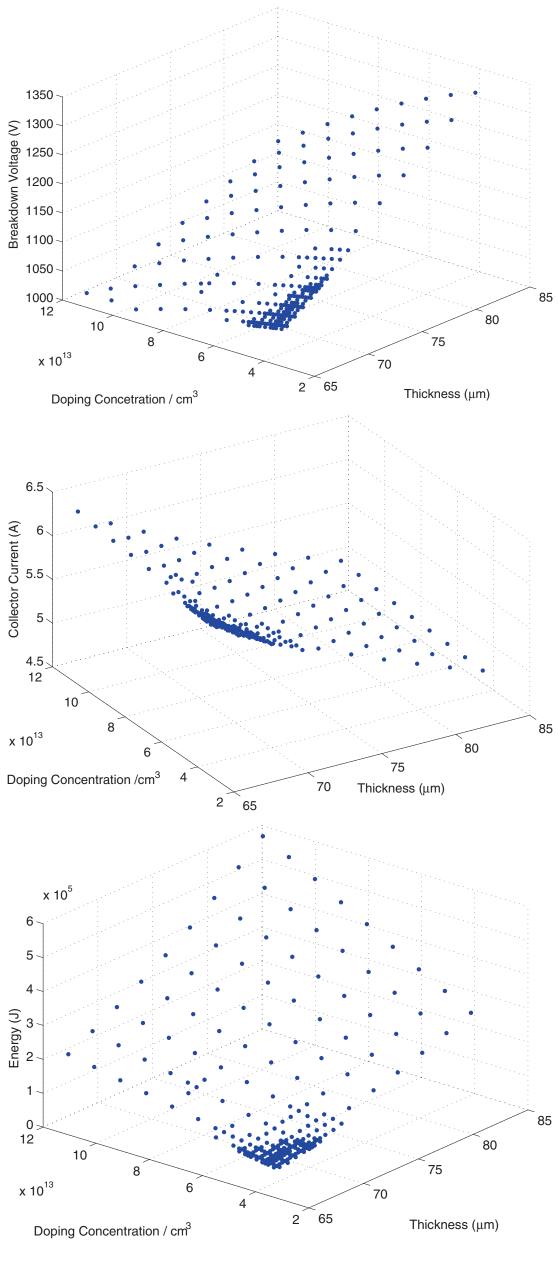

Fig. 4: The design variable space against performances.

The figure 4 shows the sampling in the design space of collector thickness and doping concentration of the collector region against each performance. The figure 5 shows the Pareto front which follows the optimization sampling. The sampling allows to characterize the optimal pair collector thickness-concentration and several alternative designs were found.

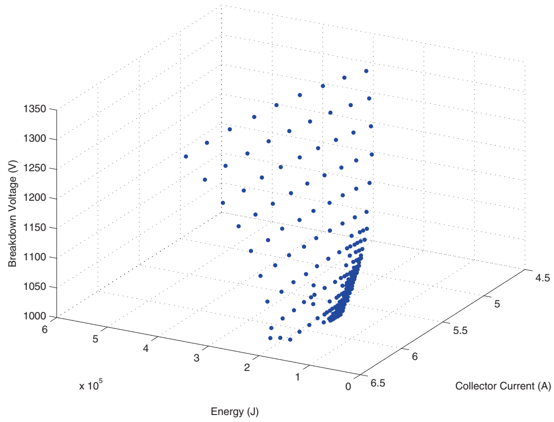

Fig. 5: Sampling in the objective space.

These results are also useful to evaluate the behaviour of the overall performances, their trade-offs, and the correlations with respect to the two design variables. For instance the following linear relations were discovered with respect to the design variable for energy (E), current flow (CF) and breakdown voltage (BV)

$$E(t,d) = 1.2972t + 2.2429 \cdot 10^{-19}d - 8.5939 \cdot 10^{-5}$$
$$CF(t,d) = -76477t + 1.7183 \cdot 10^{-15}d + 11.097$$
$$BV(t,d) = 12429000t - 1.4664 \cdot 10^{-12}d + 311.59$$

where t is the collector thickness (in μm) and d is the doping concentration (cm^{-3}) of the collector region. Also the correlations were computed and the results are shown in table 1

	Energy	Current Flow	Breakdown voltage
Energy	1	-0.83036	0.47727
Current Flow	-0.83036	1	-0.87562
Breakdown voltage	0.47727	-0.87562	1

Table 1: Table of correlation among objectives

5 Conclusion

A successful optimization test on a power device has been done. The multiobjective methodology was proved useful to guide device design. Furthermore the sampling could become a knowledge base for the future scaling of the power device towards higher breakdown voltages.

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