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Modeling the Effect of Temperature on the Nanotube Field Effect Transistors Using Neural Network

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Abstract

In this article, we modelled and simulated Carbon Nanotube Field Effect Transistors (CNTFET); this transistor has a carbon nanotube channel. *An Artificial Neural Networks (ANN) model was developed to reproduce accurately the behavior of CNTFET to predict its response for a wide range of temperature and voltage with focusing on the experimental data. The neural model is tested and validated; hence the ANN model is able to predict the CNTFET behavior with good accuracy. Finally, the proposed ANN model is integrated as a component in the library of simulation software of PSPICE electronic components.*

Keywords*: Carbon Nanotube Field Effect Transistors (CNTFET), modeling, thermal effect, Artificial Neural Networks (ANN), PSPICE, Analog Behavioral Modeling (ABM)*

1. Introduction

The MOSFETs (Metal Oxide Semiconductor Field Effect Transistor) components had large applications over the last decade. Due to the effects of short channel during the process of miniaturization; scientists were forced to seek different models for the field-effect transistor, so that these shall become free from these drawbacks. Among these models, we may mention the Carbon Nanotube (CNT) model. The field-effect transistor, having the active region as carbon nanotube has better performance than the ordinary MOSFET [1].

The short channel effects in the MOSFET, appearing during miniaturization, are reduced or very weak in the Carbon Nanotube of Field Effect transistor (CNTFETs). Thus, we can go further with the miniaturization of the device, so that the density of the integrated circuit can be increased [2].

A CNTFET is an FET that has, instead of silicon as a channel material in the traditional structure of the MOSFET, a single or set of CNTs. The CNT has a significant importance in applications of electronic components; its faculties make it as a promising material [3]. Its nano structural size has many interesting and often unexpected faculties, therefore there are plenty of opportunities for their use in nanotechnology.

We have considered in this paper, particularly for the Conventional CNTFET denoted as C-CNTFET, with highly doped source and drain contacts; these devices show better performances in terms of current report "on-off" and sub threshold slope [4-5]. Figure 1 shows a 2D representation of C-CNTFET which the conduction behavior is similar to an ordinary MOSFET one [6].

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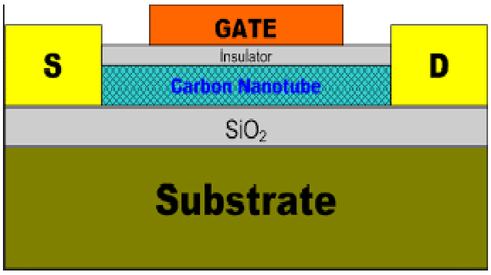

Figure 1. 2D Representation of C- CNTFET

The carbon nanotube requires a large investment before it can reach the desirable quality for the production of components. Prior to such an investment, it is necessary to address an extensive_study on electronic properties of the material. In order to consider the effect of temperature on the I-V characteristics of CNTFET, we propose a thermal model of CNTFET using neural network approach.

The main objective of this study is to model a C-CNTFET by means of neural network; this model predicts the I-V characteristics of CNTFET for different temperatures, based on results got by [3]; the ANN model is implemented as a component in a PSPICE electric simulator library, this component reproduces faithfully the C- CNTFET behavior.

2. Artificial Neural Networks (ANN)

The artificial neural network is a means of calculation that attempts to simulate the structure and functionality of the biological neuron networks [7-8].It is a powerful data modelling tool, which can capture and represent complex relationships of input / output through some internal calculations. The most common model of the neural network is the Multilayer Perceptron (MLP) [9], as show in Figure2.

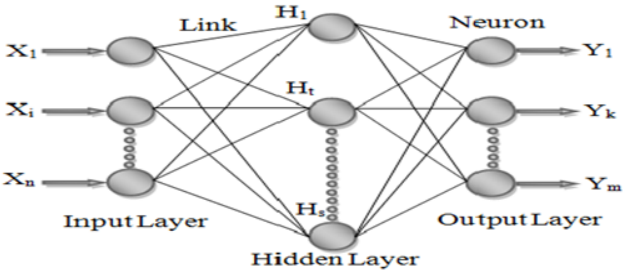

Figure 2. MLP Structure

Each link has a weight parameter corresponding thereto; each neuron is composed of a set of inputs and an activation function.

The architecture of the network consists of an input layer (X), an output layer (Y) and one or more hidden layers (H). MLP is a model that maps a set of input data on an appropriate set of outputs; a simplified overview of the proposed ANN model is shown in Figure 3.

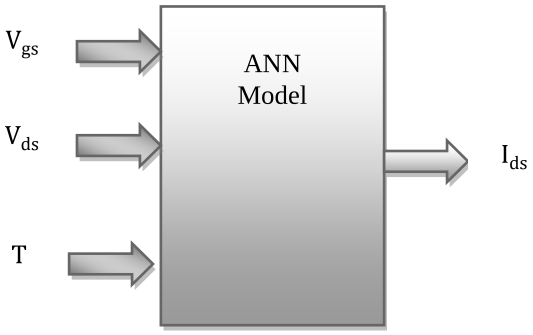

Figure 3. Simplified Overview of ANN Model

Equation 1 shows the algorithm generally used to compute the output of an artificial neuron. The output of each neuron f depends on the activation value that is the weighted sum of the inputs [10], where w_i is the weight-related input x_i and f is the activation function.

$$f(x)= \left(\sum (x_i * w_i) \right) \tag{1}$$

The MLP are trained with the standard back-propagation algorithm, which compares the output provided with the aimed output, wherein the mean square error is calculated. If the mean square error is more than a prescribed threshold value, it is backward propagated of the output to the input, and the weight will still be changed until the error, or number of iterations is in a prescribed limit.

Training a network is a process where all of adjusted parameters, weights and biases, are optimized to make the best prediction of the target variable on the basis of background variables.

To compare the results of the proposed ANN model with experimental results, we use the measure of relative error (RE) expressed as a percentage and defined by the following relationship [11], where $\mathrm{I_{pred}}$ is the predicted drain current based on ANN, $\mathrm{I_{exp}}$ shows the experimental current.

$$\mathrm{RE\%} = \frac{\mathrm{I_{exp}} - \mathrm{I_{pred}}}{\mathrm{I_{exp}}} \times 100 \tag{2}$$

The Middle Relative Error (MRE) is given by [12], where N is the number of data (database size).

$$\mathrm{MRE}=\frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{RE}|_{\mathrm{i}} \tag{3}$$

MLP networks are trained with the standard back-propagation algorithm by attempting to minimize the error.

3. C-CNTFET Modeling using Neural Networks

The output of the network is the drain current $\mathrm{I_{ds}}$, the training data consists of the set of representative points got from the experimental measurements [13] is show in Figure 4.

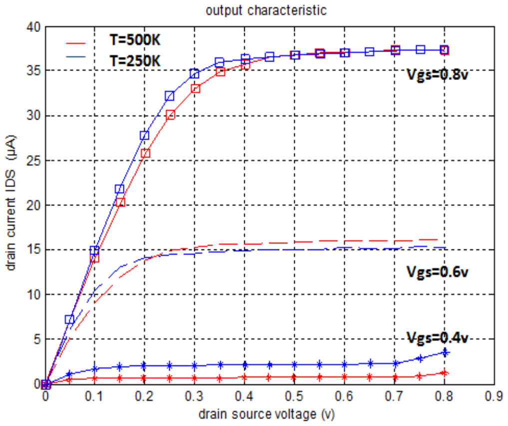

Figure 4. Experimental Output characteristic I_{ds} According to V_{ds} for Different V_{gs} and Temperature T values [13]

After choosing the type of network, we shall have to_find an optimal architecture of neural network (the number of hidden layers, the number of neurons in each layer and the activation function for each layer).

Learning and optimization of previous network is accomplished through a structured program in MATLAB, Figure 5 shows the flowchart of the steps followed

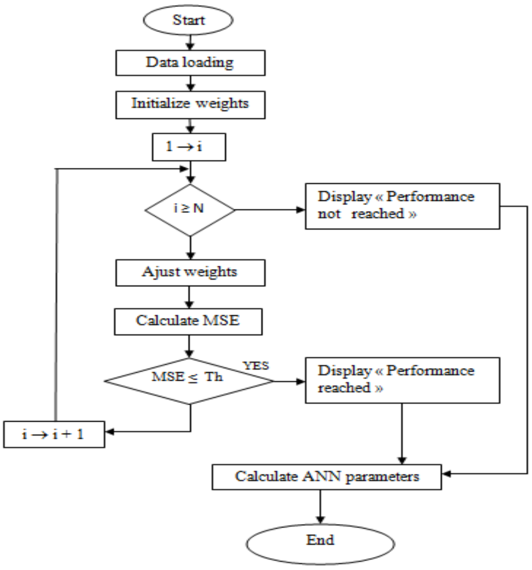

Figure 5. Flowchart Training and Optimization

The optimized network parameters for modeling the C-CNTFET are summarized in Table 3.

Table 3. Optimized Parameters of the Neural Networks Model

<table>
<tr><td rowspan="3">Database</td><td colspan="2">Training base</td><td colspan="2">380</td></tr>
<tr><td colspan="2">Test base</td><td colspan="2">190</td></tr>
<tr><td colspan="2">Validation base</td><td colspan="2">190</td></tr>
<tr><td rowspan="4">Number of Neurons</td><td colspan="2">Input layer</td><td colspan="2">3</td></tr>
<tr><td colspan="2">1st hidden layer</td><td colspan="2">5</td></tr>
<tr><td colspan="2">2nd hidden layer</td><td colspan="2">4</td></tr>
<tr><td colspan="2">Output layer</td><td colspan="2">1</td></tr>
<tr><td rowspan="3">Transfer function</td><td colspan="2">1st hidden layer</td><td colspan="2">Logsig</td></tr>
<tr><td colspan="2">2nd hidden layer</td><td colspan="2">Logsig</td></tr>
<tr><td colspan="2">Output layer</td><td colspan="2">linear</td></tr>
<tr><td rowspan="3">Input</td><td colspan="2">T(℃)</td><td>V_{ds}(V)</td><td>V_{gs}(v)</td></tr>
<tr><td>Max</td><td>500k</td><td>0.9</td><td>0.8</td></tr>
<tr><td>Min</td><td>250k</td><td>0</td><td>0.4</td></tr>
<tr><td rowspan="3">Output</td><td colspan="4">I_{ds} (μA)</td></tr>
<tr><td>Max</td><td colspan="3">38</td></tr>
<tr><td>Min</td><td colspan="3">0.7</td></tr>
<tr><td>Test MSE</td><td colspan="4">6.6158 10^{-5}</td></tr>
<tr><td>Training MSE</td><td colspan="4">10^{-5}</td></tr>
</table>

According to Figure 6, there is a good accuracy of the correlation factor (CF= 0.997) between the ANN outputs (I_{pred}: predicted) and corresponding targets (I_{exp}: experimental).

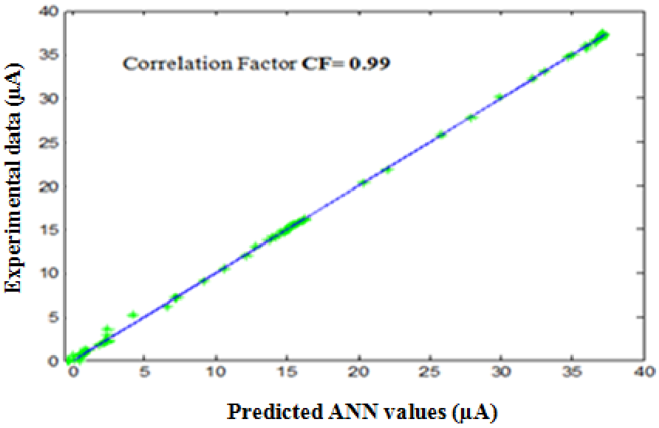

Figure 6. Comparison of the Experimental Data and Predicted (ANN) Results for Training Data

Figure 7 shows the output current I_{ds} of CNTFET depending on the voltages V_{gs} and V_{ds} at different temperatures (250K and 500K). The gate and the drain voltages are chosen so that we may make a comparison between the experimental results published in [13] and our simulations.

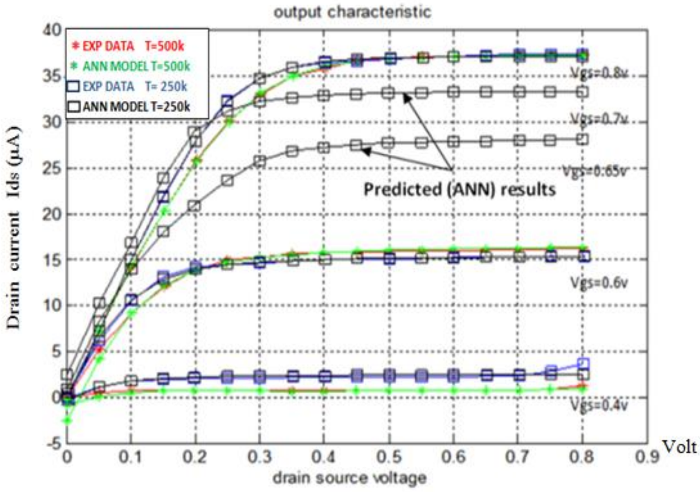

Figure 7. Output Characteristics of ANN Model and Experimental Data

The Simulations show consistency and relatively good compatibility, particularly for high gate voltages (V_{gs}). In addition to that our neuronal model has the potential to predict the behavior of CNTFET when it is subjected to new conditions, with no need to resort to experimental; the values of V_{gs} must be in the interval $[{V_{gs}}_{min}, {V_{gs}}_{max}]$ which is illustrated in the Table 1 (V_{gs} = 0.65 volts, V_{gs} = 0.7 volts).

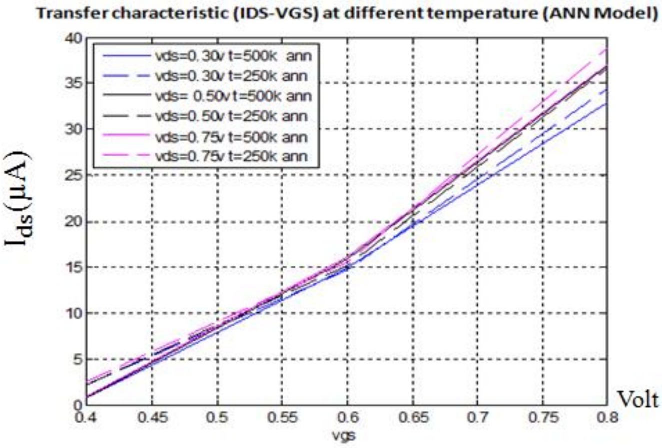

Figure 8. Transfer Characteristic of ANN Model for Different Temperature and Different V_{ds}

Figure 8 shows the transfer characteristics of the C-CNTFET ANN model for various values of voltage V_{ds} and temperature. We observed that the transfer characteristic of ANN model for different temperature and different V_{ds} has a nearly linear shape.

3.1. Implementation of the Model ANN on PSPICE

To validate our proposed neural model, we implemented it in the library of the PSPICE simulator. The results got from of the optimal architecture of the ANN, like bias and weight, are used for the implementation of a model that will be used as a component in the library of PSPICE.

The use of ABM (Analog Behavioral Modeling) boxes from the PSPICE library helps to implant the ANN model in this simulator. Figure 9 shows the ABM architecture, our model has 13 ABM boxes, each neuron ANN is replaced by an ABM box that characterizes this neuron.

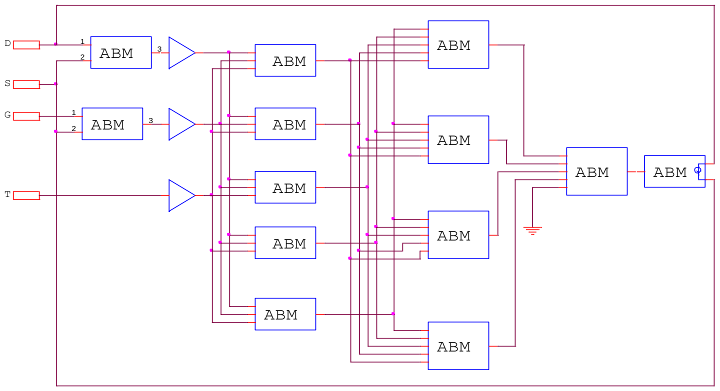

Figure 9. ABM Architecture of the Established Model in PSPICE

In Order to got the I_{ds} output characteristics according to V_{ds} (output characteristic) for different values of V_{gs} voltage and temperature, the PSPICE software allowed us to draw the following curves; we just need to apply the appropriate values of V_{ds}, V_{gs} and T to our circuit inputs Figure 10.

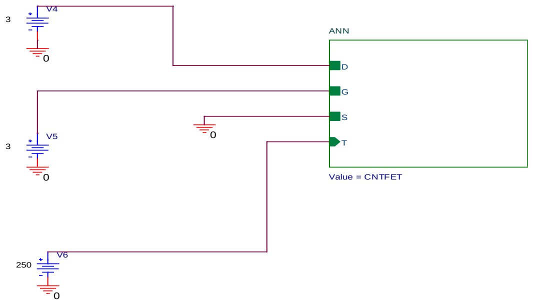

Figure 10. Simulation Circuit of the Transistor CNTFETs

By a DC-SWEEP analysis, for temperatures T = 250K and T = 500K, while varying the V_{ds} voltage of 0 volt to 1 volt with a step of 0.1 volt, and for V_{gs} which takes the values 0.4 volt, 0.6 volt and 0.8 volt, we get the curves plotted in Figure 11. It is observed that there is a good harmony between the result got through the experimental and that got through the PSPICE simulator.

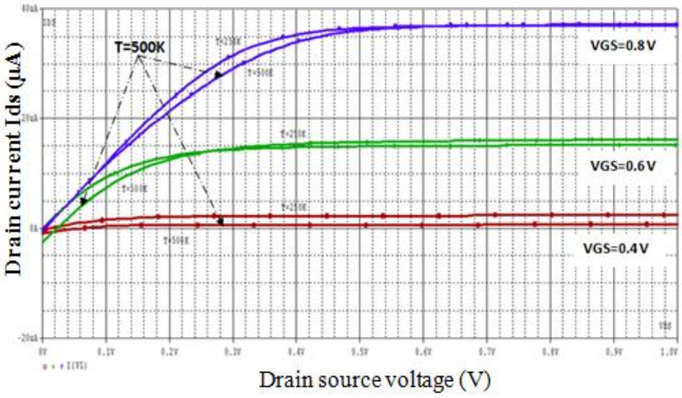

Figure 11. Current–Voltage Characteristics (I_{ds} , V_{ds}) from the ANN-Pspice Model (T=500K, T=250K)

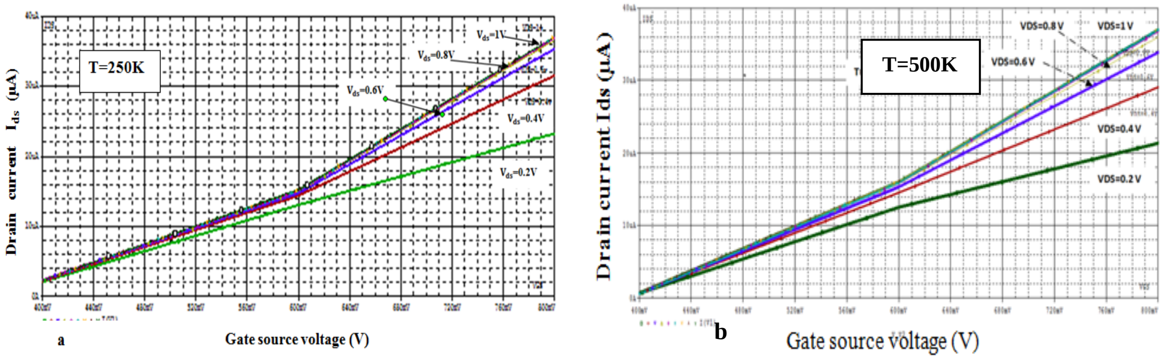

Figure 12. Transfer Characteristics (I_{ds} –V_{gs}) with ANN-Pspice Simulations

By analogy with first test made to get the characteristic of the transfer, and by a DC-SWEEP analysis for temperatures T = 250 K and T = 500 K, while varying the V_{gs} voltage from 0.4 volt to 0.8 volt, and for V_{ds} ranging from 0.2 volts to 0.8 volts, with a step of 0.2 volt, we derive the curves plotted in Figures 12-a and 12-b.

In order to demonstrate the effectiveness of our neural model, we propose the study and simulation of a ring oscillator and a nano-inverter circuit; the latter is regarded as the most important block in the design of VLSI (Very Large Scale Integration) digital circuits.

3.2. PSPICE Input / Output Signals of the ANN Model of Inverter

In order to obtain the PSPICE input / output signals of our neural inverter, we use the scheme presented in Figure 13.

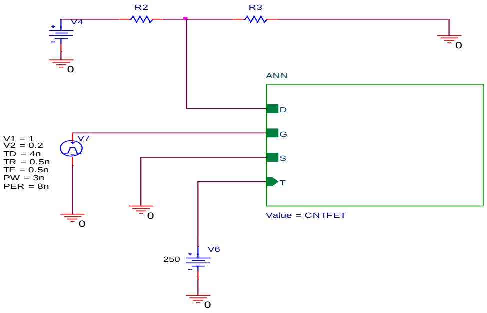

Figure 13. Neural Model of the Inverter Circuit

The input and output signals of our inverter based on the proposed neural model are represented in the Figures14 where V_{ds} = 5 Volt and T = 250 K, it can be remarked that the operation of the inversion has been well performed.

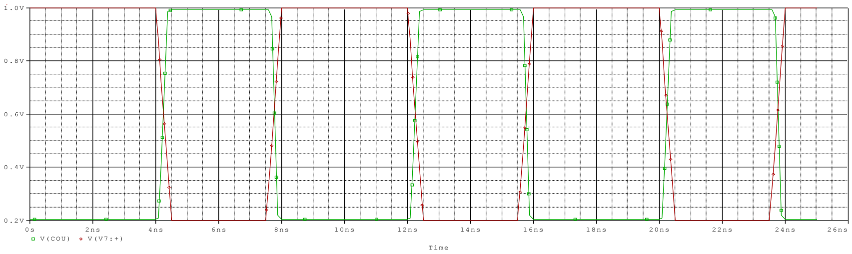

Figure 14. Response of Inverter T = 250K

3.3. PSPICE Input and Output Signals of the Ring Oscillator ANN Model

The ring oscillator is made up of several inverters in series. The inverter is formed by a neural block, as shown in Figure 13. The output of the last inverter feeds the input of the first inverter; that allows the circuit to oscillate, as shown with PSPICE simulation in Figure 15.

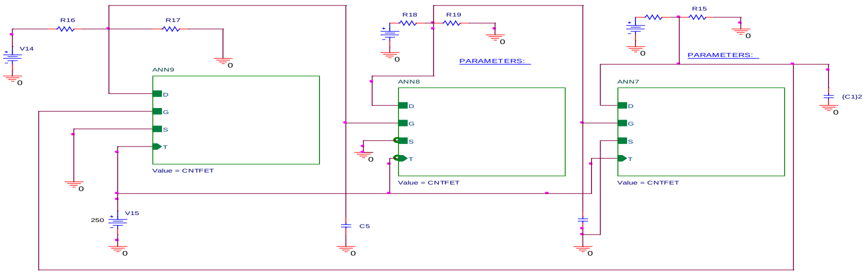

Figure 15.The Ring Oscillator by CNTFET ANN Model

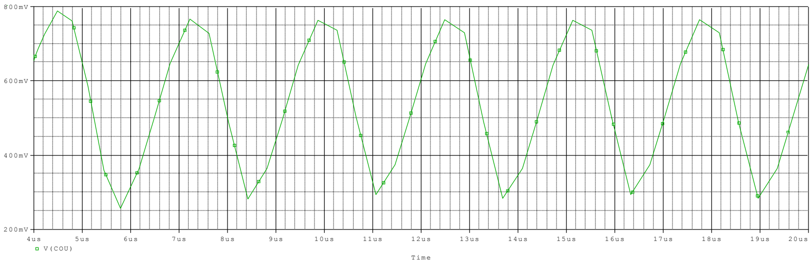

Figure 16.The Response of the Ring Oscillator Based ANN CNTFET Model

Figure 16 show the output signal of the ring oscillator based on the neural model, we observed a well-functioning of the proposed ring oscillator.

4. Conclusion

In this paper we modeled the CNTFET using artificial neural networks, the neural model is tested and validated, and this model reproduces faithfully the behavior of CNTFETs taking into consideration the effect of temperature,

In addition, the ANN model is able to predict the behavior of CNTFET in previously unknown circumstances.

The results (optimal architecture, bias, and weights of the network) were then exploited in the implementation of the model as a component in the PSPICE simulator library. The component has reproduce faithfully the CNTFET behavior

The simulations carried out in PSPICE based on the ANN model were presented as inverter and oscillator rings.

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