

# Modeling of pin photodetector using Fuzzy Logic

N.R. Das and Alakananda Mitra  
Institute of Radio Physics and Electronics, University of Calcutta  
92, A. P. C. Road, Kolkata – 700009, INDIA  
Email: [nrd@ieee.org](mailto:nrd@ieee.org)

**Abstract-** *In this paper, we propose a new approach to model a p-i-n photodetector using Fuzzy logic. In the present analysis, the thickness, the ratio of area to thickness of the active layer and the frequency are considered as the variable input parameters for the proposed model keeping other parameters fixed. Neural network-based optimization has also been done to improve the performance of the model. The frequency response, bandwidth and quantum efficiency are computed. For verification of the model, the results are compared with those obtained analytically and a reasonably good agreement has been found within the scope of the model.*

**Keywords:** *p-i-n photodetector, model, Fuzzy Logic, optimization, Neural Network.*

## I. INTRODUCTION

A photodetector has an important role in the high data rate and error-less optical communication system. High bandwidth and high responsivity are the two important figures of merit of high-performance photodetector. To design such a photodetector for best possible performance, a good representative model is required. Different modeling techniques are 1) analytical, 2) numerical, 3) Curve fitting, etc. But, in most of these cases, it is either difficult to obtain an appropriate formulation or difficult to solve, if at all. This is mainly because of the complicated physical processes inside the device under different conditions. Here, we may have to consider various effects such as electromagnetic induction, hysteresis, eddy currents, any storage of energy, effect of stray capacitance, resistance, inductance, effect of change of temperature or frequency or how it differs from one material to another. And, all these constraints are to be considered as the boundary conditions or initial conditions in various differential or integro-differential equations, which are not an easy task or sometimes it is impossible to find out such an equation.

An alternative but new approach is to use Fuzzy Logic in device modeling. It is an easy approach used earlier mainly in control application. We have first indicated [1] how it can be used for device modeling also, we have used Fuzzy Logic in passive semiconductor device modeling. But in using Fuzzy Logic we don't have to solve such a tough and tedious equations. It gives us a low cost reasonable solution. The important requirement is the expert knowledge. In the present work, we model an active device - *pin* photodetector - using Fuzzy Logic and study its performance. We have also used the Neuro-Fuzzy approach to improve the performance of the model.

## II. THEORETICAL BACKGROUND

The p-i-n photodiode chosen in our case is a InP / InGaAs junction diode in which an undoped i-region of InGaAs is inserted between p<sup>+</sup> and n<sup>+</sup> regions of InP [2]. By careful choice of material parameters and device design, very large bandwidth can be attained. The response speed and bandwidth are ultimately limited either by transit time effects or by circuit parameters.

### A. Modeling Using Fuzzy Logic

The approach of modeling using Fuzzy Logic is totally different from mathematical model in which we have to express various physical effects which controls the device performance. First we develop a Fuzzy Logic model for an InGaAs/GaAs p-i-n photodetector using initial values of data from expert knowledge. The inputs are active layer thickness, area to thickness ratio and frequency of operation of the photodetector. The procedure adopted is similar to that described in detail in our earlier paper [1]. However, the results do not show good matching are some conditions. Because the modeling by using Fuzzy Logic is a heuristic method and it needs a manual tuning of the parameters of the membership function. It produces some discrepancy and takes a

lot of time. To improve the accuracy we have made the Neuro-Fuzzy approach in our modeling, which is an optimization approach based on Neural Network.

The Neuro-Fuzzy hybrid system combines the advantages of fuzzy logic system, which deal with explicit knowledge that can be explained and understood, and neural networks [3], which deal with implicit knowledge, which can be acquired by learning. The integration of neural network and fuzzy systems leads to a symbiotic relationship, in which fuzzy systems provide a powerful framework for expert knowledge representation, while neural networks provide learning capabilities and suitability for computationally efficient hardware implementations. Recent results show that the fusion procedure of these two different technologies is very effective for nonlinear systems identification. Gradient descent and back-propagation are always used to adjust the parameters of membership functions (fuzzy sets) and the weights of defuzzification (neural networks) for fuzzy neural networks [4]-[6].

Fuzzy Logic based modeling requires knowledge of the effect of various input parameters on the system/device performance. So, the effects of different parameters, such as, thickness of the depleted region, area of the depletion region i.e. effectively the diameter of the depleted region and frequency of operation should be understood. The knowledge base has been formed in this case from the different data available in various literatures and physics based ideas. For example, the transit times depends on the carrier velocities, and thus on the electric field, which varies across the diode [7]. Primarily three inputs are chosen such as—

- i. The ratio of Area of the depletion region to the thickness of that region.
- ii. Thickness of the depleted region assuming the thickness of the depleted region is same as the length of the i-region.
- iii. Frequency of operation where we have chosen a varying optical power fell on the Photodetector.

The number of linguistic variables with shapes for input and output parameters are different for different characteristics. For frequency response plot we select three membership functions for each of the input and output. For bandwidth vs thickness plot and quantum efficiency vs thickness plot different number of membership functions are chosen. We use trapezoidal and triangular shapes of

membership function with different number of linguistic variables. The linguistic variables for different inputs are defined as—for thickness of depletion region— $0.01 \leq \text{low} \leq 0.2$  for dia  $< 15 \mu\text{m}$  and  $0.01 \leq \text{low} \leq 1$  for dia  $> 15 \mu\text{m}$ ,  $0.15 \leq \text{medium} \leq 0.35$  for dia  $< 15 \mu\text{m}$  and  $0.85 \leq \text{medium} \leq 2.5$  for dia  $> 15 \mu\text{m}$ ,  $0.3 \leq \text{high} \leq 5$  for dia  $< 15 \mu\text{m}$  and  $2.25 \leq \text{high} \leq 5$  for dia  $> 15 \mu\text{m}$ . Similarly, membership functions for (area/thickness), frequency and normalized photocurrent are defined. Then, we construct a rule base for the outputs using the experimental data from the literatures and physics based ideas.

When we enter the certain value of the variable parameters within the given range, we get the membership functions of the low output, medium output, high output from the rule base. This is the FUZZY value of the output. Defuzzification is done to get the crisp value of the output. It is done in different ways such as max-min defuzzification, centroid defuzzification etc. In our work, we have used the centroid defuzzification technique with the help of membership function from the rule base table. But results obtained from the Fuzzy Model show that there exists some discrepancy in value though nature of curves are almost similar to that obtained from analytical expressions or experimental data. But when initial Fuzzy Model is replaced by Neuro-Fuzzy Model we see a high degree of accuracy. Here instead of manual tuning as automatic tuning (by Neural Network) is used almost all results are in very good agreement with that obtained from analytical result.

### C. Modeling Using Neuro-Fuzzy System

In the Neuro-Fuzzy Model of p-i-n photodetector we consider TSK type fuzzy system instead of Mamdani-type because Fuzzy models based on the TSK method of reasoning integrate the ability of LMs for qualitative knowledge representation with an effective potential for expressing quantitative information as well. In addition, this type of fuzzy model permits a relatively easy application of powerful learning techniques for their identification from data. We shall refer to model in this category as TSK Fuzzy Models.

There is always a trade-off between readability and precision. If one is interested in a more precise solution, then one is usually not so bothered about its linguistic interpretability. As Mamdani type handles the linguistic variables, it is more general approach and gives more readability but at the cost of accuracy which is not desired in

our case because device world demands accuracy. Sugeno-type system is more suitable in such case. Though in the first half of our work, we select Mamdani-type systems as only Fuzzy models are considered and no training was concerned.

We are dealing with TSK Fuzzy model (discussed in ) in the NFS approach. Adaptive Neuro-fuzzy inference System (ANFIS) is a architecture of a neural network, in the forward pass of which the network inputs propagate forward, where the consequent parameters are identified by the least-squares method and in the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent method. When the two phases are complete, a new input from the training is set applied, and, so on. A long training time is usually required, since hundreds or even thousands of iterations may be needed.

First, we hypothesize a parameterized model structure (relating inputs to membership functions to rules to outputs to membership functions, and so on) for the photodetector. We use a 5-layer structure neural network (i.e. ANFIS). We assume a first order Sugeno type rule base.

We need to have a training data set that contains desired input/output data pairs of the target system to be modeled. We collect input/output data in a form that will be usable for training by ANFIS.

Let the crisp value of input variables are given.

1. Each neuron in layer 1 is adaptive with a parametric activation function which is ours choice and is different in different cases. Its output is the grade of membership to which the given input satisfies the membership function.
2. Every node in layer 2 is a fixed node, whose output is the product of all incoming signals. Each node output represents the firing strength  $\alpha_i$  of the  $i^{\text{th}}$  rule.
3. Every node in layer 3 is a fixed node, which calculates the ratio of the  $i^{\text{th}}$  rule's firing strength relative to the sum of all rule's firing strengths,

$$\bar{\alpha}_i = \frac{\alpha_i}{\alpha_1 + \alpha_2}, i = 1, 2$$

The result is a normalized firing strength.

4. Every node in layer 4 is an adaptive node with a node output

$$\bar{\alpha}_i y_i = \bar{\alpha}_i (c_{i1} u_1 + c_{i2} u_2 + c_{i0}); i = 1, 2$$

where  $\bar{\alpha}_i$  is the normalized firing strength from layer 3 and  $\{c_{i1}, c_{i2}, c_{i0}\}$  is the parameter set of this node. Parameters in this layer are called consequent parameters. Initially they are zero. A hybrid algorithm is applied here. It adjusts the consequent parameters  $c_{ij}$  in a forward pass and the premise parameters  $\{a_i, b_i, c_i\}$  in a backward pass. In the forward pass the network inputs propagate forward until layer 4, where the consequent parameters are identified by the least-squares method. In the backward pass, the error signals (difference between the desired output obtained from the training data and the actual output) propagate backwards, and the premise parameters are updated by gradient descent. Then a new training is started with the corrected premise parameters as the initial premise parameters emulate and this is continued until the number of specified epochs or number of training is elapsed.

5. Every node in layer 5 is a fixed node, which sums all incoming signals. This is the final output.

In some of the characteristic curves some inputs play an insignificant role so we can discard the area/thickness input for this case. So, in Neuro-Fuzzy Model the redundant inputs are discarded with the prior knowledge obtained from Fuzzy model.

### III. RESULTS AND DISCUSSIONS

The results are shown using both Fuzzy Model (un-optimized) and the optimized Neuro Fuzzy approach. Normalised photocurrent is shown in Fig. 1, bandwidth versus thickness is shown in Fig. 2 and quantum efficiency versus thickness is shown in Fig.3. The results show that with Fuzzy Model there exists some discrepancy in value though nature of curves are almost similar to that obtained from analytical expressions or experimental data. This is due to the manual tuning of parameters of membership functions. Because we have to find the parameters of membership functions by trial and error method only. With proper selection of the shapes and number of the membership functions though the problem can be solved almost but it takes much time, particularly, when the number of membership function is large.

When that Fuzzy Model is replaced by Neuro-Fuzzy (NF) Model we see a high degree of

agreement with analytical result. Here, instead of manual tuning, automatic tuning (by Neural Network). From our NF Model any value of input variables generates the output. In Fuzzy Model there is a little discrepancy though we have tried to select the number and shapes of membership function, which produces the best result. But this slight discrepancy cannot be removed. With higher and higher numbers of training data points this can be removed gradually. But it involves a long time to learn the Neural network with such large number of data points.

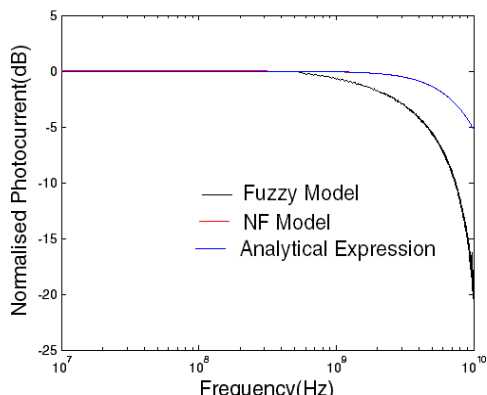


Fig.1-Plot of Frequency response plot for diameter= 50µm and thickness= 1 µm

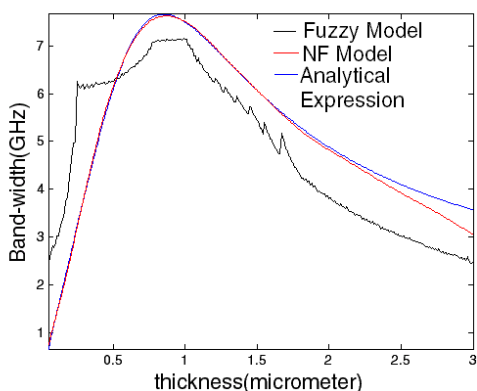


Fig.2-Plot of Frequency response plot for diameter= 50µm

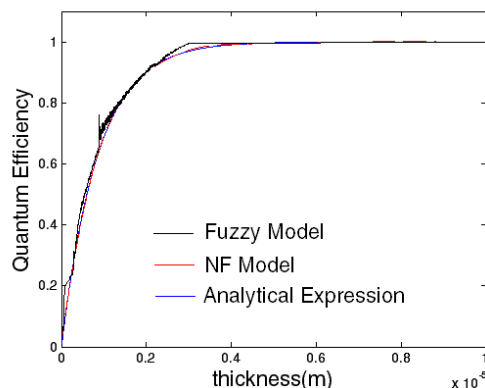


Fig.3-Plot of Frequency response plot for diameter= 50µm

#### IV. CONCLUSIONS

In this paper we proposed a new type of modeling technique of photodetector. This type of modeling avoids mathematical deductions or to express photodetector in terms of circuit parameters. This gives good results.

#### V. REFERENCES

1. N.R. Das and Alakananda Mitra, " A New Approach to the Modeling of Si-RFIC Inductor", Microwave and Optical Technology Letters, Vol.48. No.6, June, 2006, pp.1095-1101.
2. J. E. Bower, C. A. Burrus, "Ultra wide Band Long-Wavelength PIN Photo-detectors", Journal Of Lightwave Technology, Vol. LT-5, No.10, October, 1987, pp.1339-1350.
3. B. Kosko, "Neural Networks and Fuzzy Systems: A Dynamical Systems Approach to Machine Intelligence", Prentice Hall, NJ, 1992.
4. M. Brown and C. J. Harris, "Neuro Fuzzy Adaptive Modeling and Control", Prentice-Hall, NJ, 1994.
5. J. Jang, T. Sun, E. Mizutani, "Neuro-Fuzzy & Soft Computing", Prentice Hall, NJ.
6. R. R. Yager, D. P. Filev, "Essentials of Fuzzy Modeling and Control", John. Wiley & Sons, (Asia) Pt. Ltd.
7. G. Lucovsky, R. F. Scharz, and R. b. Emmons, "Transit-time considerations in PIN diodes", Journal of Applied Physics, Vol. 35, 1964, pp.622-628.

