Prediction of Cross Port Output in Electro-optic Mach-Zehnder interferometer Using Artificial Neural Network

Dilip Kumar Gayen[1] and Tanay Chattopadhyay[2*]

[1]*Department of Computer Science and Engineering,*

College of Engineering and Management, Kolaghat,

KTPP Township, Purba Medinipur, 721171, W.B, India.

[2]*Solar division, Bidyut Unnayan Bhaban, WBPDCL, Kolkata, 700106, West Bengal, India.*

Artificial neural networks are essential for the design and analysis of complex algorithms. We have designed a circuit with an electro-optic Mach-Zehnder interferometer (EOMZI) driven by a photodiode. The output from the EOMZI's cross bar port is used. Then, we have developed a photonic artificial neuron based on this setup. The outputs are validated using MATLAB, and the Artificial neural networks successfully generate the sigmoid function corresponding to the EOMZI switch's cross port.

I. INTRODUCTION

Optical electro-optic modulators are critical devices in the field of photonics. They are widely used in optical communication systems. One common configuration of the modulator is the electro-optic Mach-Zehnder interferometer (EOMZI). EOMZIs have high modulation bandwidth, low power consumption, and high performance [1–5]. EOMZIs are used in a variety of photonic applications, including optical fiber communications, optical signal processing, and optical computing. The modulation bandwidth of an EOMZI is the range of frequencies over which it can modulate an optical signal. The power consumption of an EOMZI is the amount of electrical power required to operate it. The performance of an EOMZI is measured by its modulation depth, extinction ratio, and linearity. Artificial neural networks (ANNs) are a type of machine learning algorithm that can be used to solve a wide variety of problems, including those in optics. ANNs are inspired by the human brain, and they are able to learn from data by adjusting their connections over time. The use of ANNs in optics is a rapidly growing field, and there are many exciting new research directions being explored [6–10]. For example, ANNs are being used to develop new optical imaging techniques, to improve the performance of optical communication systems, and to create new optical computing platforms. This study explores the use of a photodetector (PD) sensor to convert light into an electrical signal. The amplified electrical signal is used to drive a Mach-Zehnder interferometer (MZI), which produces an optical output at the cross port. Cross port output is used to design optical NOT gates, 1's

compliment operation in optical computing. An equivalent model of these circuits is also developed using an artificial neural network (ANN). The ANN takes light intensities as inputs and generates optical signals as outputs. The conditions required for the framework to work are derived and validated using the ANN and MATLAB. The output of the ANN is verified to be in agreement with the sigmoid activation function.

II. SCHEMATIC REPRESENTATION OF THE PROPOSED CONFIGURATION

The block diagram of the proposed scheme is shown in Fig. 1(a). The proposed scheme consists of a photodetector (PD) sensor, an amplifier and a Mach-Zehnder interferometer (MZI). The PD sensor converts light into an electrical signal. The electrical signal is amplified and used to drive the MZI. The amplifier is used to amplify the signal from the PD. This is necessary because the signal from the PD is typically very weak. The amplifier increases the signal strength so that it can be used to drive the MZI. The MZI is a type of interferometer that can be used to modulate the phase of an optical signal. The MZI works by splitting the optical signal into two paths and then recombining them. This amplified voltage creates phase shift($\Delta\delta$) of the optical signal propagated through the two arms of MZI switch. When 0, destructive interference occurs at output coupler of MZI and data is transmitted to lower cross port. But when $\Delta\delta \sim 0$, then output at cross port is absent. The EOMZI figure is shown in Fig. 1(b). According to theoretical calculation cross port output can be expressed a $P_{out} = |\cos(\Delta\delta/2)|^2$ [11].
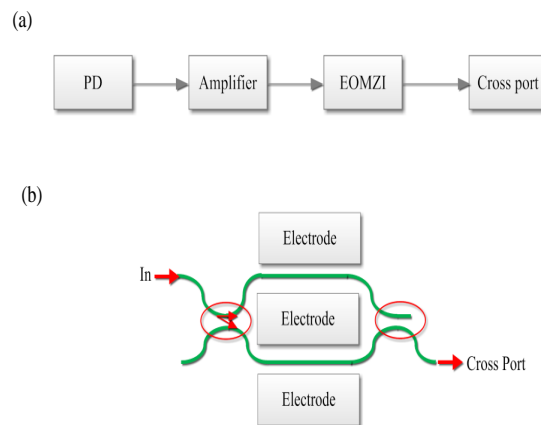

FIG. 1: (a) Block diagram of the proposed scheme, (b) EOMZI layout.

III. PREDICTION USING AN ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural networks (ANNs) are used by many researchers to build output prediction systems [12–14]. ANNs require a large number of input and output data points to be created. The neural network design in Fig. 2 has three levels: the input layer, the hidden layers, and the output layer. Each neuron in the hidden layer has a weight assigned to it. In this architecture, the input layer comprises one neurons, denoted as $a_1^{(0)}$, which represent the light intensity of the system as measured by the photodiode. In our architecture, the hidden layer is composed of six neurons, namely $a_1^{(1)}$ to $a_6^{(1)}$. The weights and activations of these neurons play a crucial role in the neural network's overall performance and output predictions. The output layer consists of one neuron, labeled $a_1^{(2)}$, representing the output optical power at cross port of EOMZI. The data set has been divided into three parts: the test data set, the training data set, and the validation data set. The data set was partitioned into three segments, with 85% allocated for training, 10% for testing, and the remaining 5% for evaluating the network's overall performance.
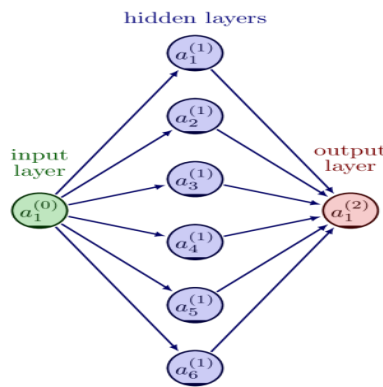

FIG. 2: ANN model layout.

Figure 3 illustrates the Mean Squared Error (MSE) variations for the training, validation, and testing data sets concerning the number of epochs at the output $a_1^{(2)}$. As depicted in the figure, the best validation performance is achieved at epoch 61, with an MSE of 8.034E-06. Beyond epoch 61, the errors begin to increase, leading us to terminate the training process to prevent over fitting.

Figure 4 shows the error values for the training, validation, testing, and overall data sets. The error factor, which is a measure of how close the neural network's output is to the desired output, is closer to 1 for all four data sets. This indicates that the neural network is able to fully associate the input data set with the model data set. The error values for the training, validation, testing, and overall data sets are 0.99999, 0.99997, 0.99998, and 0.99998, respectively. These results show that the designed neural network is performing well. After training the neural network, we tested it with different input values. Fig. 5(a) shows the distribution of
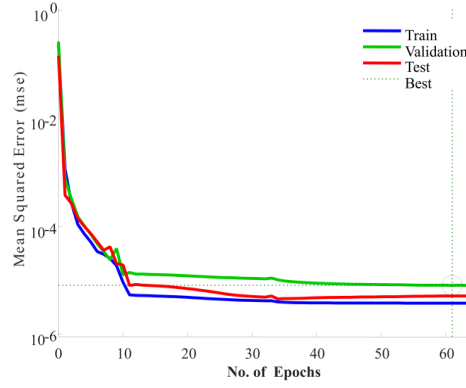
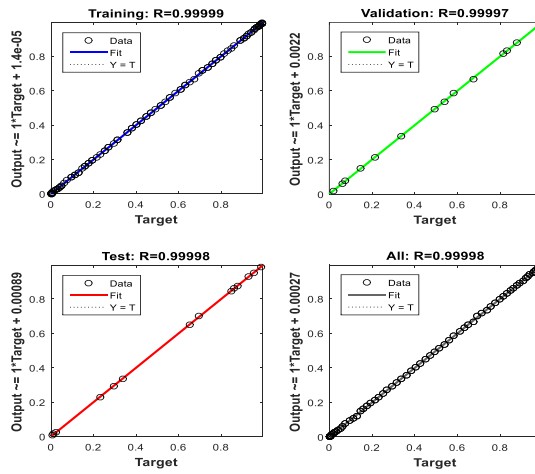FIG. 3: Error with number of iterations (Epochs) at the output $a_1^{(2)}$.

FIG. 4: Variation of error for various data sets at the output $a_1^{(2)}$.

training outputs and target outputs for different data sets: the training data set, the validation data set, and the test data set. Figure 5(b) shows the errors, which are the differences between the training output and target output, for different sets of inputs.

The results show that our constructed neural network accurately predicts the output values. This indicates that the neural network is robust and can generalize to new data sets. We can therefore be confident in using this neural network to predict output values for unknown data sets. The figure also shows that the sigmoid function is accurately modeled at the output terminal ($a_1^{(2)}$). We find the function as

$$f(x) = \left(\frac{e^{i0.022x} + e^{-i0.022x}}{2} \right)^2. \tag{1}$$

We also plot the Cross port theoretical value with ANN model value in Fig. 6. This further validates the effectiveness of our approach.
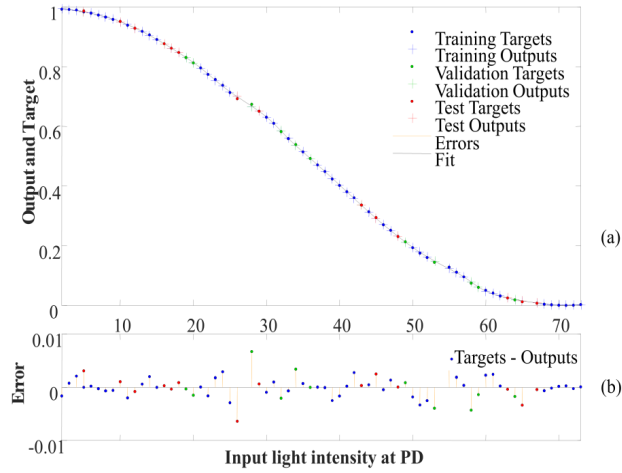
FIG. 5: (a) Displays the distribution of training outputs against input intensity of light at photo diode and target outputs for different data sets at the output $a_1^{(2)}$ and (b) the errors, calculated as the differences between the training outputs and target outputs, are depicted for various sets of inputs at the output $a_1^{(2)}$.
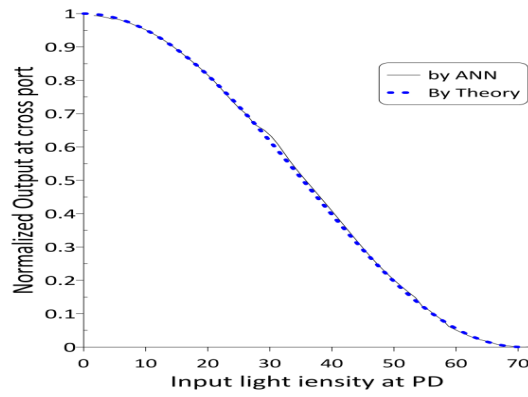

FIG. 6: Theoretical output and ANN plot of EOMZI cross output.

IV. CONCLUSION

This research effectively showcases the utilization of a photodetector (PD) sensor for converting light into an electrical signal, which in turn propels an EOMZI to generate optical outputs at the cross port. Through the implementation of Artificial Neural Networks (ANNs), precise predictions of optical outputs were achieved. The outcomes underscore the ANN's capability to accurately approximate the sigmoid function at the output terminal, reinforcing the credibility and appropriateness of the ANN model for this undertaking. Evaluation of the network's performance using testing data revealed an error factor approaching 1, signifying the successful association of input data with the model data set.

* Electronic address: tanay2222@rediffmail.com

[1] S. Awasthi *et al*, Journal of Computational Electronics **22**, 485 (2023).

[2] I. V. Kuznetsov and A. S. Perin, Journal of Optical Technology **90**, 93 (2023).

[3] H-S. Jung, Journal of the Optical Society of Korea **16**, 47 (2012).

[4] F. Valdez, V. Mere, X. Wang, and S. Mookherjea, Optics Express **31**, 5273 (2023).

[5] L. Lu, L. Zhou, X. Li, and J. Chen, Optics Letters **39**, 1633 (2014).

[6] T. Shan, J. Li, X. Hou, P. Huang, and X. Guo, 5th International Proceedings on Artificial Intelligence Circuits and Systems (AICAS), Hangzhou, China, **1-2**, (2023).

[7] T. Wang *et al*, Nature Photonics **17**, 408 (2023).

[8] Y. Du *et al*, IET Optoelectronics **17**, 1 (2023).

[9] P. Celard *et al*, Neural Computing and Applications **35**, 2291 (2023).

[10] S. R. Mohandes, X. Zhang, and A. Mahdiyar, Neurocomputing **340**, 55 (2019).

[11] C. Reis, T. Chattopadhyay, P. Andre, and A. Teixeira, Applied Optics, **51**, 8693 (2012).

[12] N. P. Juan, and V. N. Valdecantos, Ocean Engineering **259**, 111947 (2022).

[13] O. Guest, and A. E. Martin, Computational Brain & Behavior **6**, 213 (2023).

[14] D. Zhang et al., Artificial Intelligence Review **56**, 10651 (2023).