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Calculation of Excess Noise for Separate Absorption and Multiplication Avalanche Photodiodes Using a Neural Network Model

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ABSTRACT

In this paper, we calculate excess noise factor in separate absorption and multiplication region avalanche photodiodes using a multilayer perceptron neural network. We select important parameters which effect on excess noise such as bias voltage, width, energy band-gap and doping concentration of absorption and multiplication regions as inputs. Then, gain and excess noise are supposed as outputs. We assume hyperbolic tangent for activation function and obtain an efficient network whose neuron arrangement is 7-5-5-2 for input, hidden and output layers respectively. We calculate root mean square error 0.209 for training process. In testing, the model presents 0.96 for regression. To demonstrate some applications of the model, we analyze the sensitivity of gain and excess noise respect to input variations.

KEY WORDS: Avalanche Photodiode, Impact Ionization, Excess Noise, Gain, Neural Network, Sensitivity.

INTRODUCTION

The photo-detector is an essential component of an optical fiber communication system which converts optical signals to electrical signals and is one of the crucial elements which dictate the overall system performance [1]. Avalanche photodiodes (APDs) as distinct photo-detectors are operated at high reverse-bias voltages where avalanche multiplication takes place. The multiplication gives rise to internal current gain that is conjunct with undesired vibrations. They are known as excess noise [2]. As the gain is increased, excess noise becomes more. This effect can cause instability of gain and device breakdown in high voltages[1].

Separate absorption and multiplication (SAM) region APDs are widely using in optical communication and result in reduction of excess noise factor and dark current [2]. A sandwiched layer (charge layer) between the absorption and multiplication regions (SACM) can assist to reduce excess noise[3]. This layer is thin and high doped and reach the medium electric field in absorption region to high electric field in multiplication. This issue redounds the electric field distribution in multiplication region becomes almost uniform.

Difference between electron and hole impact ionizations is an issue which can be employed in excess noise reduction. Different scattering mechanisms and energy bands result in different behaviors in drift, scattering and impact ionization of electrons and holes. Experimental results show excess noise can be reduced if one type carrier be dominant in ionization events. In recent years, impact ionization engineering (I^2E) has presented to reduce excess noise. In these works, band-gap of multiplication region is deformed periodically, using several quantum wells. Consequently, impact ionization events are almost localized due to discontinuity of band gap. Hence, an important challenge in photo-detection is to decrease excess noise as far as possible[4,5].

Although, many efforts are carried out in designing and fabrication of APDs, a general model can describe excess noise has not been presented. Complexity, overlap and interference of mechanisms may be only explanation to this problem.

Today, Monte Carlo (MC) as a robust and efficient method is generally employed to follow the trajectory of carriers and simulate optoelectronic devices. Complexity, time consuming and using super computer are disadvantage issues. Respect to dead space, non-local ionization and history base ionization as recent ideas have improved MC models[6, 7]. However, modeling and simulation of excess noise have remained as an interest and applicable issue.

In this study, we try to present a systematic model which describes excess noise from macroscopic viewpoint for SAM-APDs. On the other hand, we neglect internal and complex mechanisms of photo-detectors and consider only inputs and outputs of devices. To this work, we assume a SAM-APD as a box where inputs and outputs are defined.

We use a multi-layer perceptron (MLP) neural network (NN) to predict excess noise factor and gain, because MLP-NNs are capable of predicting in engineering sciences. In recent years, Soroosh *et al*,. have presented MLP-NNs to predict different parameters of APDs such as breakdown voltage, gain and current systematically. Their works demonstrate the capability of MLP-NNs to predict characteristics of photo-detectors. In this paper, the most effective parameters on excess noise such as width, band-gap and doping concentration of absorption and multiplication regions as well as bias voltage are supposed as inputs. We have tried to gather key

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parameters of the device where directly change excess noise. Gain together excess noise factor are selected to outputs of model [8-10]. We don't use the validation data and carry out the simulation in two stages: training and test.

We use the back propagation (BP) algorithm to train and apply this process to different architected networks. Minimum root mean square error (RMSE) is used as a key criterion to select an efficient architecture of MLP-NN. To test, we compare the results of NN with experimental results of others. Finally, we calculate the sensitivity of excess noise factor with respect to inputs.

Our sensitivity analysis for excess noise demonstrates that doping concentration and width of multiplication region are main factors for determination of excess noise. Besides, doping concentration in absorption region can be neglected from input section, because its effect on excess noise factor is weak.

In next section, we introduce SAM-APD structure and whose parameters such as gain and excess noise factor. Then, we consider MLP-NN and present a model to predict excess noise factor. Finally, we show the results of NN model and consider its performance.

MATERIALS AND METHODS

SAM Avalanche Photodiode:

SAM-APDs as photo-detectors are widely employed in optical communication systems. Internal Gain is an advantage which satisfies designers to use APD in photo-receiver box. In SAM structure, absorption of photons and multiplication of photo-carriers are carried out in separate regions. Wavelength of light determines the type of material in absorption region, while to reduce dark current, wide band-gap materials can be employed for multiplication region. Doping concentration in multiplication is high and results in a p^+n^+ junction (see in Fig. 1). As a result, electric field in multiplication region becomes high, while low electric field is dominant in absorption region. Figure 1 shows the structure of SAM-APDs where are illuminated from N^+ side. Each absorbed photonin absorption region generates a photoelectron-photohole pair. Due to electric field in absorption region, photoelectrons and photo-holesdrift in opposite directions toward the contacts.

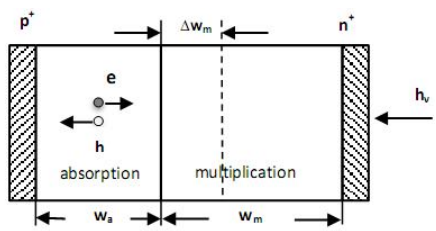


Fig.1: Structure of SAM-APD.

Photoelectrons move to multiplication region. When they reach to multiplication region, they can obtain sufficient energy (more than impact ionization threshold energy, E_{th}) to impact ionization (II) via high electric field in multiplication region. Then, they can be ionized with the following rate [2]:

$$S_{II}(E) = k\left(\frac{E - E_{th}}{E_{th}}\right)^p \tag{1}$$

where E is the carrier energy. k and p are the impact ionization parameters which are known as intensity and softness factors respectively.

In one hand, due to II events, total number of carriers is increased. This mechanism leads tointernal gain of APD. On the other hand, II mechanisms have probabilistic nature that result in variations of the gain (M). Bracket symbol for gain is as the mean concept.As the mean gain is increased, variations are become more and more. They are described with excess noise factor (F) which is given as following [2]:

$$F = \frac{< M^2 >}{< M >^2} \tag{2}$$

MLP Neural Network:

The advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modeled. The most common neural network model is the multilayer perceptron. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of MLP is to present a model can map input domain to output domain. It can then be used to predict outputs when the desired outputs are unknown. General architecture of a MLP-NN is shown in Figure 2. It contains three layers: input, hidden, and output.

Back propagation (BP) is an efficient algorithm to learn MLP-NN. Many times, input data are recursively applied to the neural network. After each presentation, outputs are compared with the desired outputs and then, an

error is calculated. This error is then fed back (back propagation) to the neural network and used to adjust the weights such that the error decreases with iteration and the neural model get closer and closer toproduce the desired outputs [8,9].

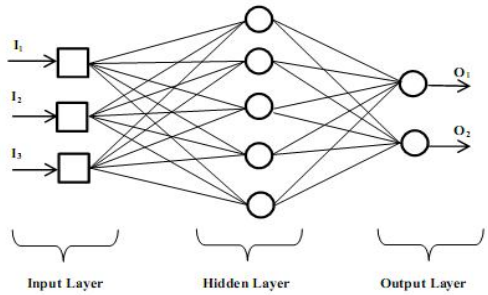


Fig. 2: A schematic of the MLP-NN.

Inputs and Outputs Selection:

According to equation (1), II rate is related to electric field exponentially. Because of high electric field in multiplication region, II events are generally occurred in this region. Therefore,the multiplication region has an effective role in value of excess noise. Consequently, we have considered the parameters which can change electric field in this region. According to physics of semiconductors and performance of SAM-APDs, we select the most effective parameters on excess noise factor such as width, band-gap and doping concentration of absorption and multiplication regions as well as bias voltage as inputs.

Width of absorption region is exponentially related to absorbed light power and affect in distribution of electric field in multiplication region. Type of used material in absorption region changes conduction band energy distribution in throughout of the device as well as distribution of carrier velocity. We use the band-gap energy as a criterion which can describe the type of material. Poisson equation demonstrates doping concentration effect in electric field distribution.

Obviously, applied bias voltage and the mentioned parameters such as width, type of material and doping concentration for multiplication region change directly electric field distribution. Consequently, we assume 7 mentioned parameters as inputs of MLP-NN model.

In reports, excess noise factor is generally plotted versus mean gain. So, we select both excess noise and mean gain as outputs of the model. Now, we are able to produce the mentioned plot and compare results of the model with desired results.

Preparation of Data

We considered many reports about excess noise in SAM-APDs. From gain-voltage and excess noise-gain characteristics, we obtained 645 patterns which included 7 and 2 elements as inputs and outputs respectively [6, 7, 10-23]. The range of inputs is tabulated in Table I.

Table 1. The values of inputs.

Input	Symbol	Range
Band-gap in abs. reg.	E_a (ev)	0.17-2.36
Band-gap in mul. reg.	E_m (ev)	0.17-2.36
Width of abs. reg.	W_a (μm)	0.02-2
Width of mul. reg.	W_m (μm)	0.02-2
Concentration of abs. reg.	N_a ($\times 10^{17}$ cm^{-3})	1-50
Concentration of mul. reg.	N_m ($\times 10^{17}$ cm^{-3})	1-500
Inverse bias voltage	V_b (v)	1-86.2

abs: absorption , mul: multiplication , reg: region

Values of inputs are in wide ranges. For example, electron-volt (~10^{-19}) is usually used for unit of bandgap and 10^{17} or 10^{18} cm^{-3} are employed for amount of doping concentration. Thus, we normalize each input in [0.05, 0.95] separately, using (3).

$$X_n = 0.05 + 0.9\frac{X_r - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

where X_n and X_r are normalized and un-normalized quantities, respectively. X_{max} and X_{min} present the maximum and minimum values of each input.

Training

We select 90% of data to train and the rest of them to test. In this stage, we try to obtain an appropriate architecture which has minimum RMSE to learn. This issue includes the determination of the number of neurons in the hidden layers and the type of the activation functions.

Two hidden layers are supposed, because the number of inputs and outputs is a little. To start, we used the hyperbolic tangent as the activation function in all layers. Then, we supposed the different numbers from 2 to 7 neurons in hidden layers. The minimum error was calculated 0.2095 with 100000 epochs when 7-5-5-2 neuron arrangement (7 neurons for input, 5 and 5 neurons for hidden and 2 neurons for output layers) was employed. To stability, we found values of learning rate, 0.3, 0.2, 0.2, and 0.15 for input, hidden and output layers respectively. Figure 3 compares RMSE values for 4 sample neuron arrangements.

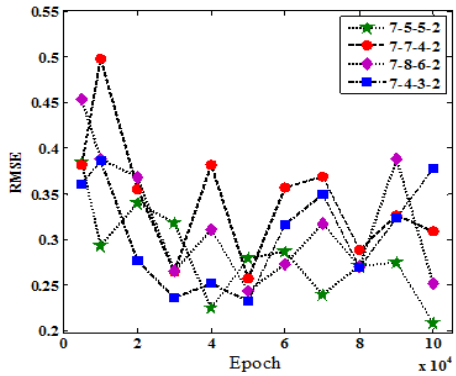


Fig. 3: RMSE versus epoch for 4 sample neuron arrangements.

RESULTS AND DISCUSSION

Using the defined network in section III, we apply the testing data to the network and compare the obtained results of network with the measured results [6, 7, 10-23]. Figure4 plots the calculated excess noise and gain versus the experimental results [6, 7, 10-23].

It's clear that, population of the points on bisector of the first quarter means the exact performance of the network. One can see the points are scattered around the bisector of the first quarter. Hence, the prediction of the proposed network is adequately close to the measured results for excess noise and gain. If we could gather more data to test set, we might improve performance of the model.

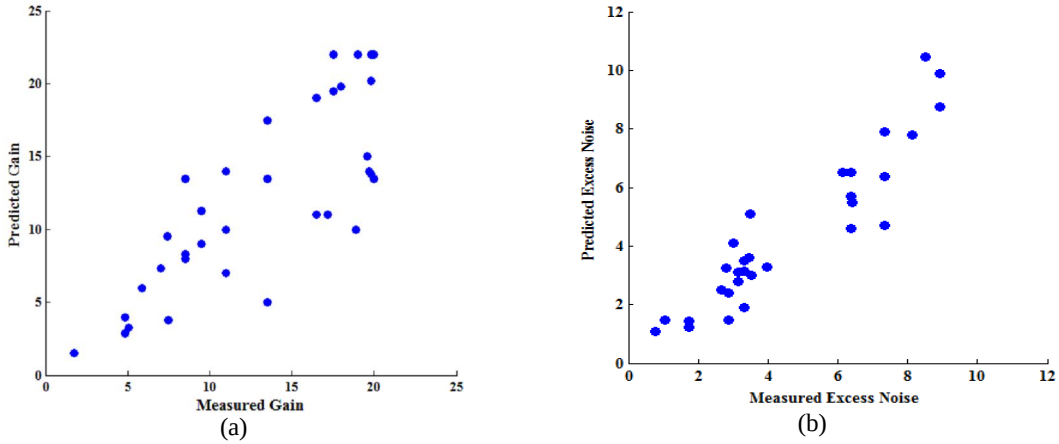


Fig. 4: The predicted results obtained from the model versus the experimental results for (a) gain and (b) excess noise [6, 7, 10-23].

It can be seen the model covers different material from 0.17ev to 2.36ev and has no complexity. This model assists us to study more details of SAM-APDs. As example, we select a sample device [21] to carry out sensitivity analysis for gain and excess noise. Table 2 gives the values of parameters for the sample device [21].

To analyze, we change an input from minimum to maximum values (see Table 1) while others be constant. We repeat this scheme for all inputs and record gain and excess noise. Then, we plot gain and excess noise versus variation of inputs. Slope of curves are known as sensitivity factors. As the slope becomes more means

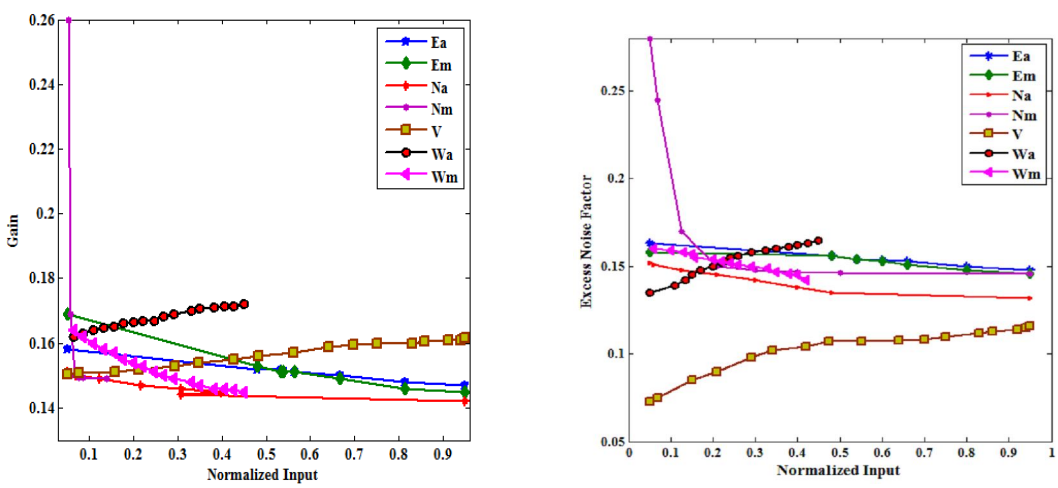
sensitivity of the output respect to the input is more. Sensitivity analysis for excess noise and gain are shown in Figure 5.

Table 2.Values of parameters in [21].

	Parameter	Value
Absorption Region	E_a(ev)	1.42
	N_a ($\times 10^{17}$ cm^{-3})	1
	W_a(μm)	0.2
Multiplication Region	E_m(ev)	1.42
	N_m ($\times 10^{17}$ cm^{-3})	5
	W_m(μm)	0.2
	V_b(v)	10.2

One can see the increasing of bias voltage results in more gain. Gain is equal to final number of carriers via II mechanism divide to initial number. Besides, the electric field in multiplication region is directly in proportion to bias voltage. Therefore, many II events are occurred in high voltage (or high electric field) regime where causes increasing of gain.

Generally, each case that redounds in increasing of electric field for multiplication region, it intensifies gain. As the absorption or multiplication regions become wider, intensity of electric field is reduced and gain is then reduced (see Figure 5).



(a) (b)

Fig. 5: Sensitivity analysis of (a) gain and (b) excess noise versus normalized inputs.

According to Poisson equation, doping concentration in both absorption and multiplication regions are key factors which determine the slope of electric fields in these regions. In general, if the doping concentration in a region is increased, 1) electric field distribution will be sloped and 2) mean electric field is reduces, because conductivity is improved. As a consequence, high doping concentration in absorption and multiplication regions reduce mean electric field in multiplication region where decrease gain of device.

In wide band-gap materials, carriers need to high energy to overcome the II threshold energy (see E_{th} in equation (1)). Wang has demonstrated $E_{th} \approx 1.5E_g$, where E_g is band-gap energy [2]. Consequently, when one use a wide band-gap material in device, gain will decrease if bias voltage being constant. This issue is approved for energy band-gap of both absorption and multiplication regions in Figure 5.

In general, excess noise factor is related to gain with equation (4) [2].

$$F = k_1 M^{k_2} \tag{4}$$

Wherek_1 and k_2 are fitting parameters. Although, Soroosh *et al.* have presented a neural network model which is capable of determining these parameters for PIN-APDs, this issue has remained as a challenge for SAM-APDs [24]. Equation (4) represents that increasing of gain intensifies excess noise monotonically. With respect to

equation (4), one can see Figure 5a is followed with 5b. In the main, if gain of APD is changed, excess noise factor will change in same direction of gain.

Mathematically, one can be expected if mean gain is increased; numerator will be intensified more than denominator in equation (2). To perceive this matter, we must use the Monte Carlo method. As the mentioned in section I, MC method presents a microscopic view which can physically simulate the trajectory of carriers in semiconductor devices. Using a MC model, Soroosh*etal*. have demonstrated that increasing of electric field results in the following effects:

a) Mean gain increases, because mean carrier II length reduces.

b) Distribution of carrier II length becomes wider.

Broadening for mentioned distribution is the main reason for increasing in excess noise factor. This agent causes that nominator becomes more than denominator in equation (2).

The presented model could adequately map inputs space to outputs space (see Figure 4). Also, it wascapable of description behavior of gain and excess noise respect to inputs variation (see Figure 5). In addition, simplicity and no time taking are other advantages of the presented model.

In this study, we considered SAM-APD as a system that contains some inputs and outputs. Although, this issue assists to present a simple model, as a disadvantage the presented model cannot cover details of designing. As an example, selection of materials for absorption and multiplication regions needs to have a technical experience. Wavelength of light applies low margin to energy band-gap of absorption region. Besides, lattice constant of layers is a main matter to growth of layers. It is clear thatthese are not respected in the presented model.

We believe the model can assist designer in determination of initial guess for parameters of SAM-APD. One can adjust input parameters to obtain the desired gain and excess noise. Then, one can use this issue before device fabrication. Besides, one can extend this model to other structures or other outputs such as dark current.

CONCLUSION

We have presented a multilayer perceptron neural network which can predict excess noise factor versus mean gain for separate absorption and multiplication avalanche photodiodes. This model is able to show some behaviors of device such as sensitivity analysis for excess noise and mean gain. The presented model has 7 inputs that are width, band-gap energy and doping concentration of absorption and multiplication regions as well as bias voltage. Outputs are excess noise factor and mean gain. This model can assist to designers which choose good values for initial designing. Also, one can extend the presented model to calculate other factors.

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