Modeling of Subthreshold Characteristics for Double Gate MOSFET using Neural Networks and Genetic Algorithm

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As the metal-oxide-semiconductor field-effect transistor (MOSFET) technology has been developed, the short-channel effects become significant. To overcome these limitations, double gate (DG) MOSFET has been considered and predicting the device characteristics according to device parameters has been important. In this paper, we present the neural networks (NNET) modeling methodology to predict subthreshold characteristics such as threshold voltage ($V_{TH}$) and subthreshold swing ($S_{SUB}$) for DG MOSFET. After the NNET model is established, the genetic algorithm (GA) is used to find the device parameters’ design space.

Introduction

To overcome the growing portion of the short-channel effects such as threshold voltage ($V_{TH}$) roll-off and subthreshold swing ($S_{SUB}$) degradation, a double gate (DG) metal-oxide-semiconductor field-effect transistor (MOSFET) has been considered (1). It is important to predict subthreshold characteristics such $V_{TH}$ and $S_{SUB}$ values according to device parameters for studying the scaling capability of the device. The neural networks (NNET) modeling is an efficient method to predict nonlinear characteristics with the limited data (2). In this paper, we propose the NNET methodology for modeling the characteristics of $V_{TH}$ and $S_{SUB}$ with respect to device parameters. In order to show the NNET advantage on modeling the nonlinear characteristics, we also compare the NNET model with the full quadratic regression model. After the NNET model is established, the genetic algorithm (GA) is used to explore the optimum device design parameters (3).

Modeling Scheme

The target data used in the NNET and full quadratic regression model are performed by a commercial 2-D ATLAS device simulation produced by Silvaco, Inc (4). The schematic structure of the DG MOSFET used in numerical simulation is shown in Figure 1, where $L$ is the channel length, $t_{si}$ is the silicon film thickness, $t_{ox}$ is the gate oxide thickness and $N_A$ is the channel doping concentration.
Figure 1. Schematic structure of DG MOSFET used in numerical simulation.

NNET generally consists of an input layer, hidden layer and output layer where each layer is linked with neurons. Each link has a weight and bias which are modified during the modeling process to minimize the total error of the network. Figure 2 shows a typical structure of NNET with one hidden layer. In this work, NNET structures with 2 hidden layers are used to model the subthreshold characteristics of the DG MOSFET.

In order to compare with the NNET model, the full quadratic regression model has the following form:

$$y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{j=i+1}^{n} \sum_{i=1}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} b_{i} x_i^2$$

[1]

where $y$ is the response variable, $n$ is the number of input parameters, $b$ is the model coefficient, and $x$ is the input parameter value. In order to build the NNET model and regression model, drain voltage ($V_{DS}$), $L$, $t_{si}$, $t_{ox}$ and $N_A$ are selected as input variables while $V_{TH}$ and $S_{SUB}$ are selected as output variables. The data are selected randomly to statistically avoid irrelevant factors that affect characteristics of the DG MOSFET. The minimum and maximum data ranges for the input variables are summarized in Table I.
Before processing the modeling, the input and output variables are normalized in the range of -1 to 1.

TABLE I. Summary of the minimum and maximum data ranges for input variables.

<table>
<thead>
<tr>
<th>Input variables</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{DS}$ (V)</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>$L$ (nm)</td>
<td>20</td>
<td>40</td>
</tr>
<tr>
<td>$t_{si}$ (nm)</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>$t_{ox}$ (nm)</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>$N_A$ (cm$^{-3}$)</td>
<td>$10^{15}$</td>
<td>$10^{18}$</td>
</tr>
</tbody>
</table>

GA, which is one of the global searching methods, is used after the NNET model is established. GA can effectively find the optimum condition having the specified target response value (3). GA operates in simple four stages which are creation of a population of strings, evaluation of each string, selection of string using the fitness value, and creation of new population of strings by genetic manipulation (3).

Results and Discussion

In order to obtain appropriate NNet structures, different NNet structures are tested with varying the number of hidden layer’s neurons. The NNET structures with 5-5-14-1 (5 neurons in the input layer, 5 neurons in the first hidden layer, 14 neurons in the second layer and 1 neuron in the output layer) and 5-17-17-1 are selected for modeling the $V_{TH}$ and $S_{SUB}$ values, respectively.

Figure 3 (a) and (b) show the NNET and regression modeling results for $V_{TH}$ and $S_{SUB}$ values, respectively. In order to verify the fitness of NNET and regression models, R-squared ($R^2$) values are calculated. The $R^2$ values for the NNET model are closer to 100 % than the regression model. The inset graph shows difference between the modeled and target values for $S_{SUB}$. As can be seen from Figure 3, the error in the NNET model is less than the regression model indicating that the NNET model has a better performance than the regression model.

![Figure 3](image-url)

Figure 3. Comparison of the NNET model and regression model with respect to the target values for (a) $V_{TH}$ and (b) $S_{SUB}$. The inset graphs show the difference between the modeled and the target values.
From the NNET model, GA is used to predict the scaling capability of the DG MOSFET getting the specified $V_{TH}$ and $S_{SUB}$ target values. Figure 4 (a) and (b) show the design space acquired from the GA for $V_{TH}=0.35$ V and $S_{SUB}=90$ mV/decade, respectively. $V_{DS}$ is fixed to 0.3 V while $N_A$ is fixed to $10^{15}$ cm$^{-3}$. The cross mark ('+') and circle mark ('o') represent the GA result and the device simulation result having the similar target values for comparison, respectively. Figure 4 also shows the X-Y projection data for the GA result. As can be seen from Figure 4, it is shown that the device simulation result is mostly included to the design space acquired from the GA. From Figure 4, it is shown that each design space has an overlap region that we can produce a DG MOSFET having the subthreshold characteristics such as $V_{TH}=0.35$ V and $S_{SUB}=90$ mV/decade.

![Figure 4](image1.png) Figure 4. The design space acquired from the GA for (a) $V_{TH}=0.35$ V and (b) $S_{SUB}=90$ mV/decade.

Figure 5 (a) and (b) show the design space acquired from the GA for $V_{TH}=0.19$ V and $S_{SUB}=65$ mV/decade, respectively. $V_{DS}$ is fixed to 0.3 V while $N_A$ is fixed to $10^{15}$ cm$^{-3}$. The cross mark ('+') and circle mark ('o') represent the GA result and device simulation result having the similar target values for comparison, respectively. For example, as can be seen from Figure 5, each design space has no overlap region which means that we cannot produce a DG MOSFET both having the $V_{TH}=0.19$ V and $S_{SUB}=65$ mV/decade.

![Figure 5](image2.png) Figure 5. The design space acquired from the GA for (a) $V_{TH}=0.19$ V and (b) $S_{SUB}=65$ mV/decade.
Conclusion

In this paper, we performed the modeling of subthreshold characteristics for a DG MOSFET such as $V_{TH}$ and $S_{SUB}$ via the NNET and full quadratic regression model. The device parameters such as $V_{DS}$, $L$, $t_{si}$, $t_{ox}$ and $N_A$ were selected as input variables. It was shown that the NNET model had better performance than the regression model for characterizing DG MOSFET characteristics. Based on the NNET model, GA was applied to predict the scaling capability of the DG MOSFET. It was shown that the GA could be used to determine the DG MOSFET design space.

Acknowledgments

This work was supported by the IT R&D program of MKE/KEIT [10039174, Technology Development of 22 nm level Foundry Devices and PDK].

References