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Parameter identification of power semiconductor device models using metaheuristics

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1. Introduction

Parameter extraction procedures for power semiconductor models are a need for researchers working with development of power circuits. It is nowadays recognized that an identification procedure is crucial in order to design power circuits easily through simulation (Allard et al., 2003; Claudio et al., 2002; Kang et al., 2003c; Lauritzen et al., 2001). Complex or inaccurate parameterization often discourages design engineers from attempting to use physics-based semiconductor models in their circuit designs. This issue is particularly relevant for IGBTs because they are characterized by a large number of parameters. Since IGBT models developed in recent years lack an identification procedure, different recent papers in literature address this issue (Allard et al., 2003; Claudio et al., 2002; Hefner & Bouche, 2000; Kang et al., 2003c; Lauritzen et al., 2001).

Different approaches have been taken, most of them cumbersome to be solved since they are very complex and require so precise measurements that are not useful for usual needs of simulation. Manual parameter identification is still a hard task and some effort is necessary to match experimental and simulated results. A promising approach is to combine standard extraction methods to get an initial satisfying guess and then use numerical parameter optimization to extract the optimum parameter set (Allard et al., 2003; Bryant et al., 2006; Chibante et al., 2009b). Optimization is carried out by comparing simulated and experimental results from which an error value results. A new parameter set is then generated and iterative process continues until the parameter set converges to the global minimum error.

The approach presented in this chapter is based in (Chibante et al., 2009b) and uses an optimization algorithm to perform the parameter extraction: the Simulated Annealing (SA) algorithm. The NPT-IGBT is used as case study (Chibante et al., 2008; Chibante et al., 2009b). In order to make clear what parameters need to be identified the NPT-IGBT model and the related ADE solution will be briefly present in following sections.

2. Simulated Annealing

Annealing is the metallurgical process of heating up a solid and then cooling slowly until it crystallizes. Atoms of this material have high energies at very high temperatures. This gives the atoms a great deal of freedom in their ability to restructure themselves. As the temperature is reduced the energy of these atoms decreases, until a state of minimum energy is achieved. In an optimization context SA seeks to emulate this process. SA begins at a very high temperature where the input values are allowed to assume a great range of variation. As algorithm progresses temperature is allowed to fall. This restricts the degree to which inputs are allowed to vary. This often leads the algorithm to a better solution, just as a metal achieves a better crystal structure through the actual annealing process. So, as long as temperature is being decreased, changes are produced at the inputs, originating successive better solutions given rise to an optimum set of input values when temperature is close to zero. SA can be used to find the minimum of an objective function and it is expected that the algorithm will find the inputs that will produce a minimum value of the objective function. In this chapter's context the goal is to get the optimum set of parameters that produce realistic and precise simulation results. So, the objective function is an expression that measures the error between experimental and simulated data.

The main feature of SA algorithm is the ability to avoid being trapped in local minimum. This is done letting the algorithm to accept not only better solutions but also worse solutions with a given probability. The main disadvantage, that is common in stochastic local search algorithms, is that definition of some control parameters (initial temperature, cooling rate, etc) is somewhat subjective and must be defined from an empirical basis. This means that the algorithm must be tuned in order to maximize its performance.
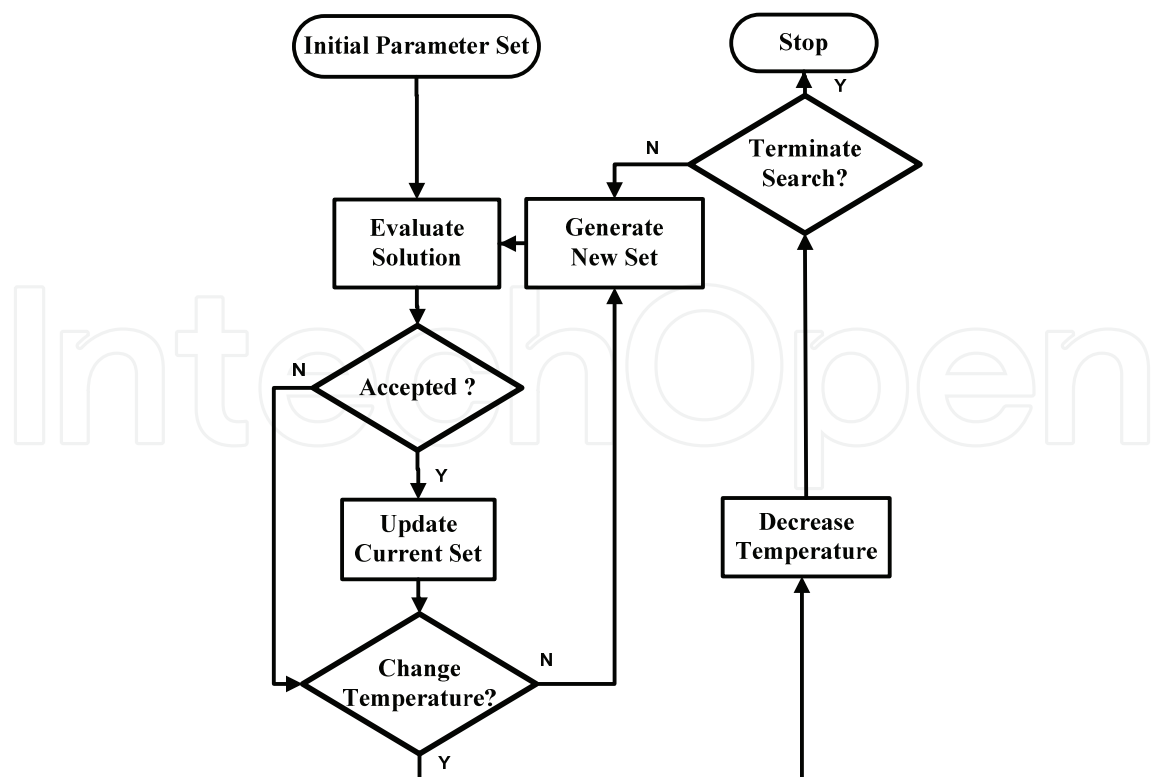

Fig. 1. Flowchart of the SA algorithm

The SA algorithm is represented by the flowchart of Fig. 1. The main feature of SA is its ability to escape from local optimum based on the acceptance rule of a candidate solution. If the current solution (f_{new}) has an objective function value smaller (supposing minimization) than that of the old solution (f_{old}), then the current solution is accepted. Otherwise, the current solution can also be accepted if the value given by the Boltzmann distribution:

$$e^{-\frac{f_{new} - f_{old}}{T}} \tag{1}$$

is greater than a uniform random number in [0,1], where T is the 'temperature' control parameter. However, many implementation details are left open to the application designer and are briefly discussed on the following.

2.1 Initial population
Every iterative technique requires definition of an initial guess for parameters' values. Some algorithms require the use of several initial solutions but it is not the case of SA. Another approach is to randomly select the initial parameters' values given a set of appropriated boundaries. Of course that as closer the initial estimate is from the global optimum the faster will be the optimization process.

2.2 Initial temperature
The control parameter 'temperature' must be carefully defined since it controls the acceptance rule defined by (1). T must be large enough to enable the algorithm to move off a local minimum but small enough not to move off a global minimum. The value of T must be defined in an application based approach since it is related with the magnitude of the objective function values. It can be found in literature (Pham & Karaboga, 2000) some empirical approaches that can be helpful not to choose the 'optimum' value of T but at least a good initial estimate that can be tuned.

2.3 Perturbation mechanism
The perturbation mechanism is the method to create new solutions from the current solution. In other words it is a method to explore the neighborhood of the current solution creating small changes in the current solution. SA is commonly used in combinatorial problems where the parameters being optimized are integer numbers. In an application where the parameters vary continuously, which is the case of the application presented in this chapter, the exploration of neighborhood solutions can be made as presented next.
A solution s is defined as a vector $s = (x_1,..., x_n)$ representing a point in the search space. A new solution is generated using a vector $\sigma = (\sigma_1,..., \sigma_n)$ of standard deviations to create a perturbation from the current solution. A neighbor solution is then produced from the present solution by:

$$x_{i+1} = x_i + N(0, \sigma_i) \tag{2}$$

where $N(0, \sigma_i)$ is a random Gaussian number with zero mean and σ_i standard deviation.

2.4 Objective function

The cost or objective function is an expression that, in some applications, relates the parameters with some property (distance, cost, etc.) that is desired to minimize or maximize. In other applications, such as the one presented in this chapter, it is not possible to construct an objective function that directly relates the model parameters. The approach consists in defining an objective function that compares simulation results with experimental results. So, the algorithm will try to find the set of parameters that minimizes the error between simulated and experimental. Using the normalized sum of the squared errors, the objective function is expressed by:

$$f_{obj} = \sqrt{\sum_c \sum_i \left(\frac{g_s(x_i) - g_e(x_i)}{g_e(x_i)} \right)^2} \qquad (3)$$

where $g_s(x_i)$ is the simulated data, $g_e(x_i)$ is the experimental data and c is the number of curves being optimized.

2.5 Cooling schedule

The most common cooling schedule is the geometric rule for temperature variation:

$$T_{i+1} = sT_i \qquad (4)$$

whit $s < 1$. Good results have been report in literature when s is in the range [0.8 , 0.99]. However many other schedules have been proposed in literature. An interesting review is made in (Fouskakis & Draper, 2002).

Another parameter is the number of iterations at each temperature, which is often related with the size of the search space or with the size of the neighborhood. This number of iterations can even be constant or alternatively being function of the temperature or based on feedback from the process.

2.6 Terminating criterion

There are several methods to control termination of the algorithm. Some criterion examples are:

    a)   maximum number of iterations;
    b)   minimum temperature value;
    c)   minimum value of objective function;
    d)   minimum value of acceptance rate.

3. Modeling power semiconductor devices

Modeling charge carrier distribution in low-doped zones of bipolar power semiconductor devices is known as one of the most important issues for accurate description of the dynamic behavior of these devices. The charge carrier distribution can be obtained solving the Ambipolar Diffusion Equation (ADE). Knowledge of hole/electron concentration in that region is crucial but it is still a challenge for model designers. The last decade has been very

productive since several important SPICE models have been reported in literature with an interesting trade-off between accuracy and computation time. By solving the ADE, these models have a strong physics basis which guarantees an interesting accuracy and have also the advantage that can be implemented in a standard and widely used circuit simulator (SPICE) that motivates the industrial community to use device simulations for their circuit designs.

Two main approaches have been developed in order to solve the ADE. The first was proposed by Leturcq *et al.* (Leturcq et al., 1997) using a series expansion of ADE based on Fourier transform where carrier distribution is implemented using a circuit with resistors and capacitors (RC network). This technique has been further developed and applied to several semiconductor devices in (Kang et al., 2002; Kang et al., 2003a; Kang et al., 2003b; Palmer et al., 2001; Santi et al., 2001; Wang et al., 2004). The second approach proposed by Araújo *et al.* (Araújo et al., 1997) is based on the ADE solution through a variational formulation and simplex finite elements. One important advantage of this modeling approach is its easy implementation into general circuit simulators by means of an electrical analogy with the resulting system of ordinary differential equations (ODEs). ADE implementation is made with a set of current controlled RC nets which solution is analogue to the system of ordinary differential equations that results from ADE formulation. This approach has been applied to several devices in (Chibante et al., 2008; Chibante et al., 2009a; Chibante et al., 2009b).

In both approaches, a complete device model is obtained adding a few sub-circuits modeling other regions of the device: emitter, junctions, space-charge and MOS regions. According to this hybrid approach it is possible to model the charge carrier distribution with high accuracy maintaining low execution times.

3.1 ADE solution

This section describes the methodology proposed in (Chibante et al., 2008; Chibante et al., 2009a; Chibante et al., 2009b) to solve ADE. ADE solution is generally obtained considering that the charge carrier distribution is approximately one-dimensional along the n^- region. Assuming also high-level injection condition ($p \approx n$) in device's low-doped zone the charge carrier distribution is given by the well-known ADE:

$$\frac{\partial p(x,t)}{\partial t} = D\frac{\partial^2 p(x,t)}{\partial x^2} - \frac{p(x,t)}{\tau} \qquad (5)$$

with boundary conditions:

$$\frac{\partial p(x,t)}{\partial x} = \frac{1}{2qA}\left(\frac{I_n}{D_n} - \frac{I_p}{D_p}\right) \qquad (6)$$

In (5)-(6) D, D_n and D_p are diffusion constants, I_n and I_p are electron and hole currents and A the device's area. It is shown that ADE can be solved by a variational formulation with posterior solution using the Finite Element Method (FEM) (Zienkiewicz & Morgan, 1983).

$$[M]\left[\frac{\partial p(t)}{\partial t}\right]+[G][p(t)]+[F]=[0] \tag{7}$$

with:

$$[M]=\frac{A_e L_{Ee}}{6D}\begin{bmatrix} 2 & 1 & & & \\ 1 & 4 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & 4 & 1 \\ & & & 1 & 2 \end{bmatrix} \tag{8}$$

$$[G]=\frac{A_e}{2L_{Ee}}\begin{bmatrix} 2 & -2 & & & \\ -2 & 4 & -2 & & \\ & \ddots & \ddots & \ddots & \\ & & -2 & 4 & -2 \\ & & & -2 & 2 \end{bmatrix}+\frac{A_e L_{Ee}}{6D\tau}\begin{bmatrix} 2 & 1 & & & \\ 1 & 4 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & 4 & 1 \\ & & & 1 & 2 \end{bmatrix} \tag{9}$$

$$[F]=\begin{bmatrix} -f(t)A_1 & 0 & \cdots & 0 & -g(t)A_{n+1} \end{bmatrix} \tag{10}$$

The symmetry of these matrices enables to solve the system (7) making an analogy with a system of equations of a RC network:

$$[C]\left[\frac{\partial v(t)}{\partial t}\right]+[G][v(t)]+[I]=[0] \tag{11}$$

where voltages in each node represent carrier concentration along the n^- zone of the device. A normalization constant (10^{17}) is used in order to limit the voltages in IsSpice simulator to acceptable values. Resistors values are defined by $[G]$ and capacitors by $[C]$. Current sources defined by $[I]$ in first and last nodes implement boundary conditions accordingly to (6) and are defined specifically to the type of device being modeled. Corresponding RC nets for the presented formulation are illustrated in Fig. 2 where A_e and L_{Ee} are, respectively, area and width of each finite element.

Fig. 2. FEM electrical equivalent circuit implementing ADE

Related values of resistors and capacitors are:

$$C_{ij} = -\frac{A_e L_{Ee}}{6D}; \quad C_i = C_j = \frac{A_e L_{Ee}}{2D}$$

$$R_{ij} = \frac{6D\tau L_{Ee}}{6D\tau A_e - A_e L_{Ee}^2}; \quad R_i = R_j = \frac{2D\tau}{A_e L_{Ee}}$$

(12)

3.2 IGBT model

This section briefly presents a complete IGBT model (Chibante et al., 2008; Chibante et al., 2009b) with a non-punch-through structure (NPT-IGBT) in order to illustrate the relationship between the ADE formulation and remaining device sub-models, as well as making clear the model parameters that will be identified using the SA algorithm. Fig. 3 illustrates the structure of an NPT-IGBT.
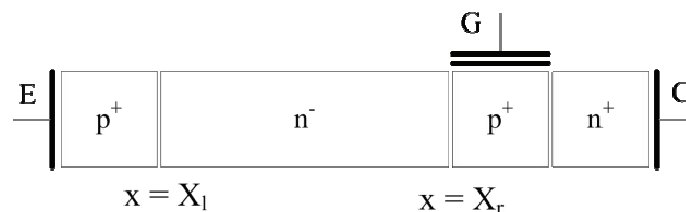
Fig. 3. Structure of a NPT-IGBT

3.2.1 ADE boundary conditions

In order to complete the ADE formulation appropriate boundary conditions must be defined, accordingly to the device being modeled. Current I_{p_l} is a recombination term modeled with the "h" parameter theory, I_{n_r} is the channel current from MOS part of the device and I_T is the total current. So, boundary conditions (6) are defined considering:

$$I_{p|x=Xl} = I_{p_l}$$
$$I_{n|x=Xl} = I_T - I_{p_l}$$
$$I_{n|x=Xr} = I_{n_r}$$
$$I_{p|x=Xr} = I_T - I_{n_r}$$

(13)

3.2.2 Emitter model

The contribution of the carrier concentration for the total current is well described by the theory of "h" parameters for high doped emitters, assuming a high injection level in the carrier storage region:

$$I_{n_l} = qh_p A p_0^2$$

(14)

That relates electron current I_{n_l} to carrier concentration at left border of the n^- region (p_0).

Emitter zone is seen as a recombination surface that models the recombination process of electrons that penetrate p^+ region due to limited emitter injection efficiency.

3.2.3 MOSFET model

The MOS part of the device is well represented with standard MOS models, where the channel current is given by:

$$I_{mos} = K_p K_f \left[\left(V_{gs} - V_{th} \right) V_{ds} - \frac{K_f V_{ds}^2}{2} \right] \times \frac{M}{1 + \theta \left(V_{gs} - V_{th} \right)} \tag{15}$$

for triode region and:

$$I_{mos} = \frac{K_p \left(V_{gs} - V_{th} \right)^2}{2} \times \frac{M}{1 + \theta \left(V_{gs} - V_{th} \right)} \tag{16}$$

for saturation region.

Transient behaviour is ruled by capacitances between device terminals. Well-known nonlinear Miller capacitance is the most important one in order to describe switching behaviour of MOS part. It is comprehended of a series combination of gate-drain oxide capacitance (C_{ox}) and gate-drain depletion capacitance (C_{gdj}) resulting in the following expression:

$$C_{gd} = \frac{C_{ox}}{1 + \dfrac{W_{sc}' C_{ox}}{\varepsilon_{si} A_{gd}}} \tag{17}$$

Drain-source capacitance (C_{ds}) is defined as:

$$C_{ds} = \frac{\varepsilon_{si} A_{ds}}{W_{sc}} \tag{18}$$

Gate-source capacitance is normally extracted from capacitance curves and a constant value may be used.

3.2.4 Voltage drops

As the global model behaves like a current controlled voltage source it is necessary to evaluate voltage drops over the several regions of the IGBT. Thus, neglecting the contribution of the high- doped zones (emitter and collector) the total voltage drop (forward bias) across the device is composed by the following terms:

$$V_{IGBT} = V_{p^+ n^-} + V_{\Omega} + V_{sc} \tag{19}$$

The p^+n^- junction voltage drop can be calculated according to Boltzmann approximation:

$$V_{p^+n^-} = V_T \ln\left(\frac{p_0^2}{n_i^2}\right) \tag{20}$$

Voltage drop across the lightly doped storage region is described integrating electrical field. Assuming a uniform doping level and quasi-neutrality ($n = p + N_D$) over the n^- zone, and neglecting diffusion current, we have:

$$V_\Omega \cong \frac{1}{q}\int_{x_l}^{x_r} \frac{J}{p(\mu_n + \mu_p) + \mu_n N_D}dx \tag{21}$$

Equation (21) can be seen as a voltage drop across conductivity modulated resistance. Applying the FEM formulation and using the mean value of p in each finite element results:

$$V_\Omega = I_T \times \sum_{e=1}^{r} \frac{l_e}{qA_e\left[\dfrac{p_e + p_{e+1}}{2}(\mu_n + \mu_p) + \mu_n N_D\right]} \tag{22}$$

Voltage drop over the space charge region is calculated by integrating Poisson equation. For a uniformly doped base the classical expression is:

$$V_{sc} = \frac{qN_D}{2\varepsilon_{si}}W_{sc}\left(W_{sc} + 2\sqrt{\frac{2\varepsilon_{si}V_{bi}}{qN_D}}\right) \tag{23}$$

3.3 Parameter identification procedure

Identification of semiconductor model parameters will be presented using the NPT-IGBT as case study. The NPT-IGBT model has been presented in previous section. The model is characterized by a set of well known physical constants and a set of parameters listed in Table 1 (Chibante et al., 2009b). This is the set of parameters that must be accurately identified in order to get precise simulation results. As proposed in this chapter, the parameters will be identified using the SA optimization algorithm. If the optimum parameter set produces simulation results that differ from experimental results by an acceptable error, and in a wide range of operating conditions, then one can conclude that obtained parameters' values correspond to the real ones.

It is proposed in (Chibante et al., 2004; Chibante et al., 2009b) to use as experimental data results from DC analysis and transient analysis. Given the large number of parameters, it was also suggested to decompose the optimization process in two stages. To accomplish that the set of parameters is divided in two groups and optimized separately: a first set of parameters is extracted using the DC characteristic while the second set is extracted using transient switching waveforms with the optimum parameters from DC extraction. Table 1 presents also the proposed parameter division where the parameters that strongly

influences DC characteristics were selected in order to run the DC optimization. In the following sections the first optimization stage will be referred as DC optimization and the second as transient optimization.

Optimization	Symbol	Unit	Description
Transient	A_{gd}	cm²	Gate-drain overlap area
	W_B	cm	Metallurgical base width
	N_B	cm⁻³	Base doping concentration
	V_{bi}	V	Junction in-built voltage
	C_{gs}	F	Gate-source capacitance
	C_{oxd}	F	Gate-drain overlap oxide capacitance
DC	A	cm²	Device active area
	h_p	cm⁴.s⁻¹	Recombination parameter
	K_f	-	Triode region MOSFET transconductance factor
	K_p	A/V²	Saturation region MOSFET transconductance
	V_{th}	V	MOSFET channel threshold voltage
	τ	s	Base lifetime
	θ	V⁻¹	Transverse field transconductance factor

Table 1. List of NPT-IGBT model parameters

4. Simulated Annealing implementation

As described in section two of this chapter, application of the SA algorithm requires definition of:

a) Initial population;
b) Initial temperature;
c) Perturbation mechanism;
d) Objective function;
e) Cooling schedule;
f) Terminating criterion.

SA algorithm has a disadvantage that is common to most metaheuristics in the sense that many implementation aspects are left open to the designer and many algorithm controls are defined in an ad-hoc basis or are the result of a tuning stage. In the following it is presented the approach suggested in (Chibante et al., 2009b).

4.1 Initial population
Every iterative technique requires definition of an initial guess for parameters' values. Some algorithms require the use of several initial parameter sets but it is not the case of SA. Another approach is to randomly select the initial parameters' values given a set of appropriated boundaries. Of course that as closer the initial estimate is from the global optimum the faster will be the optimization process. The approach proposed in (Chibante et

al., 2009b) is to use some well know techniques (Chibante et al., 2004; Kang et al., 2003c; Leturcq et al., 1997) to find an interesting initial solution for some of the parameters. These simple techniques are mainly based in datasheet information or known relations between parameters. Since this family of optimization techniques requires a tuning process, in the sense that algorithm control variables must be refined to maximize algorithm performance, the initial solution can also be tuned if some of parameter if clearly far way from expected global optimum.

4.2 Initial temperature
As stated before, the temperature must be large enough to enable the algorithm to move off a local minimum but small enough not to move off a global minimum. This is related to the acceptance probability of a worst solution that depends on temperature and magnitude of objective function. In this context, the algorithm was tuned and the initial temperature was set to 1.

4.3 Perturbation mechanism
A solution x is defined as a vector $x = (x_1,..., x_n)$ representing a point in the search space. A new solution is generated using a vector $\sigma = (\sigma_1,..., \sigma_n)$ of standard deviations to create a perturbation from the current solution. A neighbor solution is then produced from the present solution by:

$$x_{i+1} = x_i + N\left(0, \sigma_i\right)$$

(24)

where $N(0, \sigma_i)$ is a random Gaussian number with zero mean and σ_i standard deviation. The construction of the vector σ requires definition of a value σ_i related to each parameter x_i. That depends on the confidence used to construct the initial solution, in sense that if there is a high confidence that a certain parameter is close to a certain value, then the corresponding standard deviation can be set smaller. In a more advanced scheme the vector σ can be made variable by a constant rate as a function of the number of iterations or based in acceptance rates (Pham & Karaboga, 2000). No constrains were imposed to the parameter variation, which means that there is no lower or upper bounds.

4.4 Objective function
The cost or objective function is defined by comparing the relative error between simulated and experimental data using the normalized sum of the squared errors. The general expression is:

$$f_{obj} = \sqrt{\sum_c \sum_i \left(\frac{g_s(x_i) - g_e(x_i)}{g_e(x_i)}\right)^2}$$

(25)

where $g_s(x_i)$ is the simulated data, $g_e(x_i)$ is the experimental data and c is the number of curves being optimized. The IGBT's DC characteristic is used as optimization variable for the DC optimization. This characteristic relates collector current to collector-emitter voltage

for several gate-emitter voltages. Three experimental points for three gate-emitter values were measured to construct the objective function:

$$f_{obj} = \sqrt{\sum_{c=1}^{3}\sum_{i=1}^{3}\left(\frac{g_s(x_i)-g_e(x_i)}{g_e(x_i)}\right)^2}$$ (26)

So, a total of 9 data points were used from the experimental DC characteristic $g_e(x_i)$ and compared with the simulated DC characteristic $g_e(x_i)$ using (26).

The transient optimization is a more difficult task since it is required that a good simulated behaviour should be observed either for turn-on and turn-off, considering the three main variables: collector-emitter voltage (V_{CE}), gate-emitter voltage (V_{GE}) and collector current (I_C). Although optimization using the three main variables (V_{CE}, V_{GE}, I_C) could probably lead to a robust optimization process, it has been observed that optimizing just for V_{CE} produces also good results for remaining variables, as long as the typical current tail phenomenon is not significant. Collector current by itself is not an adequate optimization variable since the effects of some phenomenon (namely capacitances) is not readily visible in shape waveform. Optimization using switching parameters values instead of transient switching waveforms is also a possible approach (Allard et al., 2003). In the present work collector-emitter voltage was used as optimization variable in the objective function:

$$f_{obj} = \sqrt{\sum_{i=1}^{n}\left(\frac{V_{CE\_s}(t_i)-V_{CE\_e}(t_i)}{V_{CE\_e}(t_i)}\right)^2}$$ (27)

using n data points of experimental (V_{CE_e}) and simulated (V_{CE_s}) waveforms. It is interesting to note from the realized experiments that although collector-emitter voltage is optimized only at turn-off a good agreement is obtained for the whole switching cycle.

4.5 Cooling schedule
The cooling schedule was implemented using a geometric rule for temperature variation:

$$T_{i+1} = sT_i$$ (28)

A value of $s = 0.4$ was found to give good results.

4.6 Terminating criterion
For a given iteration of the SA algorithm, IsSpice circuit simulator is called in order to run a simulation with the current trial set of parameters. Implementation of the interaction between optimization algorithm and IsSpice requires some effort because each parameter set must be inserted into the IsSpice's netlist file and output data must be read. The simulation time is about 1 second for a DC simulation and 15 seconds for a transient simulation. Objective function is then evaluated with simulated and experimental data accordingly to (26) and (27). This means that each evaluation of the objective function takes

about 15 seconds in the worst case. This is a disadvantage of the present application since evaluation of a common objective function usually requires computation of an equation that is made almost instantaneously. This imposes some limits in the number of algorithm iterations to avoid extremely long optimization times. So, it was decided to use a maximum of 100 iterations as terminating criterion for transient optimization and a minimum value of 0.5 for the objective function in the DC optimization.

4.7 Optimization results

Fig. 4 presents the results for the DC optimization. It is clear that simulated DC characteristic agrees well with the experimental DC characteristic defined by the 9 experimental data points. The experimental data is taken from a BUP203 device (1000V/23A). Table 2 presents the initial solution and corresponding σ vector for DC optimization and the optimum parameter set. Results for the transient optimization are presented (Fig. 5) concerning the optimization process but also further model validation results in order to assess the robustness of the extraction optimization process. Experimental results are from a BUP203 device (1000V/23A) using a test circuit in a hard-switching configuration with resistive load. Operating conditions are: V_{CC} = 150V, R_L = 20Ω and gate resistances R_{G1} = 1.34kΩ, R_{G2} = 2.65kΩ and R_{G3} = 7.92kΩ. Note that the objective function is evaluated using only the collector-emitter variable with R_{G1} = 1.34kΩ. Although collector-emitter voltage is optimized only at turn-off it is interesting to note that a good agreement is obtained for the whole switching cycle. Table 3 presents the initial solution and corresponding σ vector for transient optimization and the optimum parameter set.
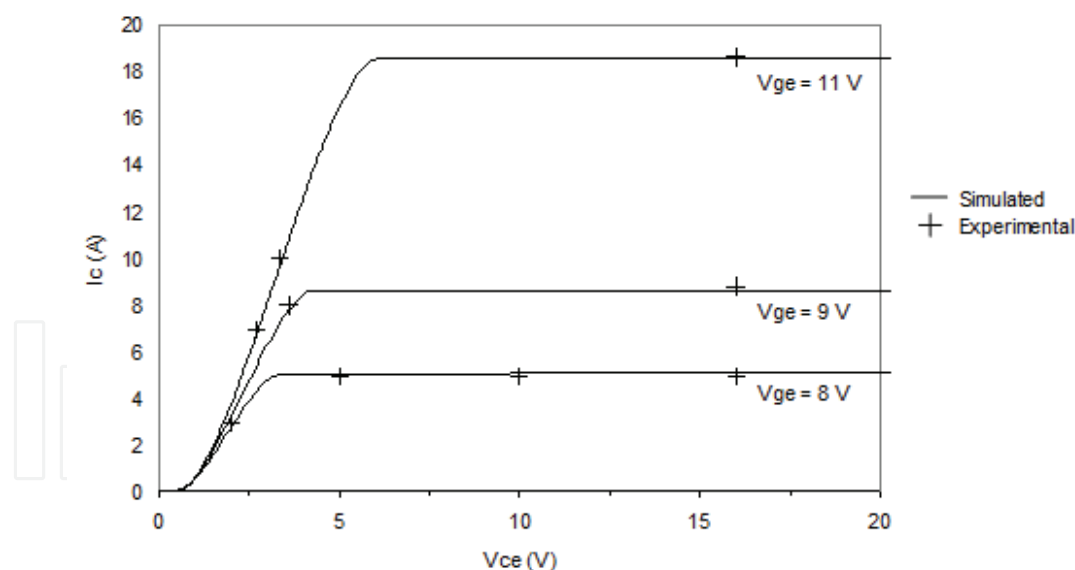

Fig. 4. Experimental and simulated DC characteristics

Parameter	A (cm²)	h_P (cm⁴.s⁻¹)	K_f	K_P (A/V²)	V_{th} (V)	τ (μs)	θ (V⁻¹)
Initial value	0.200	500×10^{-14}	3.10	0.90×10^{-5}	4.73	50	12.0×10^{-5}
Optimum value	0.239	319×10^{-14}	2.17	0.72×10^{-5}	4.76	54	8.8×10^{-5}

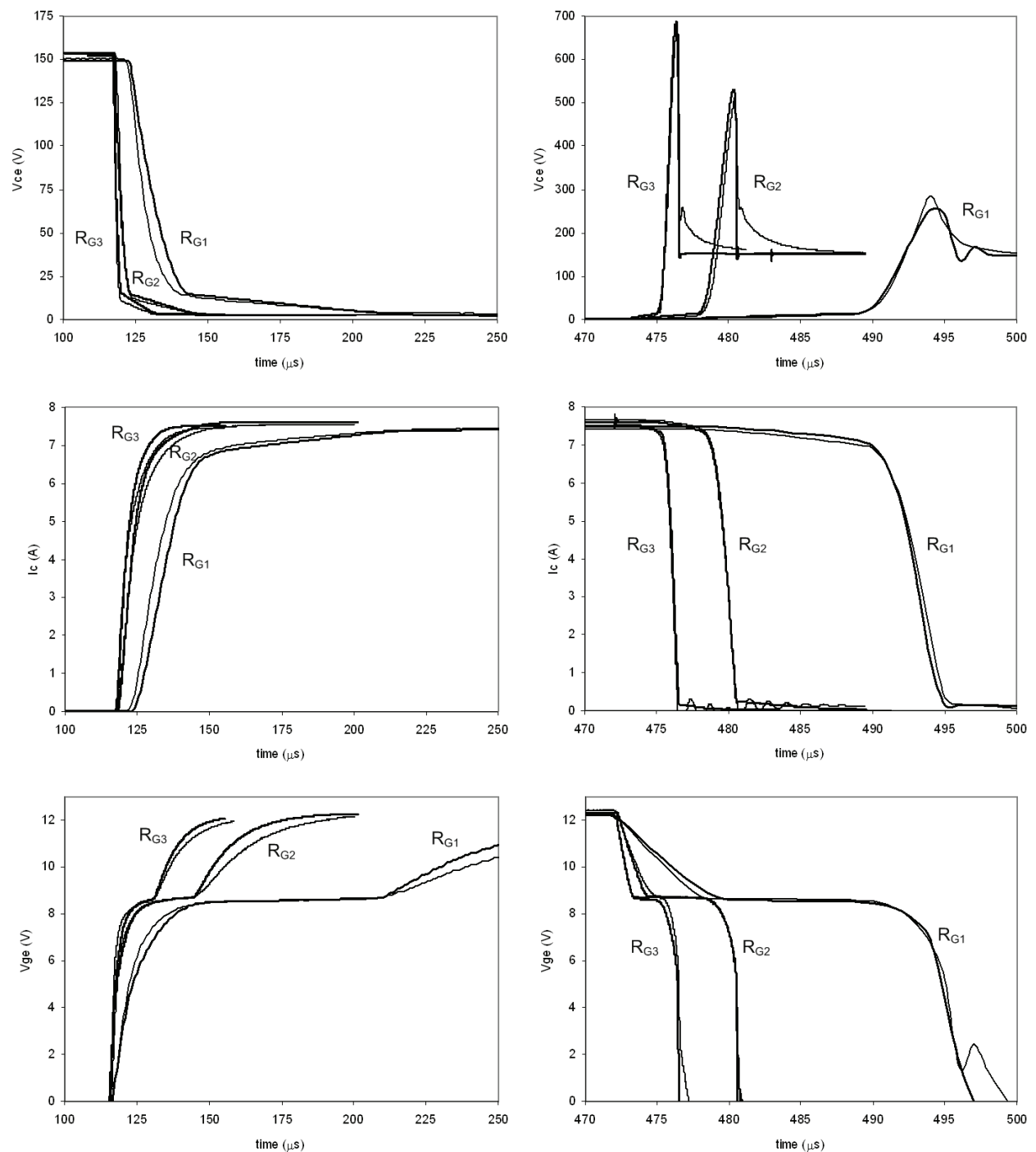Table 2. Initial conditions and final result (DC optimization)

Fig. 5. Experimental and simulated (bold) transient curves at turn-on (left) and turn-off

Parameter	A_{gd} (cm²)	C_{gs} (nF)	C_{oxd} (nF)	N_B (cm⁻³)	V_{bi} (V)	W_B (cm)
Initial value	0.090	1.80	3.10	0.40×10^{14}	0.70	18.0×10^{-3}
Optimum value	0.137	2.46	2.58	0.41×10^{14}	0.54	20.2×10^{-3}

Table 3. Initial conditions and final result (transient optimization)

5. Conclusion

An optimization-based methodology is presented to support the parameter identification of a NPT-IGBT physical model. The SA algorithm is described and applied successfully. The main features of SA are presented as well as the algorithm design. Using a simple turn-off test the model performance is maximized corresponding to a set of parameters that accurately characterizes the device behavior in DC and transient conditions. Accurate power semiconductor modeling and parameter extraction with reduced CPU time is possible with proposed approach.

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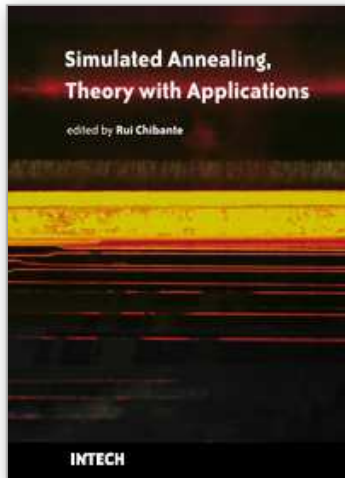
Simulated Annealing, Theory with Applications

Edited by Rui Chibante

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