ISSN: 2277-3754
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 1, Issue 4, April 2012

Comparative Study of DG-MOSFET Modeling based on ANFIS and NEGF

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Abstract*-During the last decades the electronic technology has faced drastic changes mainly to reduce the circuit as small as possible and hence came the MOS technology which find many implementation ranging from industrial process control, consumer products to medical instrumentation, information system and decision analysis. Here we are using C-MOS technology in modeling of nanoscale circuit simulator which is chiefly based on ANFIS (Adaptive Neuro Fuzzy Inference System) which tunes the fuzzy inference system with the back propagation algorithm based on collection of input output data makes fuzzy system to learn. This basic need arises because as the conventional silicon metal-oxide semiconductor field effect transistor (MOSFET) approaches its scaling limit, quantum mechanical effects are expected to become more and more important. Accurate quantum transport simulators are required to explore the essential device physics as a design aid. However, because of the complexity of the analysis, it has been necessary to simulate the quantum mechanical model with high speed and accuracy. To overcome these loop holes Double Gate MOSFET is used as promising device to replace the conventional device. Having two gate structures ensures no part of channel is far away from the gate. This gives better control of the channel by the gate electrode. In addition, the voltage applied to gate terminal determines the current flowing through the channel. This ANFIS model reduces the computational time while keeping the accuracy of physics-based models, like Non Equilibrium Green's Function (NEGF) formalism. Finally, we import the ANFIS model into the circuit simulator software as a sub circuit. The result shows that the compact model based on ANFIS is an efficient tool for the simulation of nanoscale circuits.

Keywords: **Double Gate MOSFET, Adaptive Neuro Fuzzy Inference System, Non Equilibrium Green's Function, Nanoscale Circuit.**

I. INTRODUCTION

System Modeling based on conventional mathematical tools (e.g., differential equations) is not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno, has found numerous practical applications in control prediction and inference. However, there are some basic aspects of this approach which are in need of better understanding. More specifically:

1) No standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system.

2) There is a need for effective methods for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index.

The aim of this paper is to suggest a novel architecture called Adaptive-Network-based Fuzzy Inference System, or simply ANFIS, which can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. Section 1 introduces the basics of fuzzy inference system in framework of adaptive network, we obtain the ANFIS architecture, and we describe the structures and learning rules of adaptive network. In next two sections we defined the simulation of ANFIS and DG-MOSFET which is the backbone of this paper. Application example such as describe the implementation in modeling of DG-MOSFED using ANFIS modal and it is covered in next section. After this in next section we compare the result of ANFIS &non-equilibrium Green's function formalism (NEGF) simulation. In last section concludes this paper by giving important extensions and future direction of this work.

II. BACKGROUND

The concept of neural networks started in the late-1800s as an effort to describe how the human mind performed in the olden days. As years rolled by, these neural networks started playing a very important role in the various engineering applications. Also the main idea of fuzzy logic control (FLC) is to build a model of human control expert who is capable of controlling the plant without thinking in terms of a mathematical model. The conventional MOSFET when reaches its scaling limits it produces quantum effects but due to complexity accurate quantum transport simulators are required with high speed and accuracy. In this paper we used the Double Gate MOSFET based on adaptive neuro-fuzzy inference system. The ANFIS model reduces the computational time while keeping the accuracy of physics-based models, like non-equilibrium Green's function formalism. The results show that the compact model based on ANFIS is an efficient tool for the simulation of nanoscale circuits.

III. HARDWARE IMPLEMENTATION

Functionally the ANFIS architecture is the major training routine equivalent to Tkaki-Sugeno first order fuzzy inference systems (FIS). ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type FIS. It applies a combination of the least-squares method

ISSN: 2277-3754
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and the back propagation gradient descent method for training FIS membership function parameters, to emulate a given training data set. In other words to start ANFIS learning, first a training data set is required that contains desired input/output data pairs of the target system to be modeled. The ANFIS structure used to implement fuzzy controller with five layers is shown in Figure 1. It consists of two inputs, four membership functions for each input, sixteen fuzzy rules and one output. The ANFIS applies fuzzy inference techniques to data modeling. According to this structure, the shape of the membership functions depends on parameters, so changing these parameters will change the shape of the membership functions.

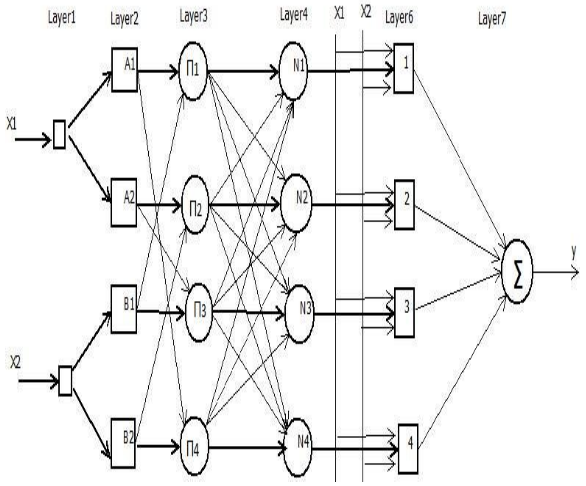

Fig. 1: ANFIS architecture of fuzzy controller model with two inputs, four membership function, 16 rules and one output in first order Sugeno type.

IV. DESCRIPTION OF THE LAYERS USED IN THIS MODEL

A. Layers 1, 2

According to the Figure 1, to create the layers 1 and 2, we proposed a new CMOS membership function generator which has differential pair structure with analog voltage crisp input and analog current outputs (Figure 2). This circuit is capable of making three types of Gaussian, Trapezoidal and Triangular shapes in comparison with before works. After ANFIS training and chose suitable shape and slopes membership. Functions, we can adapt our Fuzzifier circuit using voltage references and switch controllers to tune type and slope of shapes respectively.

1. Layer 1

Every node in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{Ai}(x) \qquad \text{i=1,2…..}$$

$$O_{1,i} = \mu_{Bi-2}(y) \qquad \text{i=3,4…….}$$

Where *i* is the membership grade of a fuzzy set (*A*1, *A*2, *B*1, *B*2) and *O*1,*i* is the output of the node *i* in Layer l. The membership function that has been used in this study is the Gaussian function given by

$$\mu_A(x) = \exp\left[\frac{-0.5(x-c^2)}{\sigma^2}\right]$$

Where *c* and σ are referred as premise parameters. So, in layer 1 CMOS membership function generator is proposed.

2 Layer 2:

Each node in this layer is a fixed node and calculates the firing strength of a rule via multiplication. The outputs are given by

$$O_{2,i} = w_1 = \mu_{Ai}(x).\mu_{Bi}(y)$$

i=1,2……..

In general, any other T-norm operator performing fuzzy AND method can be used as the node function in this layer. For layer 2 also Membership function is proposed.

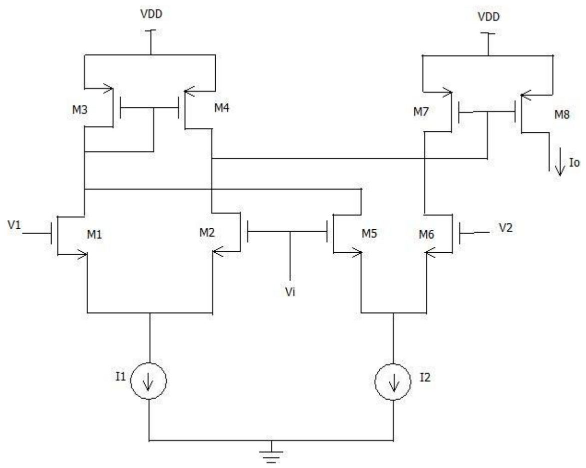

Fig 2: Proposed membership function generator containing analog voltage crisps and fuzzy current outputs.

B. Layer 3

For building of layer 3, a new integrated circuit as current mode Min operator, is proposed and shown in Figure 3. This circuit compounds the made antecedent of layers 1 and 2 to choose Min fuzzy currents. The simplicity of this circuit is high accuracy, high current range and having low devices without any complexity in comparison with before works. Every node in this layer is also fixed and performs a normalization of the firing strength from the previous layer. The outputs of this layer are called normalized firing strengths and are given by

$$O_{3,i} = \frac{w_i}{w_1 + w_2} \qquad \text{i=1,2…….}$$

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Where $O_{3,i}$ denotes the layer 3 output. For building of layer 3, a new integrated circuit as current mode Min operator is proposed. The simplicity of this circuit is high accuracy, high current range and having low devices without any complexity in comparison with before works.

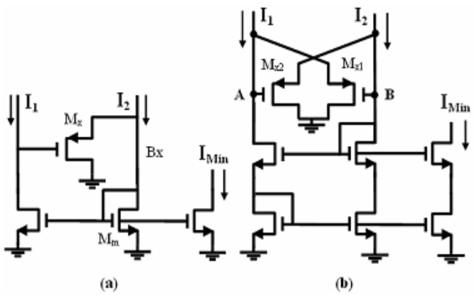

Fig 3: The structure of (a) Main idea of Min circuit and b) Proposed Min circuit in this paper

C. Layer 4 and 5

For designing needed circuits to complete layers 4and 5 of Figure 1, we proposed and improved a Multiplier/Divider to adapt these layers to the Defuzzfier block.

1. Layer 4

In this layer, all nodes are adaptive, and the output of a node is the product of the normalized firing strength and a first-order polynomial given by

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

Where $\overline{w_i}$ is the output of layer 3, and (p_i, q_i, r_i) is the parameter set. Parameters in this layer are referred to as the consequent parameters. For the layer 4 the Multiplier/Divider circuit is proposed.

2 Layer 5

The single node in this layer is a fixed node and computes the overall output as the summation of contribution from each rule:

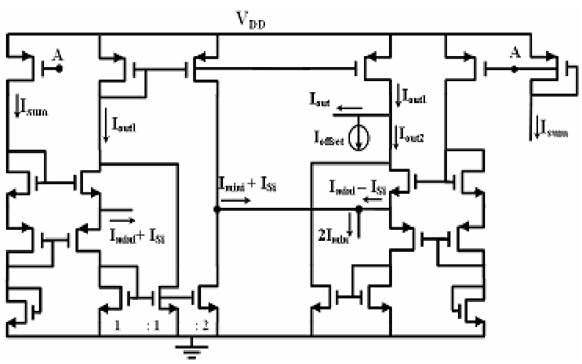

Fig 4: Improved Multiplier / Divider

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \text{i=1,2…….}$$

Where $O_{5,i}$ is the output of layer 5.

For layer 5 also Multiplier/Divider circuit is proposed.

D. ANFIS Membership Function

Fuzzification is the basic operation of fuzzy logic. It is used to detect the degree of membership of a system's input and output variables to fuzzy sets. Membership functions are characterized by degree of association curves. One of the most common shapes is the trapezoidal function. Their main disadvantage is that they are not so easily programmable. This feature is especially useful for high speed neuro-fuzzy applications. Artificial Neural Networks (ANNs) enjoy some distinguished characteristics and are composed of simple elements operating in parallel and including the ability to learn from data, to generalize patterns in data, and to model nonlinear relationships. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. These appealing features make neural networks a good candidate for overcoming some of the difficulties in traditional devices and circuit modeling and optimization. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. The ANFIS applies fuzzy inference techniques to data modeling. According to this structure, the shape of the membership functions depends on parameters, so changing these parameters will change the shape of the membership functions. The benefit of this method is that it chooses the membership function parameters automatically, that' better than just monitoring the data and estimate these parameters. According to the figure 1, to create the layers 1 and 2, we proposed a new CMOS membership function generator which has differential pair structure with analog voltage crisp input and analog current outputs (Fig. 1). After ANFIS training and chose suitable shape and slopes membership functions, we can adapt our Fuzzifier circuit using voltage references and switch controllers to tune type and slope of shapes respectively.

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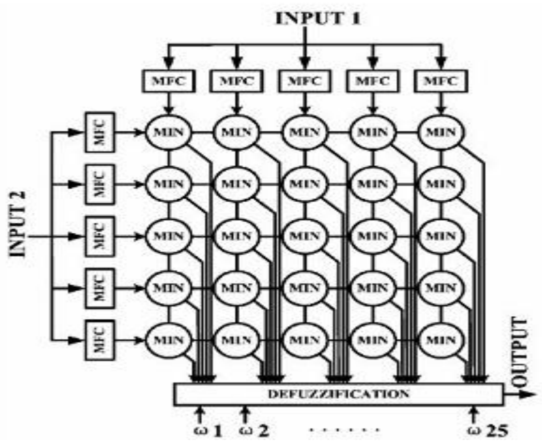

Fig: 5 Block diagram of ANFIS

V. ANFIS AS A DG MOSFET

Double gate transistors are developed to resolve short channel effect problems in actual MOSFET structures. So that such architectures are directly related to the constant reduction of the feature size in microelectronic technology. At the present time, it seems that double gate devices- going to non-planar transistor architectures- could be a solution for sub-32nm nodes. In addition, new design flexibility is allowed when gates are not interconnected. However, appropriate models must be developed. In our investigation (yet 2D), we overcome the high aspect ratio of the transistor (thin channel compared to its length), by introducing an anisotropy scale factor in its geometry description. The model shows the involved phenomenon (appearance of channels…) and gives the intended drain current curves versus gate voltages: Id(Vg1,Vg2) using a dedicated written Mat lab file.

A. WHY DG-MOSFET?

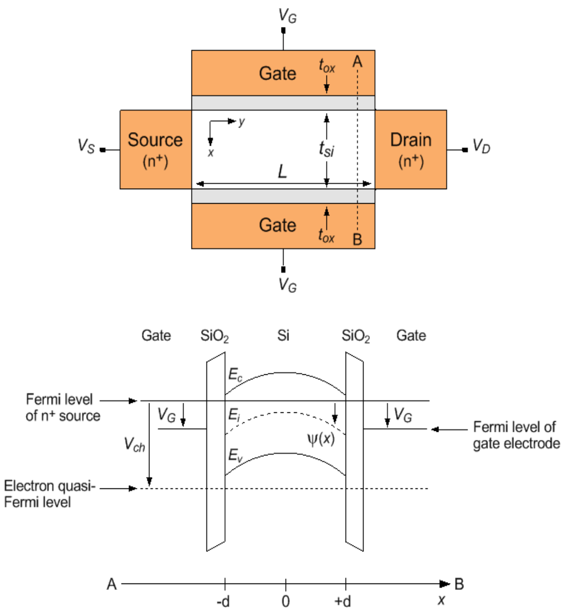

Fig: 6 DGMOSFET

DG might be the unique viable alternative to build nano MOSFETs when *Lg*<50nm

Because:-

a) Better control of the channel from the gates.
b) Reduced short-channel effects
c) Better I_{on}/I_{off}
d) Improved sub-threshold slope (60mV/decade)
e) No discrete dopant fluctuations

VI. ANFIS LEARNING ALGORITHMS

LSE used in Forward Stroke: Parameter Set: S=(S1 ∪ S2), and(S ∩ S2 =∅)Output =F□ (I ,S□)where I is the input vector H(Output) =□H_o F□ (I , S)□ where H_o F is linear in S2 – For given values of S1, using K training data, we can transform the above equation into **B=AX**, where X contains the elements of S2 – This is solved by: $\mathbf{(A^T\ A)^{-1}\ A^T\ B=X^*}$ where : $\mathbf{(A^T\ A)^{-1}\ A^T}$ is the pseudo-inverse of A (if $\mathbf{A^T\ A}$ is nonsingular**)** – The LSE minimizes the error ||AX-B||2 by approximating X with X* Rather than solving directly: $\mathbf{(A^T\ A)^{-1}\ A^T\ B=X^*}$, we resolve it iteratively (from numerical methods):

si+1 = si - (si a(i+1) si a^T(i+1))/(1+ a(i+1) sia^T(i+1)

xi+1 =xi + si a(i+1) (b ^{T}i+1 - a^T(i+1) x_i)

for i=0,1……..k-1

where

X_0=0,

$S_0=\gamma$ I , (where γ is a large number)

a^T_i =i^{th} line of matrix A

b^T_i = i^{th} element of vector B

X* =X_k

A. ANFIS Back-Propagation

Error measure *Ek*(for the kth (1≤k≤K) entry of the training data)

$$E_k = \sum_{i=1}^{N(L)} (d_i - X_{l,i})^2 \quad \text{where,}$$

N(L) = number nodes in layer L

d_i =i^{th} component of desired output vector

$X_{L,i}$= i^{th} component of actual output vector

Overall error measure E:

$$E = \sum_{k=1}^{k} E_k$$

For each parameter α_i the update formula is:

$$\Delta\alpha_i = \eta \frac{\partial E}{\partial \alpha_i}$$

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Where: $\eta = \dfrac{k}{\sqrt{\sum_i \left[\dfrac{\partial E}{\partial \alpha_i}\right]^2}}$ is the learning rate

K=is the step size

VII. SIMULATION RESULT

Functionally the ANFIS architecture is the major training routine equivalent to Tkaki-Sugeno first order fuzzy inference systems (FIS). ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type FIS. Fig. 7, a plot of the electron density within the device under on-state conditions, shows the quantum confinement of carriers in the -direction. The profile varies approximately as sin2 (z) in the source or drain regions, which indicates that most electrons reside in the first sub band (primed and unprimed) which shows in fig.11.

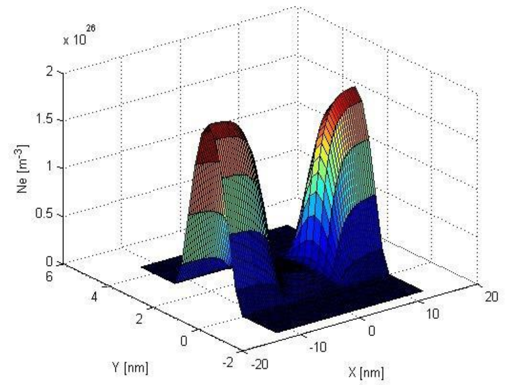

Fig 7: 3D Conduction band Profile

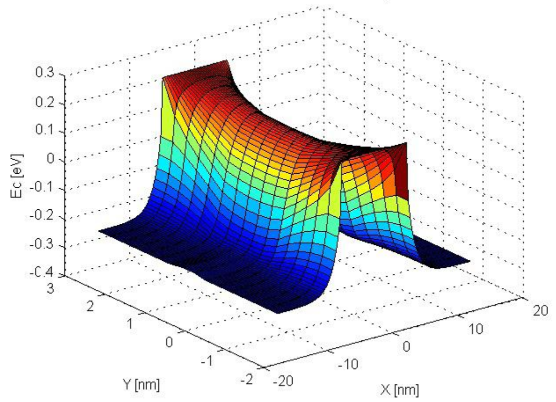

Fig 8: 3D electron density

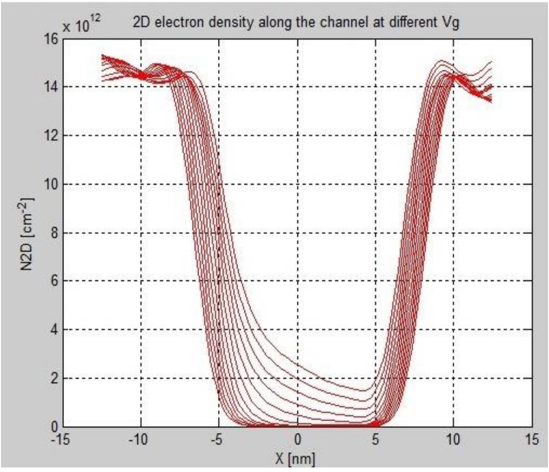

Fig 9: 2D electron density

Fig 10, 12 shows the current voltage characteristics of DG MOSFET. Even for a 10 nm channel length, MOSFETs are expected to behave classically. Quantum mechanics increases the threshold voltage and decreases the on-current at a given threshold voltage, but no quantum oscillations are observed.

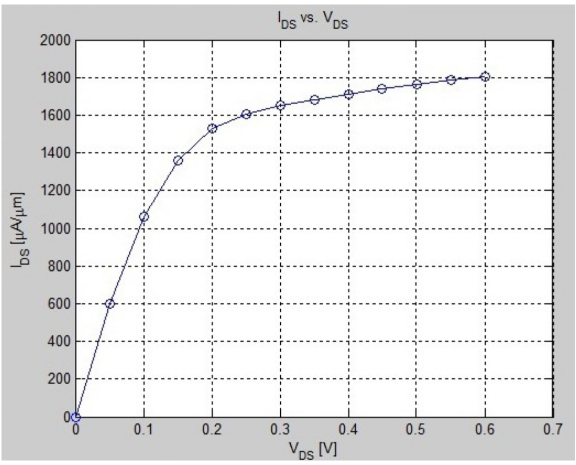

Fig 10: Id vs Vds

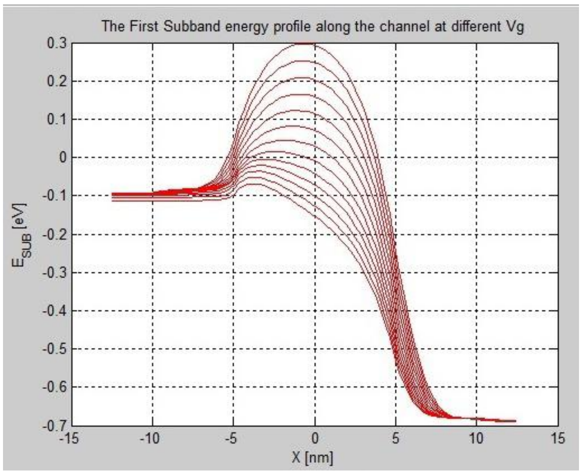

Fig 11: First sub-band energy profile

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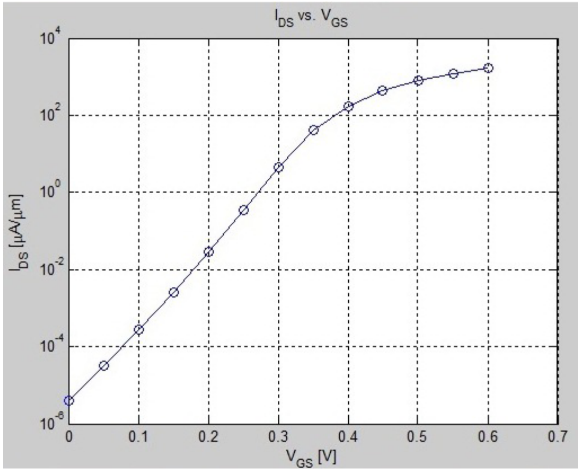

Fig 12: Id vsVgs

The Anfis structure used to implement fuzzy controller with five layers. It consists of five inputs, twenty four membership functions for each input, twenty four fuzzy rules and one output. The Anfis applies fuzzy inference techniques to data modeling. According to this structure, the shape of the membership functions depends on parameters, so changing these parameters will change the shape of the membership functions. The benefit of this method is that it chooses the membership function parameters automatically, that is better than just monitoring the data and estimates these parameters.

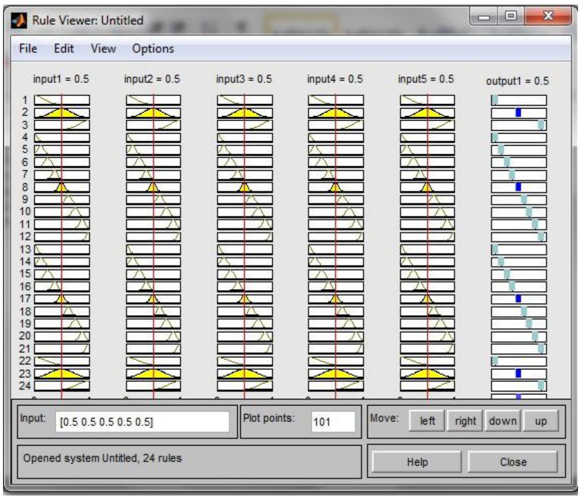

Fig 13: Rule viewer

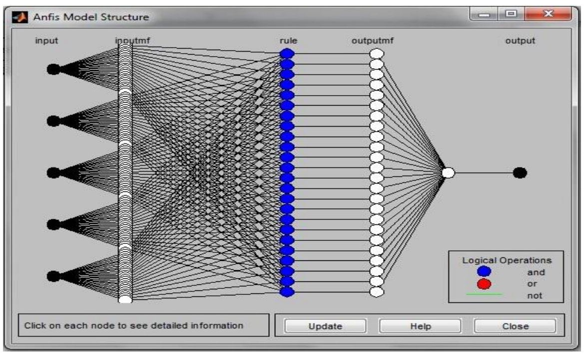

Fig 14: The Model Structure

In order to optimize the ANFIS model, about 700 data were obtained by simulation of the DG MOSFET by using Nano-MOS 2.0. About 70% of the data was selected to train the ANFIS model, and the remaining was used to test the performance of the trained ANFIS model. In fig.15 we compare the result of ANFIS & non-equilibrium Green's function formalism **(NEGF)** simulation in MATLAB ANFIS toolbox.

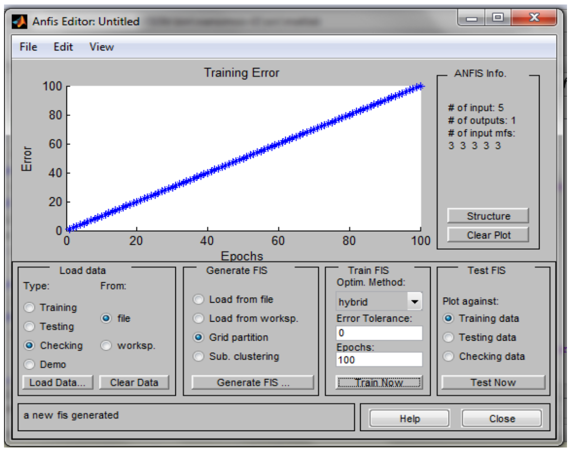

Fig 15: Comparison of the NEGF and ANFIS results for training error

VIII. CONCLUSION

We have presented the applicability of an ANFIS approach to modeling and the simulation of a DG MOSFET. We have used 2D numerical NEGF simulation of the current-voltage characteristics of an undoped symmetric DG MOSFET by using NanoMos 2.0. With this numerical model, the required database has been created in order to optimize the ANFIS structure. The comparison between numerical (NEGF simulation) and predicted (ANFIS model) values has shown that there is an excellent agreement between them with the least errors. We have measured the CPU time for the ANFIS model against the NEGF model. The result has shown that the ANFIS model is much faster than NanoMos2.0 (NEGF simulation).

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