Analysis of Analog Neural Network Model with CMOS Multipliers

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Abstract. *The analog neural networks have some very useful advantages in comparison with digital neural network, but recent implementation of discrete elements gives not the possibility for realizing completely these advantages. The reason of this is the great variations of discrete semiconductors characteristics.*

The VLSI implementation of neural network algorithm is a new direction of analog neural network developments and applications. Analog design can be very difficult because of need to compensate the variations in manufacturing, in temperature, etc. It is necessary to study the characteristics and effectiveness of this implementation. In this article the parameter variation influence over analog neural network behavior has been investigated.

Keywords

Analog neural networks, VLSI, robotic.

1. Introduction

Artificial Neural Networks is a new method wide used for information processing. Analog neural networks have the following advantages: high speed, low power consumption and compact implementation in comparison with competing digital signal processing approaches. With the help of the analog neural networks certain computations that are difficult or time-consuming for digital neural network can be done. A disadvantage of analog neural networks is their limited accuracy and nonlinear behavior. Variation in the size of discrete transistors and the local mobility will cause random parameter variation. Moreover an increase in the precision of any component has as a consequence an increase of its area. The aim of this paper is to investigate influence of some analog neural network parameters onto its recognition ability.

2. Implementation of Analog Neural Networks

Many investigations in the implementation of analog neural networks field are known [2, 3, 4, 5]. They are wide used because of their advantages, high speed, low power consumption and compact implementation. Nevertheless the analog computational hardware is typically limited to a relative precision of about 1%. For this reason it is preferable a simple ANN model to be used. The model must be compatible with the restrictions imposed by the analog VLSI technology. Otherwise the advantages of using the technology would be lost.

Fig. 1 depicts expandable neural network, which topology is though simple, a very capable one. In such a way we can implement systems of arbitrary size, fully connected between the layers.

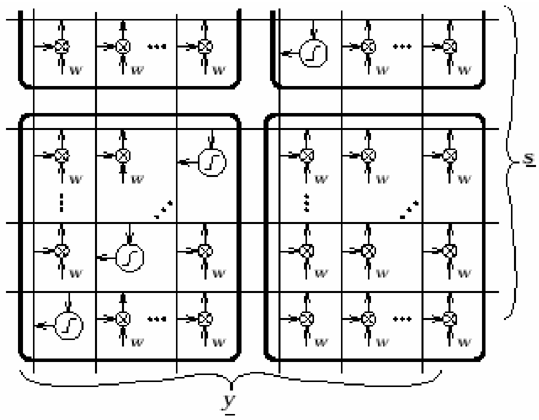

Fig. 1. Expandable neural network.

There are many ways for analog neural network implementation, but it is necessary to study the characteristics and effectiveness of their implementation.

3. Parameter Variation Influence over Analog Neural Network Behavior

Variation in the size of individual transistors and the local mobility will cause random parameter variation. In this article analog parameter variation over analog neural network behavior is investigated.

In [1], [7], VLSI implementation of an analog neural network is depicted. The synapse chip consists of a number of inner product multipliers. The authors have chosen to use the MOS resistive circuit multiplier. Weight values are stored by simple capacitive storage method with RAM Backup. The schematic of a single synapse is shown in Fig. 2.

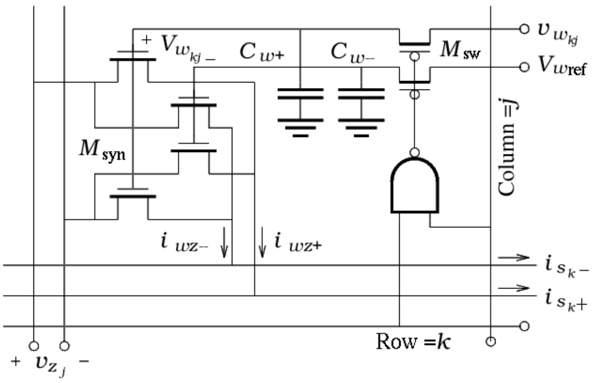

Fig. 2. Schematic of a single synapse.

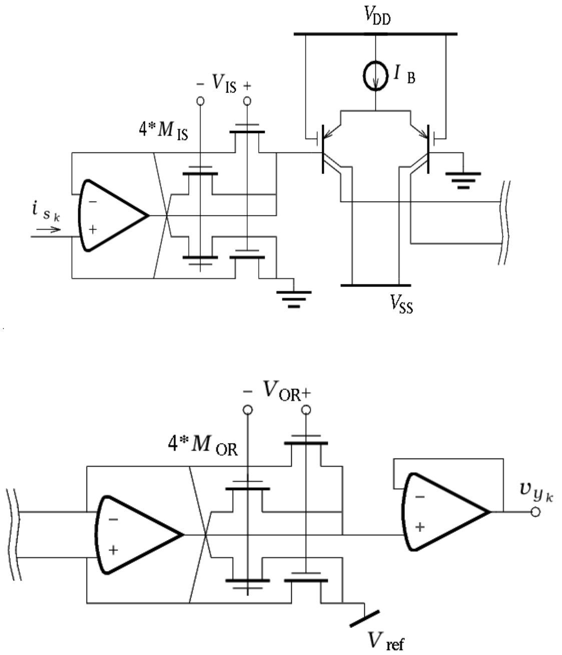

Fig. 3. Hyperbolic tangent neuron.

The transfer function of the synapse is the following

$$\mathrm{i}_{sk} = \frac{g_{mk}}{W_0 / L_0 . V_c} \sum_j W_j / L_j V_{w_{kj}} v_{zj} \tag{1}$$

where g_{mk} is the transconductance parameter, W/L are the MOS resistive circuit multiplier width/length ratios, Vc controls the total transconductance, V_{wkj} are the weight values voltages and v_{zj} are the input voltages.

Fig. 3 depicts a hyperbolic tangent neuron [1]. Its resulting transfer function is the following

$$v_{yk} = \frac{\alpha_{FC} I_b}{\beta_{OR} V_{OR}} \tanh\left(\frac{i_{sk}}{2\beta_{IS} V_{IS} V_t} \right). \tag{2}$$

On the base of the neuron and synapse equations of this implementation so as equations about analog parameter variation over analog neural network behavior have been worked out [6]. On this way we have investigated parameter variation influence over neural network behavior.

After parameter variation the synapse equation becomes

$$\mathrm{i}_{sk}^{l} = \frac{g_{mk} + \Delta g_{mk}}{W_0 / L_0 . V_c} \sum_j W_j / L_j V_{W_{kj}} v_{zj} \tag{3}$$

where l is the layer number, g_{mk} is the transconductance parameter, W/L are the MOS resistive circuit multiplier width/length ratios, V_c controls the total transconductance, V_{Wkj} are the weight values voltages, v_{zj} are the input voltages and Δg_{mk} is the step of transconductance parameter change.

Equation (4) is the neuron equation including parameter variation.

$$v_{yk}^{l} = \frac{(\alpha_{FC} + \Delta\alpha_{FC})(I_B + \Delta I_B)}{(\beta_{OR} + \Delta\beta_{OR})V_{OR}} \tanh\left(\frac{h_k^l}{2(\beta_{is} + \Delta\beta_{is})V_{IS} V_t} \right) \tag{4}$$

where l is the layer number, α_{FC} is the emitter-collector current gain, I_B is the bias current, β_{OR} and β_{is} are the MOSFET transconductance parameters, V_t is the thermal voltage, V_{IS} and V_{OR} are the control voltages, $\Delta\alpha_{FC,}$ $\Delta\beta_{OR}$ and $\Delta\beta_{is}$ corresponds to the steps of $\alpha_{FC,}$ β_{OR} and β_{is} parameters change.

On the base of the equations (3) and (4) investigation for analog parameter variation over analog neural network behavior has been done. A popular method for study of neural networks is network simulation using computers. In the analysis of any circuit it has been assumed that all the components were ideal. In this article a simulation using Matlab is presented, but in the real neural networks equations the parameters of real components take part. These parameters are: the MOS resistive circuit multiplier width/length ratios W/L, the emitter-collector current gain α_{FC}, the bias current I_B, MOSFET transconductance parameter β and thermal voltage V_t.

The value of the emitter-collector current gain α_{FC} is about $\alpha_{FC} \approx 0.5$. It's variation because of parasitic processes is in a small range: $\alpha_{FC}=(0.4\div0.55)$ [1]. In Tab. 1 for each α_{FC} value error values and boundaries of weight values are given. It can be seen from the table that α_{FC} variation is very important because this variation have effect on both: the error value and the range of weight values variation. Some of the weights can reach values of w=-93 and w=64. With α_{FC} increasing, the range of weight values variation decreases.

α_{FC}	W^1	W^2	E
0.4	-93÷64	-20÷16	0.04
0.45	-10÷5	-8÷4	0.01
0.5	-3÷2	-3÷0.3	$4.9.10^{-4}$
0.55	-1.2÷1.7	-1.8÷1.4	$1.9.\ 10^{-4}$

Tab. 1. Influence of α_{FC} over error values and range of weight values variation.

The influence of α_{FC} over error values is depicted in Fig. 4. It can be seen that for values α_{FC} =0.4 and α_{FC}=0.45 the error increases compared to that achieved at the value α_{FC}=0.5.

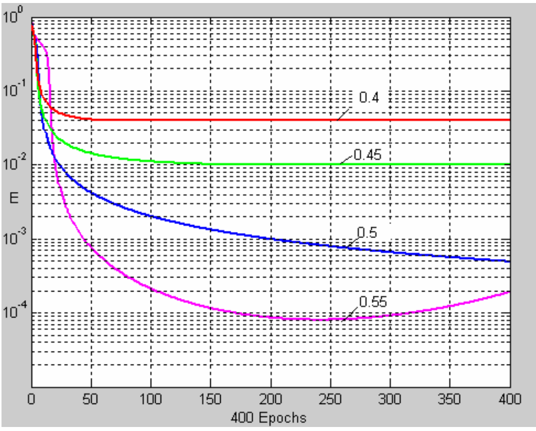

Fig. 4. Influence of α_{FC} over error values.

Because of their position in the equation (eq. 4) variations of parameters α_{FC}, I_B and β_{OR} directly reflect on the output voltage range. This is the reason for error increasing for values of α_{FC} shown at the top of the Tab. 1. The influence of α_{FC} over forward mode neuron characteristics is depicted in Fig. 5.

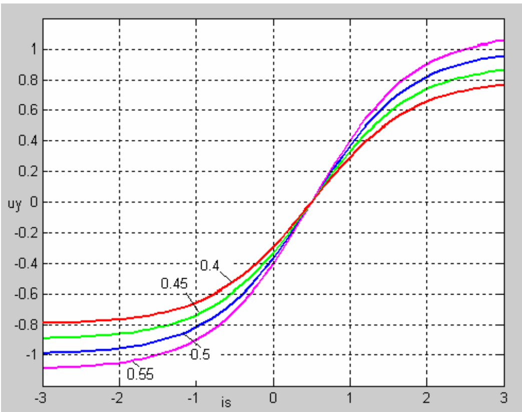

Fig. 5. Influence of α_{FC} over forward mode neuron characteristics.

The parameter α_{FC} variance strongly influences over analog neural network behavior. Regulating circuit for this parameter is depicted in [1].

The bias current I_B is investigated in the range I_B=(50 mA;70 mA). This parameter has effect on both: the error value and the range of weight values variation, too. For values 60 mA>I_B>65 mA, some of the weights can reach values of w=-47 and w=29 (Tab. 2).

The influence of I_B over error values is depicted in Fig. 6. The smallest error is obtained for the values I_B =60 µA and I_B =65 µA, but for the second one the error increases after 300 epochs.

Variation of parameter I_B directly reflects over output voltage range just like α_{FC}. Graphics of the effect of I_B on the forward mode neuron characteristics are quite similar to those of Fig. 5 and it is no reason to give them here.

I_B, µA	W^1	W^2	E
50	-47÷29	-15÷12	$2.70.10^{-2}$
55	-7÷3	-6÷3	$6.9.10^{-3}$
60	-2.7÷1.6	-3÷0.3	$4.9.10^{-4}$
65	-1.7÷1.6	-2.5÷0.6	$5.7.\ 10^{-4}$
70	-0,1÷5	-5÷14	$2.8.\ 10^{-3}$

Tab. 2. Influence of I_B over error values and range of weight values variation.

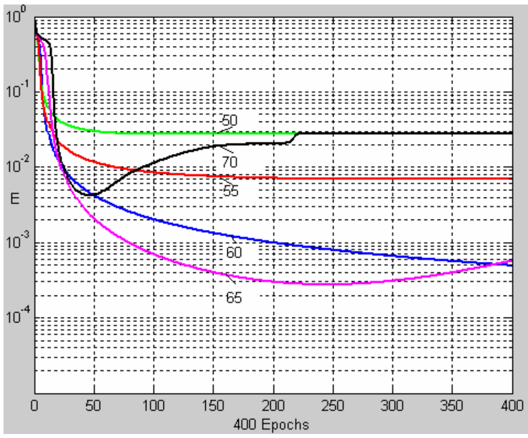

Fig. 6. Influence of I_B over error values.

The MOSFET transconductance parameter β_{OR} is investigated in the range β_{OR} =(25 µA/V^2÷40 µA/V^2). One is part of group of parameters that directly reflects over output voltage. Therefore β_{OR} variation leads to rapid increasing of the output error and the range of weight values variation.

β_{OR}, µA/V^2	W^1	W^2	E
25	-1.10^{-4}÷9	-7÷21	4.10^{-2}
30	-2.7÷1.6	-3÷0.3	$4.9.10^{-4}$
35	-27÷15	-12÷;9	$2.04.10^{-2}$
40	-229÷170	-27÷24	$6.3.\ 10^{-4}$

Tab. 3. Influence of β_{OR} over error values and range of weight values variation.

It can be seen from Tab. 3 that for values β_{OR}≠30 µA/V^2 range of weight values strongly increases. For the value β_{OR} =40 µA/V^2 one is (-229÷170). When analog neural network implementation has been discussed these are impermissible weight values.

From Fig. 7 it can be seen that the output error is maximum for the value β_{OR} =25 µA/V^2. For the value β_{OR} =20 µA/V^2 neural network cannot be learned.

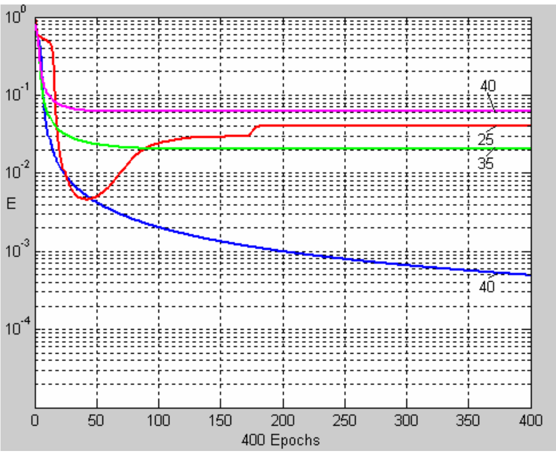

Fig. 7. Influence of β_{OR} over error values.

The thermal voltage V_t is investigated in the range V_t=(23 mV÷37 mV). This corresponds to the thermal range (-10÷150)ºC. The thermal voltage variation doesn't lead to essential increasing of weight values range (Tab. 4). Output neuron error modifies slightly, too.

V_t,mV	W^1	W^2	E
23	-2.5÷1.6	-2.8÷0.3	$4.2.10^{-4}$
26	-2.7÷1.6	-3÷0.3	$4.9.10^{-4}$
29	-2.9÷1.7	-2.9÷0.3	$5.5.10^{-4}$
32	-3.2÷1.7	-3.2÷0.3	$5.9.10^{-4}$
37	-3.4÷1.8	-3.4÷0.3	$6.2.10^{-4}$

Tab. 4. Influence of V_t over error values and range of weight values variation.

The error is comparatively low for the entire range of V_t investigation (Fig. 8).

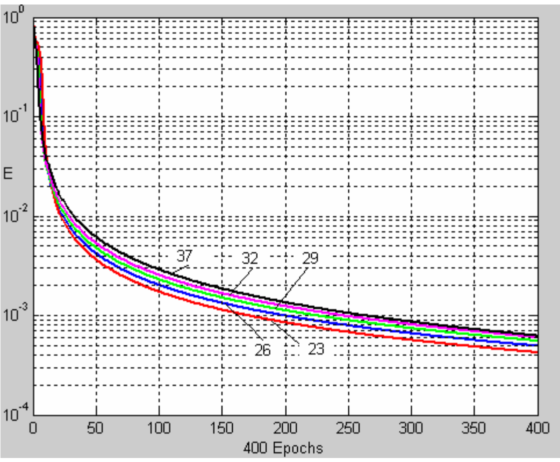

Fig. 8. Influence of V_t over error values.

The parameters V_t, β_{IS} and g_{mk} position is in the argument of tanh function. Therefore their variation doesn't directly reflect on the output voltage range. The influence of these parameters over forward mode neuron characteristics is slightly. The graphics about these parameters influence over forward mode neuron characteristics are similar; therefore we apply one of them in the paper (Fig. 9).

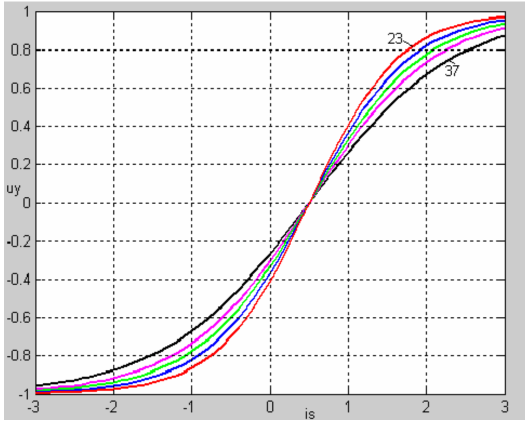

Fig. 9. Influence of V_t over forward mode neuron characteristics.

The parameter β_{is} influence (MOSFET transconductance parameter) is investigated in the range (20 μA/V^2÷80 μA/V^2). Variation of weight values range is comparatively low for the entire range of β_{is} investigation (see Tab. 4).

β_{is}, μA/V^2	W^1	W^2	E
20	-1.9÷1.5	-1.8÷0.4	$4.2.10^{-4}$
25	-1.97÷1.55	-2÷0.3	2.10^{-4}
30	-3.2÷1.7	-3.2÷0.3	$2.4.10^{-4}$
40	-3.4÷1.8	-3.4÷0.3	$3.7.10^{-4}$
50	-2.7÷1.6	-3÷0.3	$4.9.10^{-4}$
60	-2.7÷1.6	-3÷;0.3	$5.9.10^{-4}$
70	-2.9÷1.7	-2.9÷0.3	$6.2.10^{-4}$
80	-3.2÷1.7	-3.2÷0.3	$6.1.10^{-4}$

Tab. 5. Influence of β_{is} over error values and range of weight values variation.

For values β_{is} <50 μA/V^2 output neural network error decreases, but error decreasing holds on in the beginning of the learning process (see Fig. 10). For the value β_{is}=20 μA/V^2 error decreasing begins after 300 epochs. Hence the leaning process becomes slower. This process doesn't observe for values β_{is} <50 μA/V^2. In this case, error increases slightly**.**

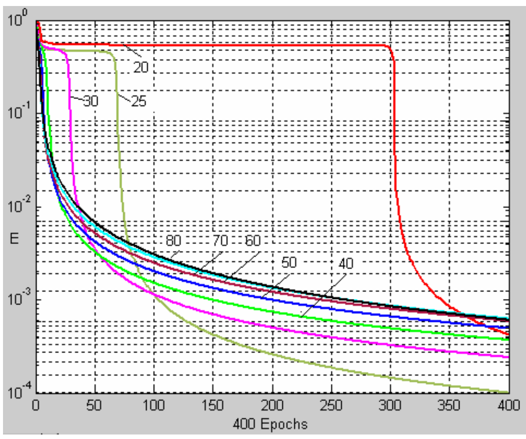

Fig. 10. Influence of β_{is} over error values.

The parameter β_{is} variation reflects on the slope of the activation function. Therefore parameter β_{is} variation slightly influences over analog neural network behavior. Parameter β_{is} variation causes output neural network error variation that is admissible in bigger range than parameter β_{OR} variation does.

The transconductance g_{mk} variation reflects on the slope of the activation function and learning process. One is investigated in the range (1 mA/V ÷10 mA/V). It can be seen from Tab. 6 that g_{mk} influence over low boundary of weight values. For the value g_{mk}=1 mA/V negative weights can reach the value w=-11.

g_{mk} mA/V	W^1	W^2	E
1	-11÷1.5	-10÷1	$2.3.10^{-3}$
2	-5.1÷1.9	-5.4÷0.6	$9.9.10^{-4}$
3	-3.5÷0.5	-3.9÷0.5	$6.6.10^{-4}$
4	-2.7÷1.6	-3÷0.3	$4.9.10^{-4}$
5	-2.4÷1.6	-2.6÷0.3	$3.8.10^{-4}$
6	-2.1÷1.5	-2.3÷0.3	3.10^{-4}
7	-2÷1.5	-2÷0.3	$2.4.10^{-4}$
8	-1.9÷1.5	-1.9÷0.3	$1.9.10^{-4}$
9	-1.8÷1.4	-1.8÷0.3	$1.6.10^{-4}$
10	-1.8÷1.4	-1.7÷0.3	$1.5.10^{-4}$

Tab. 6. Influence of g_{mk} over error values and range of weight values variation.

Fig. 11 shows the error variation versus g_{mk} variation. In the investigated range of variation error increasing is negligible. Although with g_{mk} increasing learning speed decreases, because of error decreasing holds on in the beginning of the learning process.

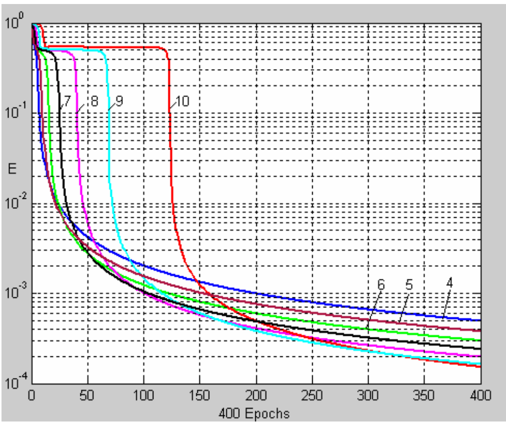

Fig. 11. Influence of g_{mk} over error values.

4. Conclusion

The aim of this paper is to find the boundaries of parameters of analog neural network variations in which neural networks operate correctly. For that purpose a simulation using Matlab is presented. In the analysis of the circuits, components are not ideal. In neural networks equations the parameters of real components take part.

It is shown that variation of the first investigated group of parameters (α_{FC}, I_B and β_{OR}) parameters directly reflects on the output voltage range. Because of this, error increasing is fast for small variation parameters.

The parameters V_t, β_{is} and g_{mk} position is in the argument of tanh function. Therefore their variation doesn't directly reflect on the output voltage range. Their variation reflects on the slope of the activation function. At significant variation of the second group of parameters learning speed decreases.

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