

A Covariance Matrix Adaptation Evolutionary Strategy Parameter Extractor for BSIM-CMG

Jen-Hao Chen

Department of Electrical Engineering
and Computer Sciences
University of California, Berkeley
Berkeley, USA
jenhaochen@berkeley.edu

Ahtisham Pampori

Department of Electrical Engineering
and Computer Sciences
University of California, Berkeley
Berkeley, USA

Chenming Hu

Department of Electrical Engineering
and Computer Sciences
University of California, Berkeley
Berkeley, USA

Sayeeef Salahuddin

Department of Electrical Engineering
and Computer Sciences
University of California, Berkeley
Berkeley, USA

Abstract—An I–V and C–V BSIM-CMG parameter extraction methodology based on the covariance matrix adaptation evolutionary strategy (CMA-ES) is proposed in this work. Using the default BSIM-CMG parameter values as the initial guess, the optimization algorithm iteratively evolves the parameters toward their optimal values, enabling the BSIM-CMG model to accurately fit the target data. This optimization approach demonstrates strong potential for extracting BSIM-CMG model parameters that achieve accurate fitting to the target data without requiring human expertise in compact modeling.

Keywords—BSIM-CMG, parameter extraction, evolutionary strategy

I. INTRODUCTION

Device compact models are essential computational tools that facilitate integrated circuit simulation. In order to ensure the accuracy of the circuit simulation, a decent fit between transistors data and the compact model’s data is required. The process of fitting the data using compact models is called “parameter extraction”. Traditionally, parameter extraction is done by a manual trial and error method until the fitting accuracy between model and data is satisfactory. [1] Naturally, parameter extraction for a compact model relies on modeling engineers’ expertise and understanding in the compact models.

TABLE 1. The selected BSIM-CMG parameters.

IV parameter	g_{ds} parameter	CV Parameter
1. PHIG	1. DSUB	1. TOXP
2. LPHIG	2. ETA0	2. QMTCENCV
3. CIT	3. MEXP	3. LQMTCENCV
4. CDSC	4. PCLM	4. QM0
5. CDSCD	5. APCLM	5. PQM
6. DVT1SS	6. BPCLM	6. CFS
7. LDVT1SS	7. PVAG	7. CGSL
8. DVT0	8. PDIBL1	8. CKAPPAS
9. DVT1	9. PDIBL2	9. VFBSDCV
10. U0	10. DROUT	10. ETA0CV
11. UP		11. U0CV
12. LPA		12. UACV
13. EU		13. PCLMCV
14. UA		14. VSATCV
15. AUA		15. AVSATCV
16. BUA		16. BVSATCV
17. ETAMOB		17. DELTAVSATCV
18. RDSW		18. ASAT
19. VSAT		
20. AVSAT		
21. BVSAT		
22. VSAT1		
23. AVSAT1		
24. BVSAT1		

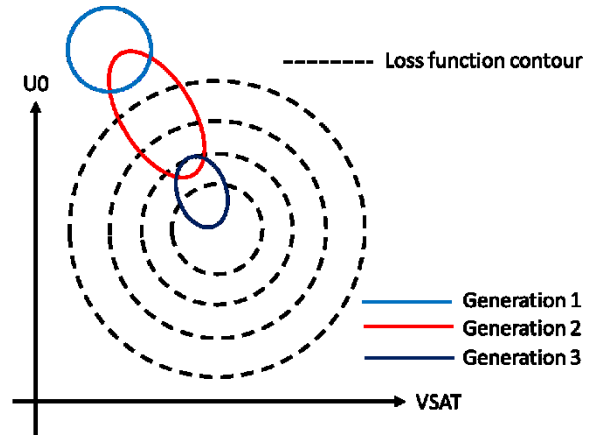


Fig. 1. A schematic diagram of evolutionary path with only two parameters shown. The Gaussian distribution will update itself and approach to the loss minimum.

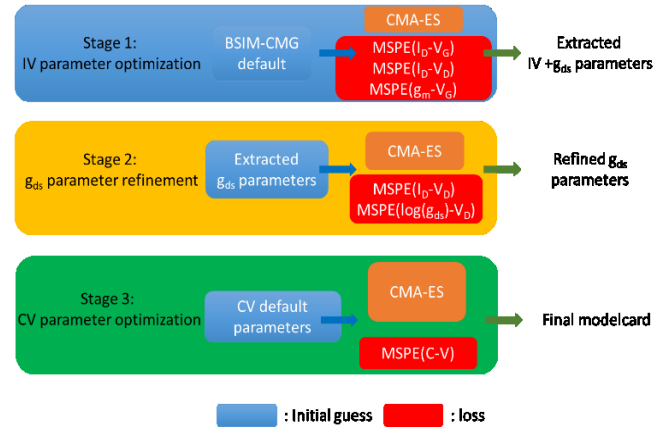


Fig. 2. The flow of this proposed CMA-ES-based BSIM-CMG parameter extractor.

To reduce the human burden in the parameter extraction process, a traditional gradient-based optimization method, Levenberg-Marquardt (LM) algorithm, is commonly used. Nevertheless, this approach strongly relies on a good initial guess, and it is more appropriate for local parameter refinement. [2] Apart from LM algorithm, some previous works [3–5] have proposed deep learning-based methods capable of generating BSIM-CMG [6] parameters for I–V and C–V data instantly. Although these approaches are promising, they still require reasonably good nominal parameter values around which the training dataset is generated. Also, training a neural network parameter extractor with a large range to cover significantly different technologies may require a large

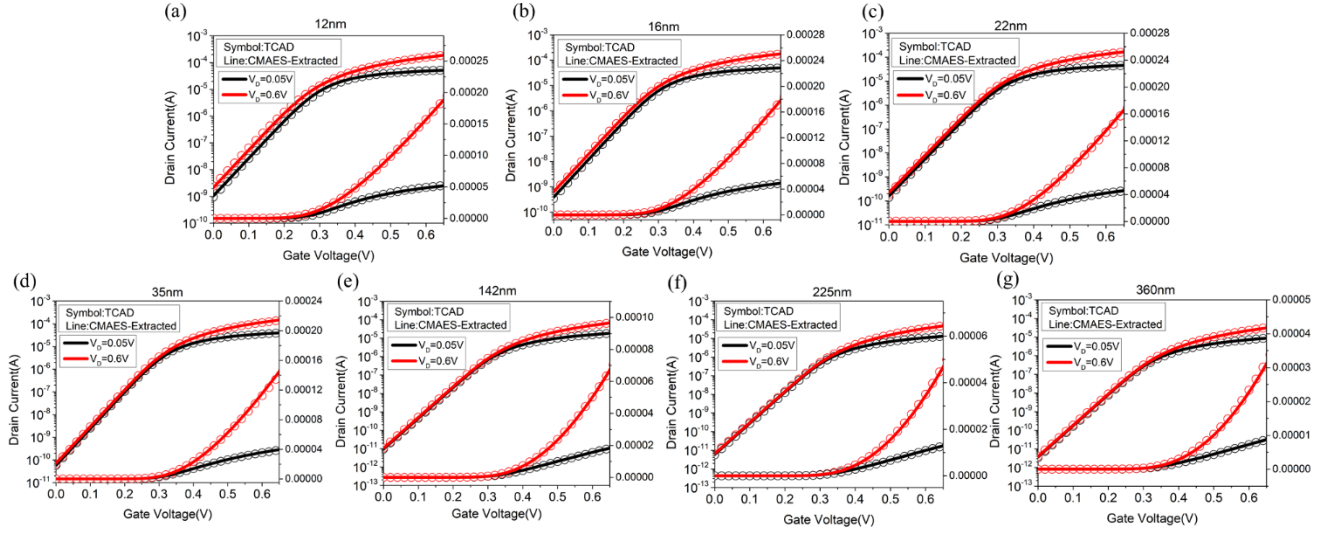


Fig. 3. Fitting result in TCAD I_D - V_G with seven various gate lengths. (a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

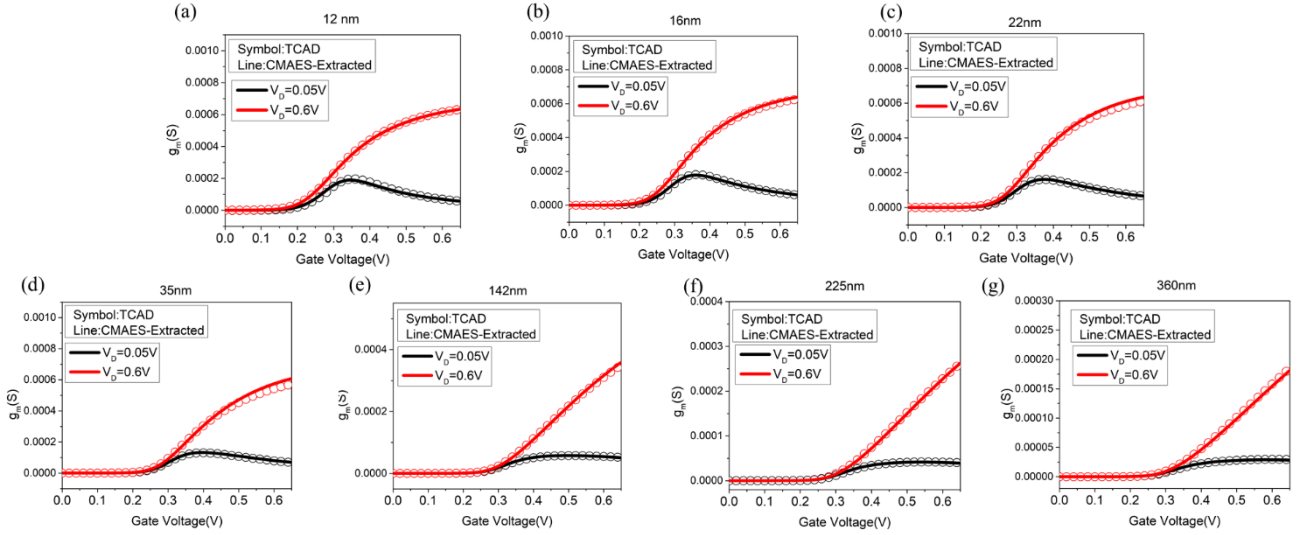


Fig. 4. Fitting result in TCAD g_m - V_G with seven various gate lengths. (a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

amount of training dataset, a long training time and compromise for fitting accuracy. In addition, once the training is completed, the input data to a neural network must follow a specific format, and the output parameters from a neural network are also rigid. These facts may still limit their practical applicability.

In this work, we present a CMA-ES-based parameter extractor to solve the above-mentioned problems. This proposed method can automatically evolve parameter values from the default values to their optimal values over a broad range.

II. COMPUTATIONAL ALGORITHM

CMA-ES [7] is an optimization algorithm in the family of evolutionary strategies. It begins with an initial guess of the parameter values in a black-box setting. Within a Gaussian distribution centered on this initial guess, a number of parameter samples are drawn, and the loss corresponding to each sample is evaluated. The center of the Gaussian distribution is then updated using a weighted sum of the top-performing samples with lower loss. Furthermore, in each iteration, the covariance matrices whose geometrical meanings are the orientation and the shape of a Gaussian

distribution is adaptive to capture the correlation between different parameters optimized. The standard deviation whose geometrical meaning is the broadness of a Gaussian distribution is also adaptive to control the search scale. These two points are important to help CMAES adapt to different landscapes of loss functions. By repeating these steps, the algorithm gradually evolves the parameter values from the initial guess toward an optimal set of values.

In this work, CMA-ES is applied to optimize 52 parameters in the BSIM-CMG model, as shown in Table 1. These parameters include the most commonly used ones based on our manual fitting experience. During the optimization, BSIM-CMG parameter set are sampled from multivariate Gaussian distributions in the parameter space. The center, scale and covariance matrix of the distributions are iteratively updated based on the loss to guide the search toward the optimal parameters. One simple schematic diagram with only two parameters shown is provided in Fig. 1. The loss function employed during the optimization process is the mean square percentage error (MSPE) of I - V , conductance, and C - V characteristics between the BSIM-CMG model and TCAD-generated data calibrated to the IRDS 1 nm node GAAFET [8].

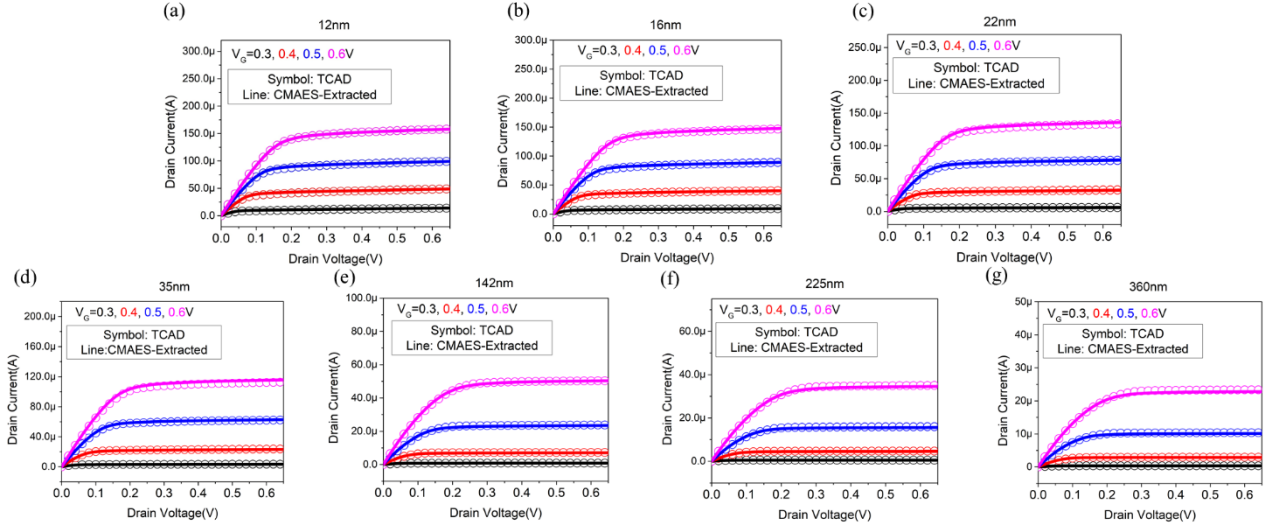


Fig. 5. Fitting result in TCAD I_D - V_D with seven various gate lengths. (a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

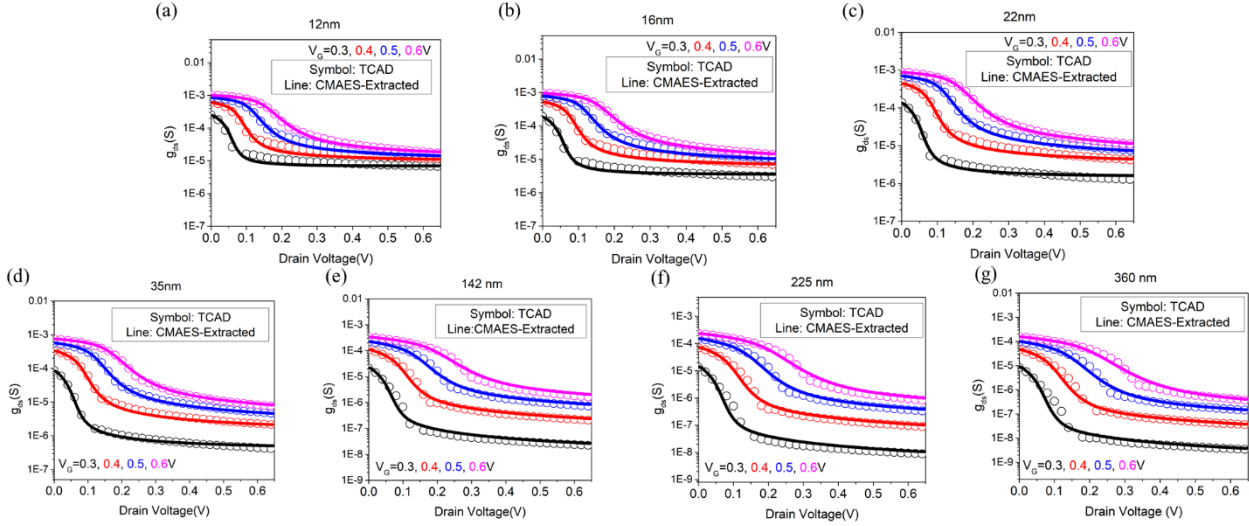


Fig. 6. Fitting result in TCAD g_{ds} - V_D with seven various gate lengths. (a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

In the proposed framework, to reduce the complexity of parameter optimization, we adopt a multi-stage CMA-ES parameter extractor, as illustrated in Fig. 2. Starting from the default BSIM-CMG parameter values as the initial guess, the first stage optimizes the I - V and g_{ds} parameters listed in the first and second columns of Table 1, using the MSPE of I_D - V_G , I_D - V_D , and g_m - V_G as the loss. In the second stage, to improve the fitting accuracy of the output conductance, only g_{ds} parameters are further optimized, with the g_{ds} parameters extracted from the first stage serving as the initial guess and the I - V parameters from the first stage kept fixed. The loss function in this stage is the MSPE of I_D - V_D and $\log(g_{ds})$ - V_D . Finally, with the extracted I - V and g_{ds} parameters fixed and the BSIM-CMG default C - V parameters as the initial guess, the third stage optimizes the C - V parameters, completing the overall parameter extraction process.

III. RESULT AND DISCUSSION

After the optimization process, the BSIM-CMG model data with CMA-ES-extracted parameters are compared with the TCAD-generated target data to evaluate the performance of the extractor.

Fig. 3 shows good I_D - V_G fitting using the CMA-ES-extracted parameters for devices with gate lengths ranging from 12 nm to 360 nm. It can be observed that this CMA-ES algorithm can evolve the BSIM-CMG default parameter values, which are far from the target, toward more optimal values with a root mean square percentage error equal to 3.84%. In addition to I_D - V_G , the fitting error of its derivative curve, g_m - V_G , is also included as part of the loss function in the first stage, as shown in Fig. 2. Therefore, the optimizer achieves not only a decent fit for I_D - V_G but also for g_m - V_G , as shown in Fig. 4, with a root mean square percentage error of 3.64%.

Fig. 5 also shows good I_D - V_D fitting using the CMA-ES-extracted parameters for the same seven devices with gate lengths ranging from 12 nm to 360 nm. More importantly, the second stage, g_{ds} parameter refinement, helps refine output-conductance-related parameters to more appropriate values, resulting in a decent fit in $\log(g_{ds})$ with a log scale root mean square percentage error of 1.56%, as shown in Fig. 6. The decent fit in both g_m and g_{ds} demonstrates the potential of this parameter extraction approach for analog circuit applications.

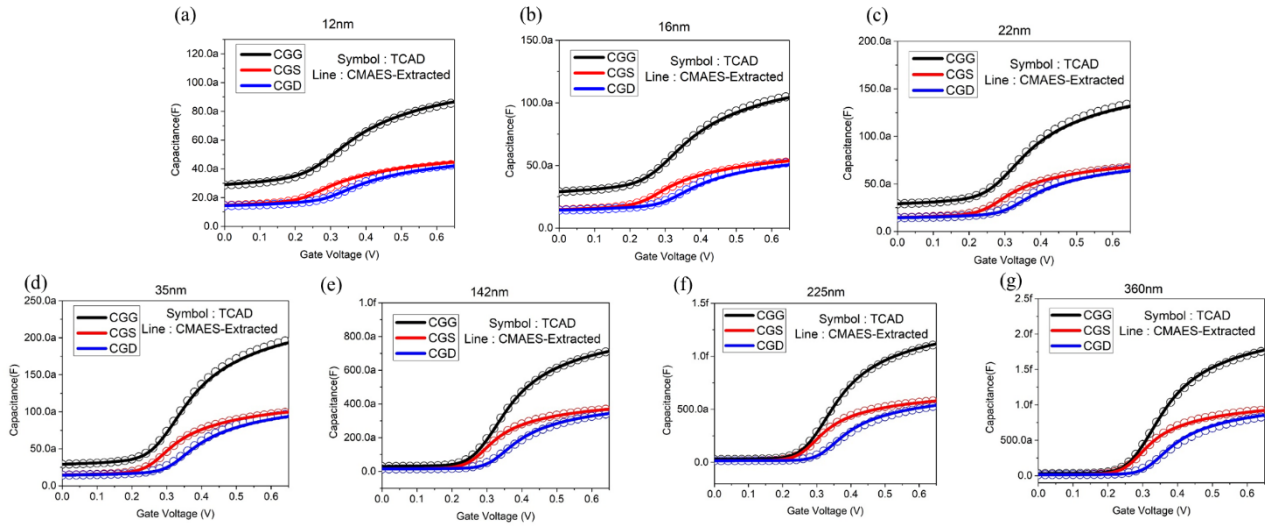


Fig. 7. Fitting result in TCAD C-V ($V_D=0.05V$) with seven various gate lengths.
(a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

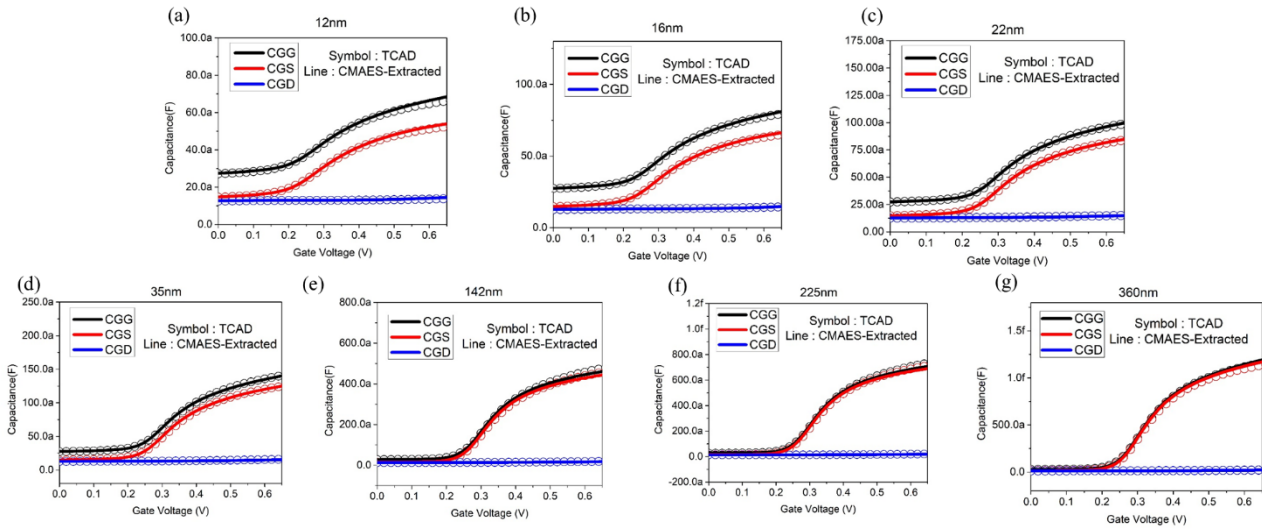


Fig. 8. Fitting result in TCAD C-V ($V_D=0.60V$) with seven various gate lengths.
(a)12nm (b)16nm (c)22nm (d)35nm (e)142nm (f)225nm and (g)360nm

Finally, Fig. 7 and Fig. 8 show good C-V fitting for the same seven devices with low and high drain biases ($V_{DS} = 0.05$ and $0.6V$). This algorithm can also evolve the default C-V parameter values toward more optimal values with a root mean square percentage error of 2.95%. Therefore, the CMAES-based parameter extraction methodology is demonstrated to achieve accuracy comparable to manual parameter extraction, while not heavily relying on human expertise.

IV. CONCLUSION

In this work, a CMA-ES-based compact model parameter extraction methodology is proposed. It successfully evolves parameter values over a broad range from their default values to more optimal ones, enabling the BSIM-CMG model to fit the target data. The level of fitting accuracy is comparable to that achieved by manual parameter extraction. This work demonstrates the strong potential of automatic parameter extraction without heavily requiring human effort and expertise.

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