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Smart Universal Parameter Fitting Method for Modeling Static SiC Power MOSFET Behavior

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***Abstract*—For efficient converter design, modeling of switching components must be both accurate and fast. A variety of simulation models for SiC Power MOSFETs has been developed. To achieve adequate accuracy, models are adjusted to experimental data by applying fitting methods. However, proposed universal fitting methods result in high-dimensional optimization problems. Their computational inefficiency leads to either long run times or low accuracy. This paper proposes a new universal parameter fitting method that is at least twice as fast and yields a more accurate outcome than presented methods under comparable conditions. It effectively reduces the dimensionality of the parameter fitting optimization problem by sensitivity-based reduction of optimization parameters. Thereby, it optimizes both model adjustment speed and accuracy, which are critical factors for an efficient converter design process. The method does not compromise flexibility as it is universally applicable to any SPICE model and can meet any model architecture preference.**

***Index Terms*—SiC, WBG, MOSFET, SPICE, Model Adjustment, Sensitivity Analysis, Fitting, Model Optimization**

I. Introduction

Silicon Carbide (SiC) exhibits a great potential to replace Silicon (Si) as the most popular base material for state-of-the-art power electronic devices [1]. Accurate switch component modeling is crucial for exploring how to utilize the superior characteristics of SiC devices and to accelerate the design process of converters. Recent research on SiC MOSFET modeling has focused on single models [2]–[9]. The degree of given information that is necessary for rebuilding the model varies greatly. Even a reproducible model may lack a parameter fitting method, or a given method is specific to the presented model [2]–[9]. Efforts in creating a generic approach to parameter fitting have resulted in an interface to MATLAB® optimization algorithms [10]. For any given PSpice device model, parameters are defined as variables that are then fitted to experimental data. This versatile approach does not depend on the model origin. However, if the considered model is not well-known, the relevance and variability of its parameters remain unclear. Consequently, optimization will be performed using a multitude of parameters. The resulting high-dimensional optimization problem is computationally demanding and exhibits long run time.

To address this issue, this paper proposes a parameter adjustment method that reduces the demand for computational resources when solving the optimization problem while preserving the accuracy of the fitted model. This is achieved by enabling smart selection of only highly influential parameters for optimization. Thus, it is as flexible as existing methods, but more accurate and significantly faster.

The paper is organized as follows. In Section II, the principle of the proposed fitting method is explained in detail. This includes model preparation steps, the sensitivity analysis, parameter optimization. In addition, several aspects that have an additional influence on the fitting result but are not specific to the proposed method, are discussed. Section III presents an exemplary application of the proposed method, fitting the manufacturer SPICE model of a SiC MOSFET to static ID-VDS characteristic data obtained from a Power Device Characterizer (PDC). The findings are summarized in Section IV.

II. Proposed Model Adjustment Method

The proposed parameter fitting method determines locally optimal values for the highly influential SPICE MOSFET model parameters to resemble experimental data with the highest possible accuracy. In this paper, the proposed method was applied to the static output characteristic ID-VDS of a SiC power MOSFET. PDC ID-VDS measurements served as fitting reference. A SPICE circuit imitates the measurement setup and contains the chosen MOSFET model in the Device Under Test (DUT) position for the simulation.

The proposed method comprises three major steps for any optimization objective.

- First, the previously chosen SPICE MOSFET model is made adjustable by transforming model constants into variable parameters.
- Second, the sensitivity values of all model parameters are calculated. The most influential parameters are chosen as optimization parameters.
- Third, values of these parameters are determined by a local optimization algorithm so that the deviation of the simulation output from measurement data is minimal.

This paper focuses on the fitting of model parameters to static ID-VDS characteristic data as an optimization objective.

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.subckt gmos_proposed d_ext d_int g_int s Tj Tc


B3      NET3    0    V=20u*(V(Tj)**2)-0.0082*V(Tj)+2.7086
R_C     NET3    0    1E6
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(a)

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.subckt gmos_proposed d_ext d_int g_int s Tj Tc

B3      NET3    0    V=p_gmos_1*(V(Tj)**2)+p_gmos_2*V(Tj)+{V_th_0}+p_gmos_3
R_C     NET3    0    1E6
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(b)

Fig. 1. Substitution of model constants by variables (SPICE parameters) from original (a) to parameterized form (b)

A. Choice of SPICE Model

As a preparation step, a SPICE MOSFET model is chosen. It is up to the user to decide on a preferred model type, structure and implementation. The freedom of model choice is one of the main advantages of the proposed method. It is universally applicable to any SPICE MOSFET model given that adjustments to the model code are possible as described below.

B. Parameter Establishment in a SPICE Model

SPICE models contain equations that describe the behavior of the modeled component. Figure 1a shows an exemplary excerpt from a SPICE MOSFET model approximating the temperature dependent threshold voltage as a second-degree polynomial. As a first step, the SPICE model is made adjustable by substitution of equation constants by variables, i.e. SPICE parameters. Figure 1b shows a possible outcome of applying this step to the code snippet from Figure 1a. SPICE allows for a variety of expressions, among others, if/else statements, exponential, trigonometric and hyperbolic terms as well as user-defined lookup tables. To illustrate the proposed method, the simple temperature dependent threshold voltage equation, that takes the form of a second-degree polynomial, has been chosen as an example. The proposed method, however, is equally applicable to more complex expressions.

C. Metric for Model Adjustment

To measure deviation between two sets of data, the Root-Mean-Square-Error (RMSE) can be used. It is defined as

$$RMSE = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} (y_{1,i} - y_{2,i})^2} \tag{1}$$

with N being the number of data points. It is assumed that the two sets of data share the same x data. To ensure this, one of the data sets is evaluated at the x data points of the other using linear interpolation.

In case of two data sets with a different resolution, the set with the higher resolution is first evaluated at the data points of the other set using linear interpolation and then the RMSE is calculated. Interpolating the lower resolved data would not increase its quality but instead lead to unnecessary data generation and numerical operations. In addition, linear interpolation distorts nonlinear data. Thus, the more often linear interpolation is applied, the greater the influence of this distortion. By interpolating only the higher resolved data, the number of interpolations is minimized as well as the interpolation error that causes distortion. Thereby, the validity of the RMSE as a deviation metric is ensured.

It has to be noted that the simulation is set to generate roughly ten times the resolution of the given experimental data to avoid interpolation distortion of the simulation data as described above. This also means a greater RMSE calculation effort if two simulation results are compared.

For the rare case that a parameter set causes severe convergence issues, the objective function features a timeout. After that, the simulation is aborted and a deviation of 0 is returned. Experiments have shown that two conditions may lead to such convergence issues. Either the model behavior is so degenerated that very high values occur, or there are boundary parameter values in control statements that lead to oscillations as a consequence of unsteady function definitions. In both cases, the zero-deviation choice is questionable regarding the aim of describing an actual deviation. On the other hand, this also has the effect of lowering the probability of convergence issues during the optimization procedure, since a zero-deviation value lowers the chance of a high sensitivity value and thus choosing the parameter in question is unlikely. For this paper, various handling strategies of convergence issues have been investigated and the zero-deviation strategy has lead to adequate results. The timeout for simulations has been set to 30 minutes.

D. Optimization Parameter Choice

Previously presented model fitting methods suffer from either long run time or low accuracy, which are interrelated factors. By lowering the demand on accuracy, it is possible to obtain results from a long run time method within reasonable time limits. This way, the run time issue is alleviated but the outcome is of lower quality.

Previously presented model adjustment methods apply an optimization algorithm blindly to all model parameters. The user can reduce the long run time and increase accuracy of the result by manually reducing the parameter set that is subject to optimization. However, knowledge concerning the role and importance of every single model parameter is limited in most practical cases. Hence, the manual preselection of parameters is challenging, if at all possible.

As opposed to previously presented methods, the smart preselection of parameters is assisted by a so-called sensitivity analysis. The outcome of this analysis is a sensitivity value for each parameter that describes, how much this parameter impacts the model behavior. It serves as the main decision criterion for whether a parameter is either included in or excluded from the optimization procedure. Only the parameters with high sensitivity values are chosen as optimization parameters.

Sensitivity Analysis: A SOBOL type sensitivity analysis [11] is used in the proposed method. The SALib library for python [12] was used for this purpose. For the SOBOL sensitivity analysis type, an objective function that evaluates a parameter set to a scalar value, needs to be defined.

To find impactful parameters, the scalar objective function result has to represent changes in the model behavior. The input to the objective function is an arbitrary set of parameters. With this parameter set, the simulation is performed. Then, the RMSE between the simulation result and the reference, i.e. the simulation result with the manufacturer parameter choice, is calculated. This way, an arbitrary set of parameters is evaluated to a scalar value that represents the magnitude of change from the original state of the model.

Model parameters may be largely different in magnitude. To optimize the sensitivity analysis performance, relative values with respect to the manufacturer parameterization are used. Additionally, the relative values are centered around 0 instead of 1. Also, the parameters are subject to boundaries, which can be changed individually for each parameter. Choosing individual parameter boundaries is a fine-tuning step to avoid convergence issues of the simulation provoked by changes of very sensitive parameters. Although this step is very application specific, global boundaries of $\pm 14\%$ for all parameters yielded consistent and reliable results in the experiments conducted for this paper. The $\pm 14\%$ boundary has been identified during experiments for this paper, balancing exploratory behavior and stability of the simulations conducted in the course of the sensitivity analysis.

According to the SOBOL analysis procedure, a fixed number of sample parameter sets are created obeying the parameter boundaries using a suitable algorithm [13]. Afterwards, the objective function is evaluated for all sample parameter sets. Since all sample parameter sets are known after generation and all simulation results are needed for the calculation of the sensitivity values, the task of simulation can be parallelized.

When all simulation results are available, the sensitivity values are calculated. The SOBOL analysis result contains so-called sensitivity indices of varying order. First order indices describe the impact that changes in a single parameter have on the objective function result. There are as many first order indices as there are parameters. Second order indices describe the interaction of two parameters and therefore, the number of second order indices adds up to the factorial of the parameter number. Finally, the total sensitivity indices describe the cumulative effect one parameter has on the objective function result [14]. Hence, there are also as many total sensitivity indices as parameters. The total sensitivity index is chosen as the sensitivity metric for the proposed method because of its comprehensive nature.

Parameter Choice: The total sensitivity index of one parameter is a relative value and only meaningful in the context of all other total sensitivity indices. A visualization of an exemplary sensitivity analysis result is presented in Figure 2.

The parameters with the highest sensitivity values are then chosen for the optimization procedure, because the biggest effect of a parameter adjustment is expected from these parameters. In some cases, a few very sensitive parameters may hide the effect of less impactful ones that are nevertheless of high relevance. For example, the threshold voltage at room temperature, V_th_0, has a much lower sensitivity index than the three parameters p_gmos_1, p_gmos_2 and p_gmos_3. It might be of interest to set the latter parameters constant and repeat the sensitivity analysis, especially, if only few parameters exhibit very high sensitivity values. Then, more parameters might reveal high sensitivity and would therefore be included in the choice of optimization parameters.

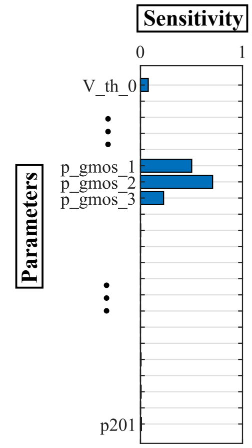


Fig. 2. Exemplary total sensitivity indices

E. Model Parameter Optimization

With the choice of parameters made above, the same SPICE model is used for simulations. The same objective function is used to evaluate a parameter set, but with experimental data gathered from a PDC [15] as reference instead of another simulation result. More information on the reference data will be given in Section III-A.

Optimization Procedure: During the optimization procedure, a gradient-descend type local optimization algorithm determines a set of values for the adjustment parameters that minimizes the deviation of the simulation from the measurement result. The objective function described above is designed to be evaluated with any given parameter set, using the mean characteristic derived from the PDC measurements as a reference. Therefore, the objective function can be passed to a general purpose gradient-descent type local optimization algorithm [16], [17]. Due to the generalized form of the objective function, the method is not restricted to local optimization algorithms. Nevertheless, using a local optimization algorithm yielded good results in the proposed method and simultaneously offered a run time advantage compared to global optimization alternatives.

F. Setting the Adjustment Focus

Various factors influence the adjustment focus, e.g. on different operation regions. In part, the proposed method can be manipulated to shift the adjustment focus. An example for this is the deviation metric explained in Section II-C. Choosing the RMSE as a metric will result in evenly distributed weight among all measurement series. Another metric could use relative instead of absolute errors. This would favor low over high amplitude data. For example, such a metric could be a relative RMSE:

$$RMSE_{rel} = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(\frac{y_{1,i} - y_{2,i}}{y_{1,i}} \right)^2} \quad (2)$$

Apart from that, data choice and experiment design are relevant factors for the outcome of the model adjustment method and should be considered in light of the intended model application. By choosing a different experimental design in which, for example, only high gate source voltages are used, the model adjustment could be concentrated on the linear region at high gate voltages. Another example could be the usage of only high drain source voltages to obtain a better fit to the saturation region of the device.

G. Advantages of the Proposed Method

The proposed method improves run time significantly because of the optimization space reduction. In addition, accuracy is improved because of two factors.

- If a large optimization parameter number is not reduced at all, the solution of the optimization problem takes a long time for a given accuracy. To obtain a solution after an acceptable amount of time, the accuracy aim may be relaxed, leading to a result of poorer quality.
- Alternatively, the reduction of parameters may reduce the run time of the given optimization problem. Without adequate information on the parameter relevance for the model, accuracy may suffer if relevant parameters are excluded from the optimization.

These disadvantages are addressed in the proposed method. The sensitivity based parameter reduction enables an informed selection of optimization parameters. Thus, highly relevant parameters are not excluded from the optimization and the parameter number is reduced at the same time. Thereby, both accuracy and run time are improved in a smart way.

In addition, the proposed method is flexible. It allows for usage of any model architecture that supports the establishment of parameters. Moreover, the optimization algorithm can be freely chosen due to the standard formulation of the optimization problem.

III. Method Application and Results

To show both efficacy and efficiency of the proposed method, an application is presented in the following. Discrete MOSFET devices have been statically characterized and the manufacturer SPICE model has been used as an input to the proposed method.

A. Manufacturer Model and Experimental Data

The proposed method has been applied to adjust the manufacturer SPICE model (v2) of Wolfspeed C3M0075120K MOSFETs [18]. The behavior of the 3-terminal C3M0075120D MOSFET, which was used for lab experiments, was imitated by shortening the source and kelvin source terminals of the C3M0075120K model.

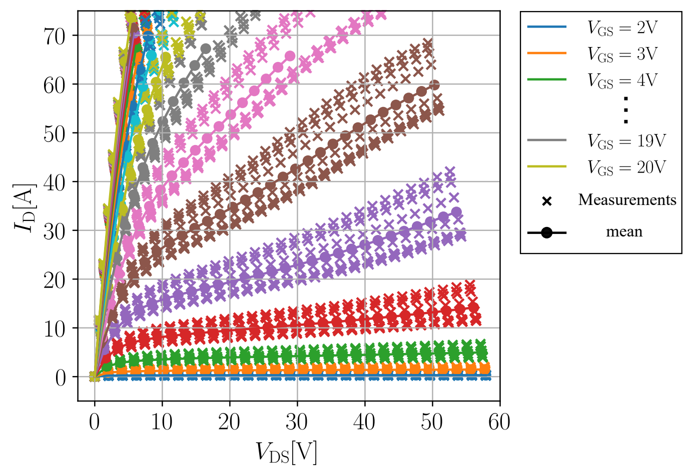


Fig. 3. PDC Measurements (10x C3M0075120D)

Experimental data has been derived measuring the static ID-VDS characteristic of 10 discrete MOSFET devices of type C3M0075120D [19]. The measurements were performed at room temperature. Then, the mean of all measurement series was calculated. This mean is referred to as the mean characteristic in the following. The measurement result and the mean characteristic can be seen in Figure 3. The data show considerable device spread in the static characteristics at low gate-source voltages close to the threshold voltage that reduces towards higher gate-source voltages. The average device spread measured by the RMSE from the mean characteristic is 2.56 A.

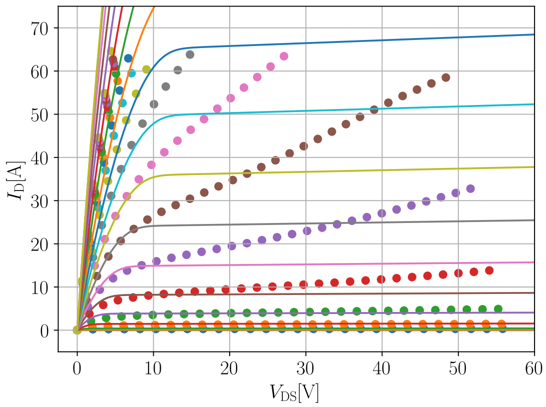
B. Results

The effect of applying the proposed fitting method to the manufacturer SPICE model is visualized in Figure 4. The deviation of the model behavior from the measurements is significantly higher before the application of the proposed method (Figure 4a) than afterwards (Figure 4b). The RMSE with reference to the experimental data could be reduced from 16.58 A to 2.66 A by applying the proposed method. This deviation is in the same range as the individual device spread and thus regarded an accurate representation of the device behavior.

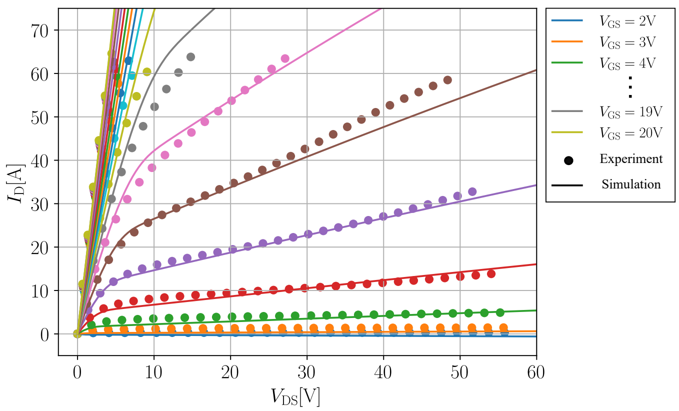
The run time of the proposed method was on the order of $\mathcal{O}(1\text{h})$ for the sensitivity analysis and $\mathcal{O}(1\text{h})$ for the optimization. Therefore, the method achieved considerable time savings and accuracy improvement compared to the reference method [10] that took $\mathcal{O}(6\text{h})$ arriving at a residual of 8 A RMSE.

IV. Conclusion

A highly effective and efficient method of SPICE model parameter fitting has been developed. Unlike existing parameter fitting methods, a sensitivity analysis is employed before the parameter optimization. Choosing only highly sensitive parameters for the optimization procedure reduces the dimensionality



(a)



(b)

Fig. 4. Simulation results vs. experimental data.
(a) initial parameterization (16.58 A RMSE)
(b) after applying the proposed method (2.66 A RMSE)

of the optimization problem and thereby the run time of the parameter fitting. At the same time, high accuracy is preserved.

The method was applied to the manufacturer SPICE model of C3M0075120K SiC MOSFETs. Experimental data was obtained using a PDC and used as the fitting reference. In this application, the proposed method achieved results with an accuracy in the range of individual device spread, reducing the model deviation from experimental data by 83.9 %. Compared to alternative methods (e.g. [10]), the execution time is reduced multiple times. At the same time, the model error is decreased by more than 60%. The combination of high accuracy and reduced run time makes this method valuable for applications in converter and especially gate driver design, where model accuracy and development time are critical factors.

Acknowledgment

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