Photodetector Performance Prediction with Machine Learning

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Abstract: Four machine learning algorithms are tested to predict the performance metrics of modified uni-traveling carrier photodetectors from their design parameters. The highest accuracy ($> 94\%$) is achieved with artificial neural networks.

1. Introduction

Photodetectors, which convert incident light into electrical current, are essential components in RF-photonic systems and often limit their performance. In order to achieve high link gain, high-speed operation, low signal distortion, and a large spurious-free dynamic range, highly linear and ultra-fast photodetectors with high power handling capability are needed [1]. Uni-traveling carrier (UTC) photodetectors meet these demands by only using electrons as active carriers in the drift region [1–5]. The modified UTC (MUTC) includes a "cliff" layer to keep the electric field strength relatively small in the absorber and collector regions, which improves photodetector linearity [3–5].

We have developed numerical models based on the drift-diffusion equations to efficiently design photodetectors [5]. These models include many important real-world effects and have demonstrated excellent agreement with experiments when these photodetectors operate in both the continuous-wave and pulse modes. However, these simulations can require several hours of compute time even using modern high-performance computing facilities. In this work, we investigate four different machine learning algorithms. We find that it is possible to rapidly and efficiently estimate the photodetector performance. Among the algorithms that we tested, we concluded that the artificial neural networks are the most accurate.

2. Implementation

We first created a dataset [6] by assigning bounded random values to the layer thicknesses and doping levels of 17-layer MUTC photodetectors [4, 5]. The semiconductor types of these layers, which can be found in [5], are fixed. Minimum and maximum layer thicknesses are 5 nm and 2 μm, respectively. The doping levels in the p- and n-regions change between 5×10^{17} cm^{-3} and 2×10^{20} cm^{-3} and between 10^{14} cm^{-3} and 5×10^{17} cm^{-3} in the i-region. Then, we calculated the phase noise, output average current, and impulse response of 1750 different designs. We derived two performance metrics from the impulse response: "IR Max" (maximum value of the impulse response) and "decay time" (the time it takes for the impulse response to decay from its maximum value to 1% of that maximum value). Hence, our input and output vectors have 34 elements (thicknesses and doping levels of 17 layers) and 4 elements (phase noise, average current, IR Max, and decay time). The four machine learning algorithms, linear regression (LR), k-nearest neighbor (kNN), random forest (RF), and an artificial neural network (ANN), are run on Google Colaboratory. The ANN is implemented with Keras' functional application program interface running on top of TensorFlow. Figure 1(a) shows the ANN used in this work. There are 5 layers that all have 48 neurons connected either in series or sequential. The first and second two layers are expected to learn from layer thicknesses and doping levels, respectively, while the last layer is expected to combine those learnings to make predictions. A 20% dropout is applied after each layer to prevent overfitting. Adamax is used as the optimizer to minimize the mean squared error. The number of epochs and learning rate are set to 400 and 0.001, respectively. We use 80% of the data for training, and we use the rest for testing. The blue and orange curves in Fig. 1(b) show how validation (during training) and test losses decay with the number of epochs, respectively. These smoothly decaying and converging losses confirm that our ANN indeed learns from data. The inset of Fig. 1(b) shows actual vs. predicted phase noise for the 350 cases used in the testing. The high concentration of red circles around the $x = y$ line implies a high prediction accuracy, as we discuss next.

3. Numerical Results

In Table 1, we show the minimum and maximum values of the four performance metrics. To have a better understanding of the relative dispersion of these variables, Table 1 also shows their coefficient of variations (CV). Based on these coefficients, we can expect to have a higher accuracy for the prediction of the phase noise. The last four columns of Table 1 show the prediction errors of the four machine learning models for the four metrics in the first column. As

expected, all the models are able to predict the phase noise with errors less than 0.4%. However, for the remaining three metrics, the ANN performs better than the LR, kNN, and RF implementations. Since the training of the RF model takes a much shorter time than the ANN model, it can be considered as a good alternative.

Table 1. Dark Gray Region: Basic statistics (minimum, maximum, and coefficient of variation) of the performance metrics of the 1750 photodetectors studied. Light Gray Region: Mean absolute prediction errors (PEs) in percentile for the four ML models implemented.

	Minimum	Maximum	CV	LR (%)	kNN (%)	RF (%)	ANN (%)
Phase noise	−178.62 dBc/Hz	−161.51 dBc/Hz	−0.022	0.38	0.39	0.19	0.18
Ave. Current	1.46 mA	9.9 mA	0.65	16.81	5.16	3.5	2.47
IR Max	28.5 ns^{-1}	97.56 ns^{-1}	0.22	4.81	5.48	3.06	2.88
Decay Time	22.22 ns	184.77 ns	0.5	9.91	11.34	7.12	5.21

To determine the number of samples that is needed for an accurate prediction, we plot the errors of the four models in their predictions of the phase noise and average current as a function of the number of samples in the dataset, see Fig. 1(c) and (d). Again in each case, 80% of the data is used for training and the rest is used for testing. We observe that even a dataset with 100 samples is enough to predict the phase noise with less than an error of 1%, but to predict the current, we need at least 600 samples in order to have errors that are less than 5% for the ANN and RF models.

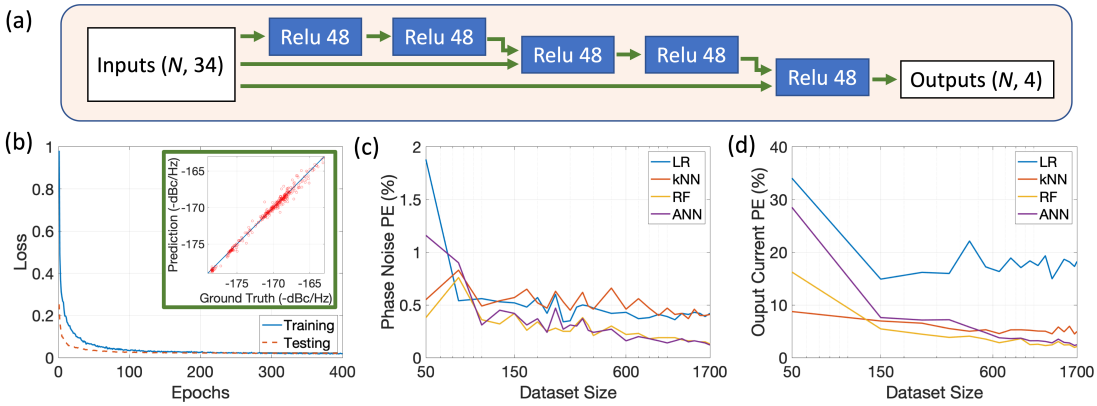

Fig. 1. (a) ANN design. (b) Training loss (blue curve) and validation loss (red dashed curve) vs. epoch number, inset: actual vs. predicted phase noise. Prediction error vs. number of samples in the dataset for (c) phase noise and (d) output current.

4. Conclusion

We use four machine learning algorithms to predict the performance metrics of photodetectors with a certain number of layers and a fixed set of semiconductor materials. Among the four algorithms that we tested, the artificial neural networks algorithm is the most accurate. We conclude that the random forest algorithm is the better alternative despite its slightly lower accuracy due to its significantly shorter computation time. These preliminary results demonstrate that machine learning algorithms can be used to rapidly and accurately estimate the performance of photodetectors with any given sets of layer thicknesses and doping levels.

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