Automatic optimization of doping profile for high performance Single-Photon Avalanche Diodes

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***Abstract*— A method to efficiently optimize doping profile for high performance Single-Photon Avalanche Diodes is presented. The method aims at maximizing the photon detection efficiency while minimizing the timing jitter and keeping the breakdown voltage in a reasonable range by optimizing the doping profile of the device. Two different optimization methods are compared, and their performances are evaluated on a one-dimensional model of a Si-SPAD.**

INTRODUCTION

Single-Photon Avalanche Diodes (SPADs) are optoelectronic devices that aim at detecting light with a single photon sensitivity. They are used in a wide range of applications such as optical time-of-flight (TOF) ranging, optical communication, and optical imaging. SPADs are usually made of a p-n junction operated in reverse bias to generate a strong electric field in the active region that can trigger self-sustained generations of carriers by impact ionization process, which leads to a detectable current pulse. The voltage at which the avalanche breakdown occurs is called the breakdown voltage (BV) and must be kept in a reasonable neighborhood of 20V for a Si device to be used in embedded applications. The SPAD is then operated at an excess bias voltage (VEX) of around 3V above the BV. The probability for an optically generated electron-hole pair to generate an avalanche is called the avalanche breakdown probability (BrP). The statistical distribution of timing between the generation of the electron-hole pair and its detection is called the timing jitter.

MODEL AND OPTIMIZATION

For efficiency purposes, we consider a one-dimensional model of a SPAD, that represents a cut in the middle of the device along its depth. Given a doping profile, the electrostatic potential is computed by solving the Poisson equation using an iterative Newton scheme coupled with a finite difference method. The BrP and the BV are computed using the McIntyre model as described in [1]. The timing jitter performance is evaluated by measuring the extension of the depletion region, also called depletion width (DW) region in the device. The relevance of this proxy will be discussed at the conference. The optimization process then consists in finding the doping profile that maximizes the BrP and minimizing the timing jitter, together with a breakdown voltage constraint. Formally we minimize the following function:

$$\mathrm{F}(\mathbf{W}) = \beta\cdot(\mathrm{BV}-\mathrm{BV}_{Target})^2-\alpha\cdot\mathrm{BrP}_{\mathrm{VEX=3V}}-\gamma\mathrm{DW}_{\mathrm{VEX=3V}}$$

where $\mathbf{W}$ is the input doping profile and α, β and γ are the weights of the three objectives. The doping profile is described through a set of parameters, as shown in Fig. 1. The cost function is expected to depend in complex ways on the doping profile parameters, admitting many local minima, saddle points and an ill-defined gradient. The optimization process has therefore to be performed with global optimization methods that do not require the knowledge of the gradient of the cost function. Hereafter, we compare two different methods: a Simulated Annealing (SA) method and a Particle Swarm Optimization (PSO) method [2]. An illustration of the PSO method is shown in Fig. 2 and the electric field resulting from the optimization process is shown in Fig. 3. All the steps are implemented in an in-house C++ program which takes advantage of the parallelization capabilities of modern CPUs.

RESULTS AND DISCUSSION

The cost function evolution during the optimization process is plotted in Fig. 4. Both methods are able to decrease the cost function, at different rates. The PSO method has the advantage of showing a regular decrease of the cost function, while the SA method shows a more erratic behavior. This feature may be useful to pick an intermediate point in the optimization process that satisfies a desired compromise between the different figures of merit (see Fig. 5).

In conclusion, we have demonstrated that it is possible to optimize the doping profile of a SPAD to maximize the photon detection efficiency while minimizing the timing jitter using a simple one-dimensional model of the device. This work is a first step towards the optimization of SPAD on complex two- or three-dimensional geometries with more advanced models of device operation.

REFERENCES

[1] R. Helleboid *et al.* *IEEE Journal of the Electron Devices Society*, vol. 10, pp. 584–592, 2022.
[2] S. Luke, "Essentials of metaheuristics," vol. 2, pp. 25, 55–58, Lulu Raleigh, 2013.

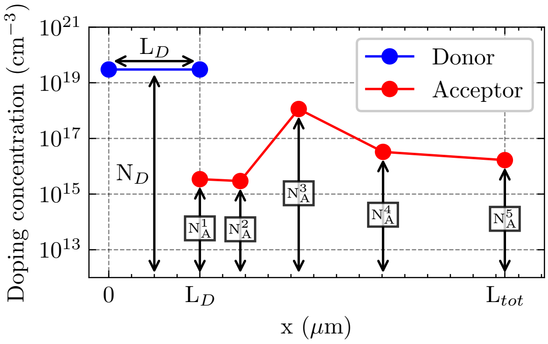

Fig. 1. Sketch of the doping profile structure. The N side is described by its length and level, while the P side is described by a piecewise exponential function defined by n_A acceptor levels (here n_A=5). The x coordinate of the points are not optimized and are chosen to be well distributed. The total number of variables to optimize is N_{opt} = n_A+2.

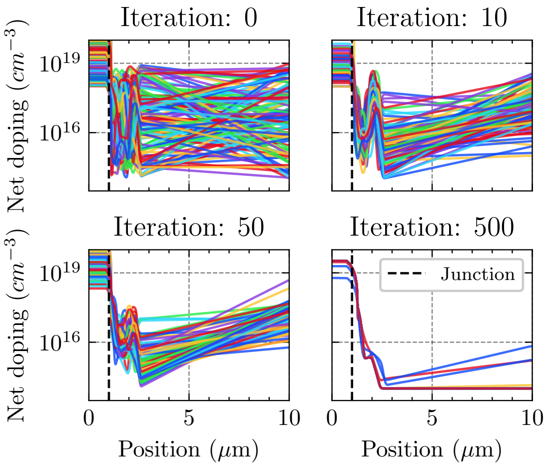

Fig. 2. Illustration of the PSO algorithm where each line represents a particle of the algorithm. The initial population is randomly generated (Iteration 0) and then evolves during the optimization process in order to find a global minimum. For visualization purposes, the N+ length L_D was kept constant.

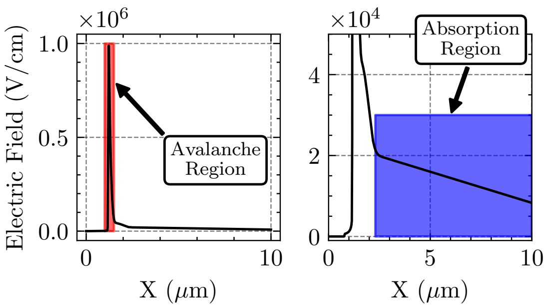

Fig. 3. Electric field at the end of the optimization process that favors depletion. (Right figure is a zoom of the left one.) The device is fully depleted in the absorption region as desired. Yet pushing the electric field within the back of the diode led to a reduction of the thickness of the avalanche region, causing a low breakdown probability (see Fig. 5).

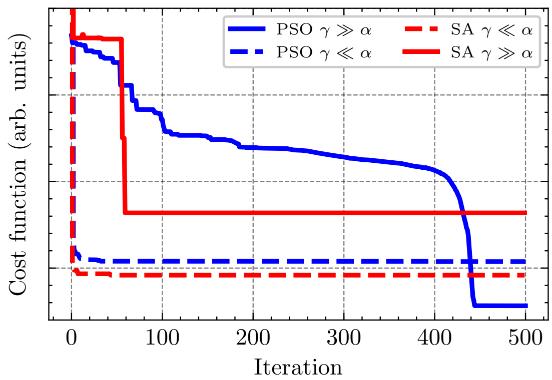

Fig. 4. Cost function evolution during the optimization process for the two methods. The convergence rate highly depends on the meta-parameters of the algorithm and makes it difficult to conclude on the best method. The best set of meta-parameters depends on the problem at hand and must be found empirically. The different α to γ ratios are discussed in Fig 5.

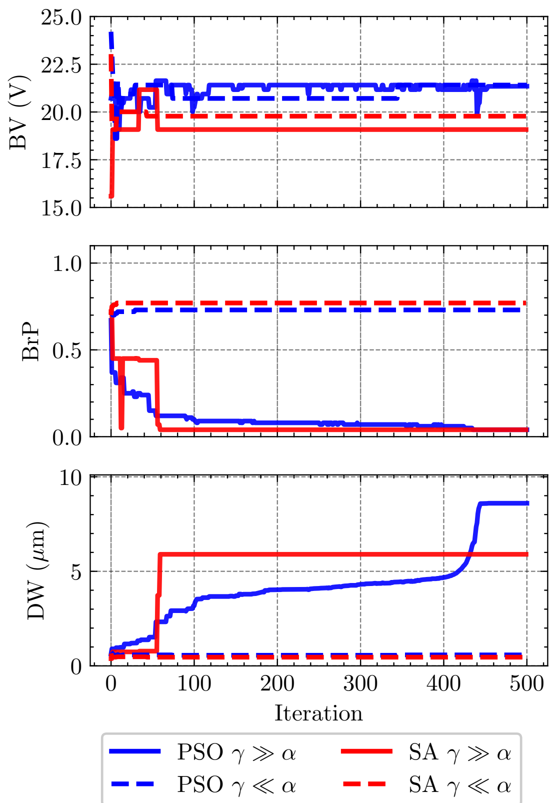

Fig. 5. Evolution of the different figures of merit of the SPAD that are optimized during the process for two different weights scenarios. The scenario $\gamma \gg \alpha$ favors the depletion width at the expense of the breakdown probability. The optimization is very efficient and leads to a fully depleted SPAD (see Fig. 3). In the scenario $\gamma \ll \alpha$, the optimization favors the BrP, and reaches an optimum very quickly. The scenario $\gamma = \alpha$ tends to favor the depletion width, and is not shown here.