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Efficient Parameters Selection for CNTFET Modelling Using Artificial Neural Networks

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Abstract
In this article different types of artificial neural networks (ANN) were used for CNTFET (carbon nanotube transistors) simulation. CNTFET is one of the most likely alternatives to silicon transistors due to its excellent electronic properties. In determining the accurate output drain current of CNTFET, time lapsed and accuracy of different simulation methods were compared. The training data for ANNs were obtained by numerical ballistic FETToy model which is not directly applicable in circuit simulators like HSPICE. The ANN models were simulated in MATLAB R2010a software. In order to achieve more effective and consistent features, the UTA method was used and the overall performance of the models was tested in MATLAB. Finally the fast and accurate structure was introduced as a sub circuit for implementation in HSPICE simulator and then the implemented model was used to simulate a current source and an inverter circuit. Results indicate that the proposed ANN model is suitable for nanoscale circuits to be used in simulators like HSPICE.

Keywords: Artificial intelligence networks, CNTFET modelling, Fettoy, Fuzzy system, HSPICE.

1. Introduction

With respect to the Nano scale devices, most of them can be used in circuits. Due to the limitations such as short channel effects, quantum effects and reduction of gate control on channel, performance of Nano scale silicone MOSFET transistors will be declined [1]. Since the discovery of CNTs in 1991, due to the suitable electrical and mechanical properties of carbon nanotubes, they were used in Nano electronic devices and they can be a good replacement for silicon base devices [2]. Because of high current carrying capacity and low charge carrying scattering of CNTs, CNTFETs are proper replacement for silicon transistors and will have found many practical applications in electronic industry in the near future [1].

In addition to time-consuming numerical analytical methods such as NEGF (non-equilibrium green's function) which is used to solve the Schrödinger equations and finding the surface charge and the density of states [3], or a simulation which is based on numerical piece-wise non-linear approximation of the non-equilibrium mobile charge density for CNTFETs [4], recently some new ways have been used to speed up the simulation in integrated circuits. Simulation with artificial intelligent networks is one of the powerful simulation methods. For Nano scale devices, because of some constraints and quantum mechanical effects, the calculation of analytical equations are complex and time consuming. Since the computation time in large- scale circuits such as VLSI must be done effectively, a model with fast calculations is really needed. The artificial neural network (ANN) model can be replaced with the Nano devices in simulators such as ADS, Hspice and Cadence. In previous studies, nanotransistors such as Double Gate FinFets, DG- MOSFETs, Nanoscale MOSFETs. CNT- MOSFETs were simulated by various intelligent neural networks such as MLP (Multi-Layer Perceptron), RBF and Neuro-fuzzy [1], [5], [6], [7].

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In [1] an MLP network with two hidden layers (9, 8 hidden neurons) was used to simulate the CNTFET drain current with mean relative error (MRE) of 1.09, after 1000 epochs. Train and test data were obtained by moscnt.1.0 model. To simulate the output drain current in DGMOSFET in [6] with RBF network, the residual error was 0.008. A Neuro-fuzzy structure with 15 neurons was used in drain current simulation of nano scale MOSFET and 1.2705 mean square error (MSE) was obtained [7].

CNTFET transistor doesn't have the nanoscale silicon transistors limitations and many researchers have been studied to find the suitable model for its simulation. Ballistic effects are only included in some models such as FETToy. Of course this model is not applicable in circuit simulators like HSPICE, so we need a model for elimination of time consuming steps such as charge calculation process and the analytical solution for Fermi Dirac integral [8].

In this paper we examine the simulation of CNTFET transistor by MLP and neuro-fuzzy networks. To obtain the training data, the CNTFETToy model in Matlab R2010a is used. CNTFETToy, is a product of Nanohub and Purdue University. Optimized geometry of CNTFET consisting of a single carbon nanotube semiconducting channel, completely surrounded by the gate oxide, and perfectly contacted ends is taken into consideration in this model (Fig.1) [9].

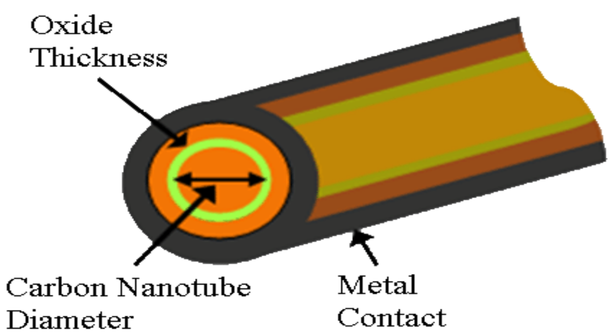

Fig.1. Optimized geometry assumed for CNTFETToy.

The basic parameters for CNTFETs will depend on three groups including device, environment and model. The device parameters are the diameter of the nanotube, the gate dielectric thickness and dielectric constant of the gate insulator. Parameters of the model are specific to the underlying physics and are the Fermi level of source, gate control parameter and drain control parameter. Environmental variables are temperature, voltage and values in the source/drain series resistance [10].

In next section, MLP and Neuro-fuzzy networks are introduced for modelling the device. Then feature selection method is described. Finally, we show that the proposed ANN model is applicable to run in simulators such as HSPICE and it can be used in nanoscale circuits.

2. Neural Networks Calculation

In this section, we will use an Artificial Neural Network (ANN) to simulate CNTFET. Seven CNTFETToy parameters and two voltages (vgs, vds) are considered as inputs and Ids current as single-output for the network. The sufficient data for training of the network are selected using CNTFETToy environment. CNTFETToy's seven parameters are shown in Table 1.

Table.1.
Seven CNTFETToy's input parameters.

parameter	Explanation
D	Nanotube diameter, nm
TOX	Oxide thickness, nm
T	Temperature
K	Dielectric constant, k
Ef	Source Fermi level
Gα, alphag	Gate control parameter
Dα, alphad	Drain control parameter

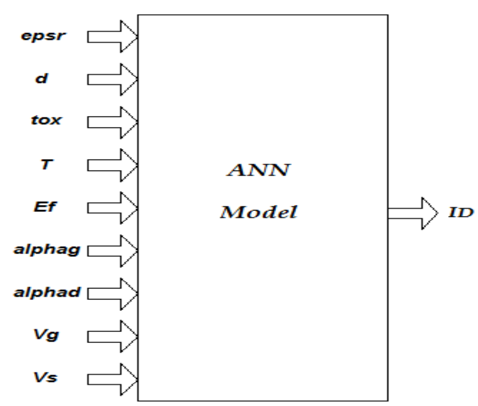

Fig.2. Simulation of CNTFET by ANN model.

Artificial intelligent networks (AINs) can be used in the form of a block in circuit simulators for a device and sub-circuits as shown in Fig.2.

2.1. Multilayer Perceptron (MLP)

MLP networks are composed of layers of neurons that each one has an activation function and they are connected through weight coefficients. By employing an algorithm such as back propagation, training errors are reduced. One of the most common activation functions is hyperbolic tangent [11].

$$\varphi(x) = a \tanh bx = a\left(\frac{1-e^{(-2bx)}}{1+e^{(-2bx)}}\right) \quad (1)$$

In MLP networks, several examples should repeatedly be presented to the network, the network must be trained to identify the desired output (2) by modifying the weight coefficients using back propagation algorithm through minimizing local gradient of errors ($\frac{\partial Eav}{\partial Wji}$). Mean square error is recalled in (4) and should be minimized. Wji is the weight and m is the number of inputs applied to neuron j.

$$Yj = \varphi j(\sum_{i=1}^{m} Wji.Yi) \quad (2)$$

$$E = \frac{1}{2}\sum_j (Dj - Yj)^2 \quad (3)$$

The number of training samples is N.

$$E_{ave} = \sum_{k=1}^{N} E_k \quad (4)$$

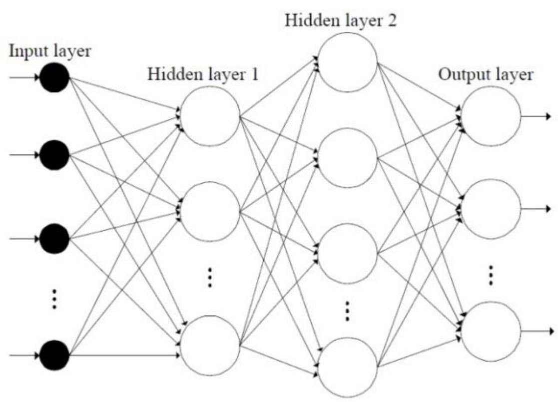

Fig.3. Schematic diagram of MLP structure.

Yj and *Dj* are MLP network's output and the desired output respectively. The MLP neural network structure to simulation is shown in Fig.3.

2.2. Neuro-Fuzzy Network

Neuro-fuzzy networks consist of two parts of neural network system and fuzzy logic system. Data can be logged into system as fuzzy sets. To obtain the optimal values of the free parameters which presented in the fuzzy if-then rules and also the desired output, the neural network is used. Parameters are modified during learning process by gradient descent algorithm. For this work, the center average method and Gaussian is used for defuzzifier and membership function respectively. The system's output is obtained as follows (5):

$$f(out) = \frac{\sum_{L=1}^{M} Wl \prod_{i=1}^{N} exp\left(-\left(\frac{ini-ti}{si}\right)^2\right)}{\sum_{L=1}^{M} \prod_{i=1}^{N} exp\left(-\left(\frac{ini-ti}{si}\right)^2\right)} \quad (5)$$

In above relation, *t* and *s* are free parameters for center and width of the *if* part in fuzzy rules and *w* is the free parameter for center in *then* part of the rule. *N* is the number of training features and m is the number of neurons.

2.3. UTA Method for Feature Selection

Feature selection methods are used for the validation of network's features. Feature selection can be used either before training or after that. For this purpose, there are several ways. In this work UTA method [12] which is done after training is used to obtain the importance effect of CNTFET features. In the UTA method, instead of each feature the constant average value of that feature in all samples is replaced and MSE error is re-measured each time and the results impact on network features are determined. If a feature is constant in all samples it cannot be effective in identifying classes. Therefore the MSE error occurs in three forms.

a) If the new MSE compared with the original MSE unchanged, we can conclude that the feature is not effective and the network will not depend on it.

b) If the new obtained MSE is greater than the original MSE, it indicates that the feature is effective.

c) If the obtained MSE is less than the original MSE the feature is not only ineffective but also can be damaging.

3. Implementation into HSPICE

The proposed ANN model can be implemented as a voltage-dependent current source depends on CNTFET input parameters in HSPICE simulator. By using the neural network weights and biases and simple equations, the complex and time consuming quantum equations can be simulated in HSPICE. We can state the output current obtained by ANN as a sub-circuit as follows:

.Subckt CNTFET nd ng ns

Ig ng ns 0

Gdrain nd ns cur="ANN equations of the proposed model"

.Ends CNTFET

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Which nd, ng and ns are drain, gate and source nodes respectively. Ig is the current between gate and source and gdrain is the voltage-dependent current source where the current Id is derived from the input parameters of CNTFET (d, epsr, tox, T, alphag, alphad, Ef, vgs and vds).

4. Results and Discussion

In order to get the ANN model, 12,500 data obtained by CNTFET model is used, half of them for training and the other half for testing. Seven CNTFETToy input parameters and voltages of vgs and vds are considered as input data and output current id as single output. The range of minimum and maximum values is shown in Table 2 [10].

Table.2.
Input data ranges used in ANN.

PARAMETERS	Min	Max
d، nm	0.4	15
tox، nm	1	30
K	1	40
Rs ،ohm-um	0	10000
T، Kelvin	100	450
EF	-0.01	-0.5
α_G	0.5	1
α_D	0.001	0.1

Trying different structures, the MLP network with two hidden layers (20, 10 neurons) with 0.1 learning rate was selected. Also, the back propagation algorithm and tangent hyperbolic activation function is used. For the Neuro-fuzzy network, from the other hand, a structure consisting about 20 neurons as fuzzy rule is selected. Comparison between these two networks is shown in Table3.

Table.3.
Comparison between MLP and neuro-fuzzy networks.

Net. Name	Layers	Max abs error (in e-6)	Min abs error (in e-10)	Train time	Test time	Test MSE (ine-5)
MLP	20-10	6.077	20.664	0.36609	0.1583	9.935
Neuro -fuzzy	20	7.53	1.937	0.26307	0.1574	6.133

By comparing the two structures, it seems the neuro-fuzzy structure for low computation is relatively fast and has somewhat lower error rate. According to the results, to obtain the substitutive building block, the neuro-fuzzy structure was implemented in HSPICE simulator. Figure 4 compares the (i-v) properties obtained from the numerical FETToy model, with the neuro-fuzzy output which has been implemented in HSPICE. According to figure 4, it can be concluded that, for all bias points the neuro-fuzzy proposed model is coordinate closely to numerical FETToy model.

The comparison between numerical FETToy model and proposed ANN model, for testing data is shown in Fig.5.

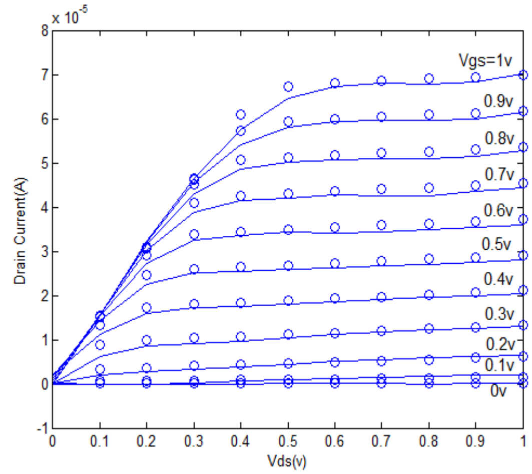

Fig.4. Current-voltage characteristics curve (Id-Vds) for CNTFET using CNTFETToy model (circle) and proposed ANN model (solid line).

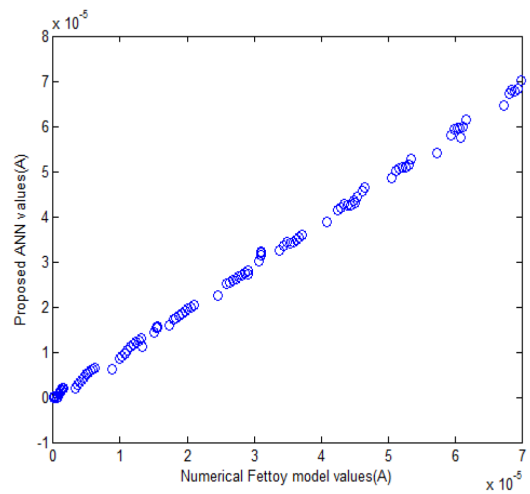

Fig.5. The testing results of proposed ANN model.

In Table 4, after performing feature selection with UTA method, test MSE for all CNTFET trained features of CNTFETToy model, are shown for MLP and neuro-fuzzy structures. Test MSE ratio for CNTFET features after feature selection for both structures are shown in Fig.6.

Table.4.
Test MSE after feature selection with UTA method.

network	MLP	Neuro-fuzzy
epsr	0.002	0.002
d	0.0017	0.0017
Tox(e-4)	3.56	4.89
T(e-4)	1.44	0.72
Ef	0.008	0.008
alphag	0.002	0.0023
Alphad(e-4)	2.2217	2.111
Vg	0.0237	0.0240
Vd	0.01	0.01

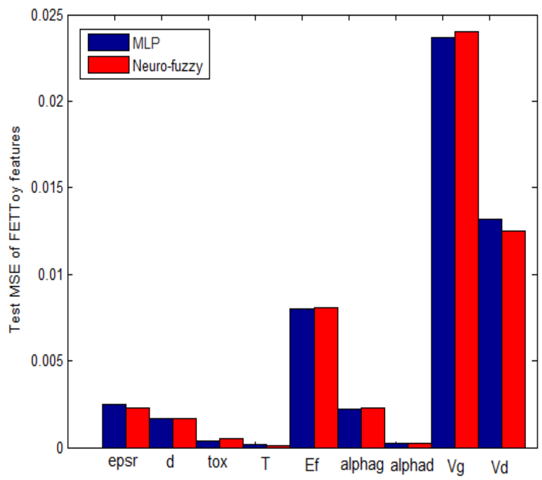

Fig.6. Test MSE ratio for CNTFET features.

By comparing the impact of various parameters on the output current, it can be seen that the input voltages has greatest effect and temperature parameter impact is minimum. Although nanotubes have good effects even at very high temperatures, but the effect of temperature on the performance of CNFET is more complex and unknown. In the survey, a large change based on temperature, in simulation results have not been seen and obviously, the impact of all sources influence on temperature has not been determined [10]. Some experimental devices at low temperatures have been reported [13], but we need to acquire devices which work near the room temperature.

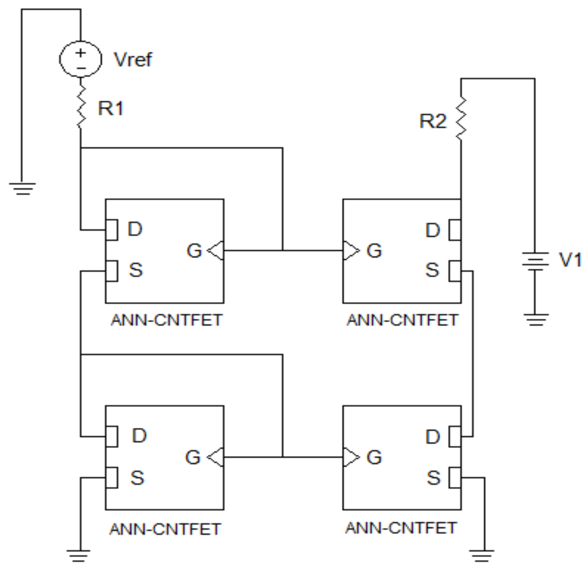

Fig.8. ANN CNTFET current source.

To validate our proposed ANN model, we have discussed CNTFET inverter and current source circuits. In figure 7 the input- output signals for CNTFET inverter with d=1.6e-9, tox=8e-9 and epsr=20 is shown. The proposed model can be also used in expanded circuits like current source (Fig. 8). In Fig. 9, the output current and the reference current, in the current source based on CNTFET circuit is shown.

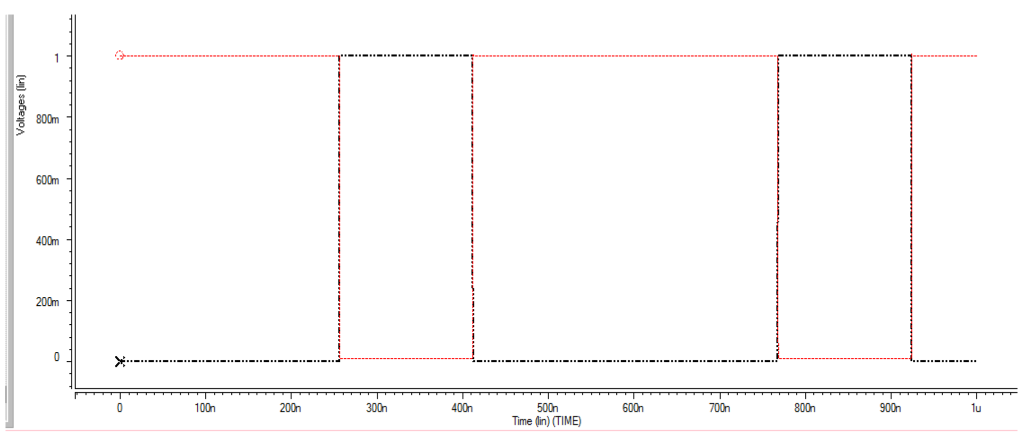

Fig.7. The input-output signals for ANN CNTFET inverter.

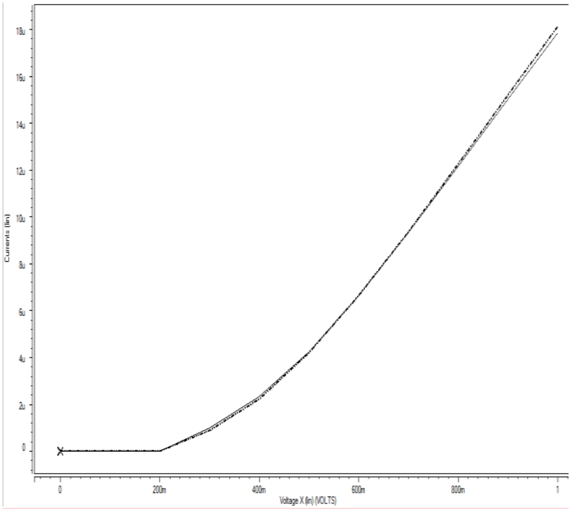

Fig.9. Output characteristic for ANN CNTFET current source (I-V) solid line for (Iref) and dashed line for (iout).

5. Conclusion

In this work, two types of neural networks were employed to simulate the CNTFET. With comparing the advantages and disadvantages of these two structures, the appropriate structure is selected to be implemented in HSPICE simulator. With respect to accuracy and simulation speed in proposed model against the numerical FETToy model, it can be concluded that the Neuro-fuzzy network model is suitable for modeling the CNTFET transistors. Comparing the results with those obtained in [1], the elapsed simulation time is 1.2 seconds for 100 samples in [1], whereas in this paper and for 6050 samples, the result takes the time of 0.15 seconds. Feature selection algorithm running with UTA method, we can see that the input voltages and temperature are the most effective and the least effective parameters respectively for determining the output current. Finally with using our proposed ANN model, we have discussed the analysis of nanoscale circuits which can be also extended in large scale circuits to save analysis time.

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