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# A 1.55 $\mu\text{m}$ Wideband $1 \times 2$ Photonic Power Splitter With Arbitrary Ratio: Characterization and Forward Modeling

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**ABSTRACT** Chip-based photonic systems have undergone substantial progress over the last decade. However, the realization of photonic devices still depends largely on intuition-based trial-and-error methods, with a limited focus on characteristic analysis. In this work, we demonstrate an in-depth investigation of photonic power splitters by considering the transmission properties of 16,000 unique ultra-compact silicon-based structures engraved with  $\text{SiO}_2$ ,  $\text{Al}_2\text{O}_3$ , and  $\text{Si}_3\text{N}_4$  nanoholes. The characterization has been performed using finite-difference time-domain (FDTD) simulations for each dielectric material and both TE and TM polarizations at the fundamental modes in a wideband optical communication spectrum ranging from 1.45 to 1.65  $\mu\text{m}$ . The corresponding transmissions, splitting ratio, and reflection loss were calculated, generating a dataset that can be used for both forward and inverse modeling purposes, using Machine Learning (ML) and Deep Learning (DL) algorithms. With an optimized hole radius of 35 nm, the proposed device area footprint of  $2 \mu\text{m} \times 2 \mu\text{m}$  is among the smallest with the best transmission reported to date.  $\text{Si}_3\text{N}_4$  holes show excellent transmission because they offer 90% transmittance in 96% of the data while exhibiting maximum fabrication tolerance. Forward modeling analysis, predicting the transmission properties, was performed using both Linear Model (LM) and Artificial Neural Network (ANN), where LM showed marginally better accuracy than ANN in foreseeing the transmittance. The proposed observation will aid in achieving robust, optimized optical power splitters with a wide range of splitting ratios in lesser time.

**INDEX TERMS** Forward modeling, machine learning, optical power splitter, artificial neural network.

## I. INTRODUCTION

Recent advances in fabrication techniques have enabled ultra-scaling of both optical and electronic devices [1]. Especially, the last decade has seen a significant push towards integrated optical circuits and devices [2]. A plethora of probable application areas [3]–[7] has been demonstrated leveraging the benefits of nanoscale photonic devices. The primary motivation is that the same amount of data can be handled using much less amount of power with optical signals compared to electronic ones.

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One of the primitive components for integrated optics involves optical interconnects [8] and photonic power splitters are a significant member of the interconnect family [9]. A good photonic splitter can direct the light input of a certain wavelength to multiple ports at varying intensities with minimum losses. These passive devices may lend themselves to applications ranging from signal distribution [10], [11], feedback circuits [12], to power equalization [13], or even in-mode multiplexers [14]. Popular designs of photonic power splitters [15]–[18] include a symmetrical pattern of silica or uniform distribution of pores etched onto the silicon substrate for guiding the electromagnetic wave [14], [19]. Unfortunately, these simple, yet easily conceivable structures are bound to explore only a limited number of architectures.

Hence, a broad range of transmittance ratios at the output ports remains unexplored. Having no empirical formula relating geometry, and transmission for power splitter, the analysis triggers a complex scenario. As a result, little has been known regarding the influence of materials and modes on split waves or the etched dielectric hole density and dimension optimization.

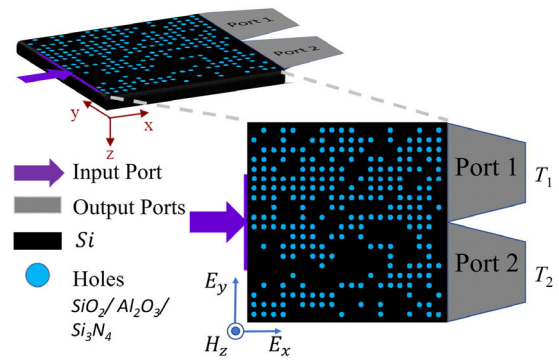
This study presents a comprehensive analysis of the characteristics of silicon-based photonic power splitters, having holes with three different dielectric materials ( $\text{SiO}_2$ ,  $\text{Al}_2\text{O}_3$  and  $\text{Si}_3\text{N}_4$ ) for a 200 nm operating window keeping 1.55  $\mu\text{m}$  as central wavelength. First, 16 thousand random blueprints of power splitters are generated, then their performances are simulated and finally, the results are statistically analyzed. Traditionally, securing the desired transmission requires a long iterative process, where we guess the device geometry, solve Maxwell’s equations and finally achieve a design with reasonable performance. To circumvent the intuitive approach, we took the advantage of our 16 thousand training instances and applied the concept of ANN. Being universal function approximators [20], deep learners like ANNs can accurately predict the properties of the splitters [21] in any forward modeling problem. In general, these algorithms offer productive solutions as once trained, they can estimate the response accurately of any random system [22]–[24]. Other numerical and topological optimization techniques [25] or genetic algorithm [26] based methods can be employed for similar purposes. These methods, however, are expensive in terms of time and computational resources compared to Artificial Intelligence (AI)-based techniques like ML and DL. Hence, by implementing ANN in this work, we bridge the gap between characterization and performance evaluation of photonic power splitters, avoiding time-intensive and computationally exhaustive steps. This also enables us to achieve higher performance at smaller footprints with arbitrary structure, which opens up possibilities to achieve a broad range of desired responses.

To the best of our knowledge, this work is the first one to make the data pool of photonic power splitter open-sourced [27]. As AI-based solutions are currently going through a generalization crisis [28], open-source solutions and datasets are crucial to achieving more viable, robust and practical solutions.

The organization of the paper is as follows: Section II discusses the design and characterization of the photonic power splitters with respect to mode, material and hole dimensions. Section III depicts the inclusion of DNN in our current study to accurately monitor transmittance and reflection losses. Finally, Section IV concludes.

## II. DESIGN METHOD AND CHARACTERIZATION

A robust photonic power splitter is mainly composed of optical branching waveguides [29], which direct the optical signals of intended power density, through the device and to the designated ports. In this work, a silicon substrate of dimension  $2 \mu\text{m} \times 2 \mu\text{m}$  area and  $0.01 \mu\text{m}$  thickness has



**FIGURE 1.** 2D and 3D schematic of a  $1 \times 2$  nanostructured photonic power splitter with a footprint of  $2 \mu\text{m} \times 2 \mu\text{m}$  on a Silicon substrate. Circles are indicating the locations of each hole, with an optimized radius of 35 nm. A broadband light is illuminated at the input port; transmitted through the device and an output signal is collected at output ports of port 1 ( $T_1$ ) and port 2 ( $T_2$ ).

**TABLE 1.** Dielectric properties of materials at 1.5  $\mu\text{m}$  wavelength.

Material	Permittivity( $\epsilon$ )	Refractive Index( $\eta$ )
Silicon (Si)	12.1	3.48
Silicon Dioxide ( $\text{SiO}_2$ )	2.08	1.44
Aluminum Oxide ( $\text{Al}_2\text{O}_3$ )	3.05	1.75
Silicon Nitride ( $\text{Si}_3\text{N}_4$ )	6.07	2.46

been adopted to design an optical power splitter working in the range of 1.45 to 1.65  $\mu\text{m}$ . Here,  $T_1$  and  $T_2$  are the outputs of ports 1 and 2, respectively. Here, the transmitted outputs are estimated by keeping the power monitors at the edge of the structure. The lengths of the monitors are half of the length of the substrate. Since the monitors cover the whole length of the structure, no edge loss was required to be calculated. The total surface area is considered to be composed of  $20 \times 20$  pixels, where each pixel corresponds to either a dielectric hole with optimized dimension or a solid. The holes are etched at different matrix positions to enable the optical wave interaction with the structure to guide the EM wave in the desired path and different combination of holes and substrate have been explored. Si as substrate material exhibits low loss at the concerned wavelength [30] and as for holes, three distinct dielectric materials are adopted: silicon dioxide ( $\text{SiO}_2$ ), aluminum oxide ( $\text{Al}_2\text{O}_3$ ) and silicon nitride ( $\text{Si}_3\text{N}_4$ ). Relative variations of refractive indices ( $\Delta\eta = \eta_{\text{substrate}} - \eta_{\text{holes}}$ ) between substrate and hole materials affect effective dielectric properties of the media and hence the propagation phenomena. The schematic of the structure and the dielectric properties of the constituent materials are given in Fig.1 and Table 1 respectively. In Fig. 1, the black surface represents the substrate; blue circles indicate the dielectric holes.

In this work, we have done the characterization analysis at the concerned spectrum for both fundamental transverse electric (TE) and transverse magnetic (TM) modes. Commercial FDTD based software, Lumerical has been used to perform the numerical study. Performance optimization has been done

in terms of hole dimension, material selection, effects of TE and TM modes on transmittance and splitting ratios and the influences of hole positions on the transmission direction by using 16 thousand unique photonic power splitters.

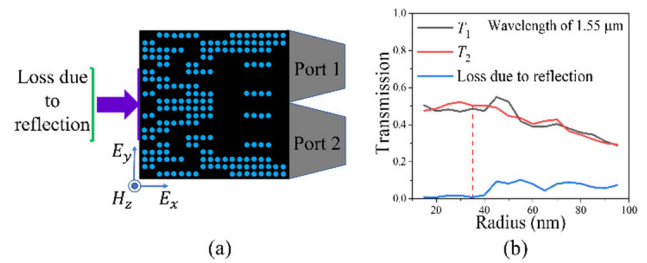
**A. UNIQUE PATTERN GENERATION**

The geometry of the hole pattern significantly *alters* the performance of the splitter. Therefore, a set of 16 thousand random patterns of holes are generated to characterize different aspects of the splitter. The whole substrate was considered to be composed of  $20 \times 20$  array positions. A random number generating algorithm was implemented to define the values of each position as 1 or 0 arbitrarily with a 40%-60% hole occupancy in the structure. This constraint has been set to ensure a realistic power transmission scenario. The design sets are unique with random irregularities and the transmission through either port follows a normal distribution (Discussed further in section C).

**B. HOLE RADIUS OPTIMIZATION**

The existing literature on power splitters lacks clarity regarding the determination and optimization of the radius of the dielectric holes [31], [32]. To achieve the best performance of the power splitter, hole radii are optimized in terms of transmittance and reflectance.

First, a random distribution of holes that has a 1:1 power splitting ratio in TE mode has been chosen to be engraved onto the silicon substrate (Fig. 2(a)). The hole radii are varied from 15 nm to 90 nm at 5 nm intervals for a Gaussian source of wavelength ( $\lambda$ ) of 1.55  $\mu\text{m}$ . With the advancement of various promising nanolithography process providing high resolution, precision and low line edge error for fabrication of nanostructures, such small feature size is now made possible to fabricate with negligible error.



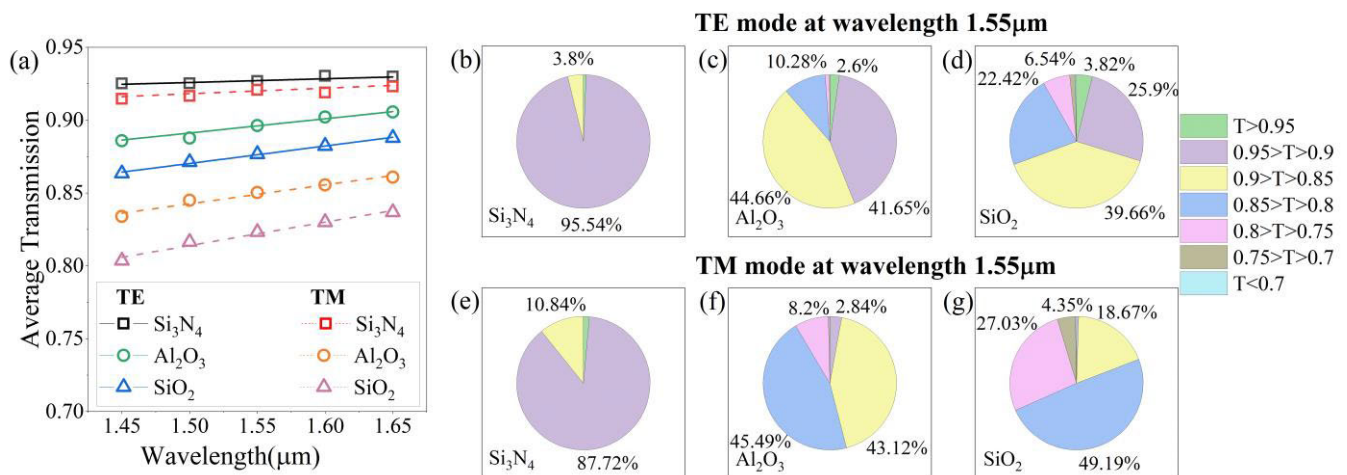
**FIGURE 2. (a) A power splitter with hole ( $\text{SiO}_2$ ) configuration corresponding to equal splitting at the output ports, to calculate transmission and reflection loss at different radius; (b) the transmission vs radius curves, where the optimized radius of 35 nm is marked with red dashed line. We defined the figure of merit as  $\text{FOM} = \text{max transmission, } (T_1 + T_2) - \text{min reflection, } (R)$ . Maximum FOM at the wavelength of 1.55  $\mu\text{m}$  is observed at 35 nm. Reflection loss increases after around 35 nm.**

From Fig. 2(b), at 35 nm, the reflection loss is minimum (0.008) with a transmittance of 0.99. This estimation has also been performed and validated for 1.45  $\mu\text{m}$  and 1.65  $\mu\text{m}$  and a few other designs (not shown in Fig. 2). This indicates that a hole radius of around  $\lambda/40$  should provide optimum performance.

**C. MATERIALS AND MODES DEPENDENT TOTAL TRANSMISSION**

Next, the total transmissions for the 16,000 random structures, are shown in Fig. 3 for TE and TM mode.

Transmission =  $P_{\text{out}}/P_{\text{in}}$  has been calculated where  $P_{\text{in}}$  designates the input power through port 1 and  $P_{\text{out}}$  as the total transmitted power from the two output ports. Transmission over the whole frequency range of 1.45  $\mu\text{m}$  to 1.65  $\mu\text{m}$ , which is the most used band for optical communication, is shown in Fig. 3(a). The maximum and minimum change from the central wavelength is only 0.27% ( $\text{Si}_3\text{N}_4$ ) and 2% ( $\text{SiO}_2$ ) respectively. This variation being very low indicates the fact



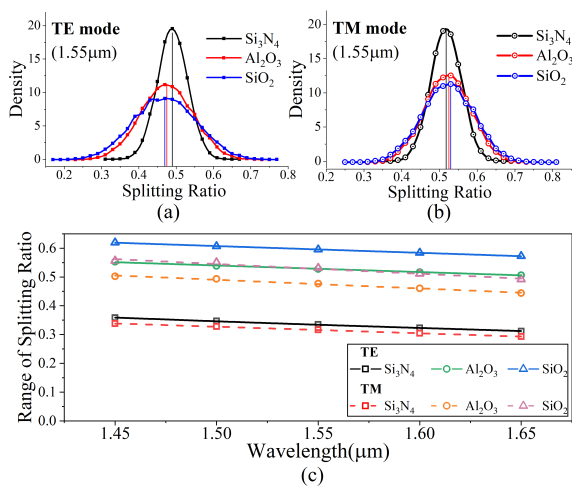
**FIGURE 3. (a) Average transmission for 16 thousand random configurations at the wavelength range of 1.45  $\mu\text{m}$  to 1.65  $\mu\text{m}$  for TE (solid lines) and TM (dashed lines) modes. Total transmission of the random configurations for (b)-(d) TE and (e)-(g) TM mode, and for 3 dielectric materials of (b), (e)  $\text{Si}_3\text{N}_4$ , (c), (f)  $\text{Al}_2\text{O}_3$ , and (d), (g)  $\text{SiO}_2$  as holes at the center wavelength of 1.55  $\mu\text{m}$ .**

that the response of the representative data for the center frequency of 1.55  $\mu\text{m}$  can be chosen for further analysis. The probability of higher transmission is found when the TE mode (Fig. 3(b) –(d)) is applied, in comparison to the TM mode (Fig. 3(e) –(g)) as a source.

**D. MATERIAL AND TRANSMISSION MODE DEPENDENT SPLITTING RATIO (SR)**

To investigate the effects of TE and TM modes for different hole materials on a larger scale, splitting ratios are calculated for all 16,000 unique structures. Fig. 4(a) and (b) represent the percentage of occurrence of SRs, for 3 different dielectric materials at both fundamental modes. Here, the splitting ratio (SR) is defined in (1).

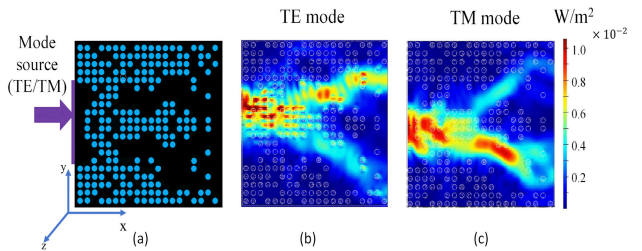
$$SR = \frac{T_1}{T_1 + T_2} \tag{1}$$



**FIGURE 4.** Distribution of splitting ratios at 1.55  $\mu\text{m}$  of 16 thousand random configurations for three hole materials, illuminated by two-mode sources, (a) TE and (b) TM. The mean values of the distributions are marked with lines. (c) The dynamic range of splitting ratio ( $3\sigma$ ;  $\sigma$  = standard deviation) over the wavelength range of 1.45  $\mu\text{m}$  to 1.65  $\mu\text{m}$  for both TE (solid lines) and TM (dashed lines) displays the smallest range for  $\text{Si}_3\text{N}_4$ , then for  $\text{Al}_2\text{O}_3$  and the largest range in  $\text{SiO}_2$ .

The peaks of the curves in Fig. 4(a) and (b) show that TE mode structures are more inclined toward  $SR < 0.5$  and TM mode structures toward  $SR > 0.5$  at the central wavelength. This indicates that in TE polarization, enhanced propagation occurs towards port 2, while for TM, port 1 is more favorable. This trend is evident in 60% of the structures, irrespective of hole materials. If we define the dynamic range of SR by  $3\sigma$  deviation ( $\sigma$  being the standard deviation of the distribution) from the corresponding mean, covering 99.7% of the data, there is a gradual increase from 0.33 for  $\text{Si}_3\text{N}_4$ , 0.53 for  $\text{Al}_2\text{O}_3$  to most variation or highest dynamic range of SR for  $\text{SiO}_2$  which is 0.6 for TE mode source.

Another observation from the curves of Fig. 4(a) and (b) is that, compared to  $\text{SiO}_2$  and  $\text{Al}_2\text{O}_3$ ,  $\text{Si}_3\text{N}_4$  has the narrowest range of SR, suggesting most of the ratios are near the peak. Also, for  $\text{Si}_3\text{N}_4$ , as verified by thousands of random



**FIGURE 5.** (a) A random hole distribution of a photonic power splitter with optimized radius, (b) and (c) Poynting vector corresponding to the structure in (a) with mode source of TE and TM respectively.

configurations, the ratios vary the least with the change of configurations.

Dynamic ranges are also recorded for the overall bandwidth of 200 nm (Fig. 4(c)). Upon obtaining linear fittings of the data points, the slopes obtained for TE and TM polarization are around 0.23 for all three materials. Again, negligible frequency dependency is observed within the range, justifying our selection of single-center frequency for further rigorous analysis. The lower dynamic range of power distribution occurs due to the small difference in refractive indices between Si and  $\text{Si}_3\text{N}_4$ . For TM mode source, structures have a slightly lower range for all materials compared to their corresponding TE mode structures in the concerned window.

The power distribution ratio between the two ports mainly depends on the effective length of the coupled region i.e., the splitter geometry, branching angles towards two ports, and the optical properties of the materials. Divergence near the output ports adds excess attenuation, by introducing local mode to the radiating field. Hence, TE and TM modes at the same frequency incorporate different propagation vectors with varying splitting ratios. For a random structure, as shown in Fig. 5(a), the typical power flow distribution for both TE and TM mode are provided in Fig. 5(b) and (c), respectively. Here, holes of  $\text{SiO}_2$  with optimized radius are implemented where, splitting ratio (SR) (defined in eq. (1)) is 0.61 for TE mode, and for TM mode, it is 0.33. The coupling ratio between the two output ports occurs in M:N form, where M and N take any value from 1 to 5.

**E. SENSITIVITY TO FABRICATION ERROR**

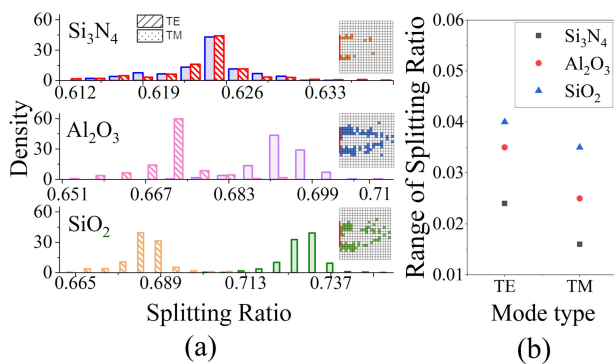
Complex fabrication processes, for example, during etching, can sometimes lead to additional or missing holes. To investigate which locations of the holes are more sensitive to fabrication errors, we select a base random structure and then toggle the hole at each position, to see its impact on the output transmission. The hole toggle means turning each matrix position ON (hole present), if there is no hole at that position, or OFF (hole absent), when there is a hole present, one at a time.

It is to be noted that all three dielectric materials are shown in Fig. 6 (a) have the same base random structure, each having 400 data points for the  $20 \times 20$  matrix. The same observations were found with few other random structures. In all cases,

**TABLE 2.** Comparison of previously reported photonic crystal power splitter.

Year (Ref)	Dimension ( $\mu\text{m} \times \mu\text{m}$ )	Average Transmission (%)	Hole Distribution	Hole dimension (nm)	Materials used
2013 [19]	10 $\times$ 8	100	Controlled/Systematic	128 (Uniform)	Si-GaAs (Triangular lattice)
2019 [31]	2.6 $\times$ 2.6	90	Random	45 (Uniform)	Si-SiO <sub>2</sub> (Square lattice)
2020 [33]	10 $\times$ 10	97	Controlled/Systematic	370 (Uniform)	Si-Air- defect rods at the bend (Hexagonal lattice)
2020 [32]	2.25 $\times$ 2.25	91.8	Random	40 to 72 (Non-Uniform)	Si-SiO <sub>2</sub> (Square lattice)
Proposed	2 $\times$ 2	94.935	Random	35 (Uniform)	Si- SiO <sub>2</sub> , Si-Al <sub>2</sub> O <sub>3</sub> , Si-Si <sub>3</sub> N <sub>4</sub> (Square lattice)

most configurations followed the base SR ratio, and those that varied most are considered as the “outliers”. Hence, those positions of the outlier holes are mostly sensitive to fabrication uncertainties. The positions responsible for outliers (points beyond  $\sigma$  distribution from the mean) are highlighted in the square structures representing the power splitter and are shown in the inset of Fig. 6(a). A significant observation from the patterns is that the outliers are mostly near the edge of the device where the source is positioned, irrespective of materials; this necessitates careful considerations to avoid any fabrication defects close to the source.



**FIGURE 6.** (a) Occurrence of splitting ratio (SR), as defined in (1), with hole toggling for three dielectric materials, (b) dynamic ranges of SR at different modes. Significant outlier positions (beyond  $\sigma$  distribution from the mean) for each material are highlighted in the schematic structures in the inset of (a). The source is shown with the red line on the surface.

The dynamic range of SR (defined as  $3\sigma$  to  $-3\sigma$  distribution from mean) extracted from Fig. 6(a), is shown in Fig. 6(b). Considering minimum error occurring in one-hole position at a time, Fig. 6(b) shows that the lowest variation of SR (dynamic range of SR) is obtained when holes are made of Si<sub>3</sub>N<sub>4</sub>. Also, the structure is least tolerant to fabrication errors for SiO<sub>2</sub> and most tolerant for Si<sub>3</sub>N<sub>4</sub> holes.

## F. COMPARISON WITH PREVIOUSLY REPORTED PHOTONIC POWER SPLITTERS

The performance of our proposed design is compared with previously reported power splitters with photonic crystal in the Table 2. As observed from the table, the structures having controlled or systematic hole (or rod for 2D photonic crystal) distribution, rather than random distribution as in this work, [19], [33] show higher average transmission than our structure. But for such systematic distribution, structures with much larger dimensions are required, to prevent sharp bending angles. Hence, all the structures in [19], [33] have a significantly larger size compared to the randomly distributed ones. Also, losses due to sharp bending can be avoided by placing randomly distributed holes. Among the randomly distributed power splitters, our proposed structure is of the smallest dimensions reported up to date with the higher average transmission of 94.935% for equally power splitting configuration compared to the transmission reported by [31], [32] in recent times.

## III. FORWARD MODELING FOR 1.55 $\mu\text{m}$ OPTICAL POWR SPLITTER

Next, we use the ML algorithm to perform forward modeling analysis only on the dataset for the splitter with hole material made up of Si<sub>3</sub>N<sub>4</sub>, consisting of 16 thousand random configurations. Here, our predictions of transmission response for arbitrary Hole Vector (HV) structures are based on the device working at 1.55  $\mu\text{m}$  and bandwidth ranging from 1.45 to 1.65  $\mu\text{m}$ . For this purpose, LM and ANN were used to build the regressors for a forward model. We found that the prediction of transmission response could be done using a shallow ANN, and the LM made marginally better predictions compared to the ANN. In the following subsections, we present the implementation details of our ML pipeline followed by the forward modeling performance results.

**A. DATASET**

As stated in the previous sections, the dataset for dielectric material of  $\text{Si}_3\text{N}_4$  has a total of 16,000 HV structures, where each of the HV containing  $\mathbb{R}^{400}$  binary input features, represents a unique  $20 \times 20$  HV structure. The problem is constructed as a regression task, where the  $T_1$  and  $T_2$  transmissions for an arbitrary HV structure were predicted. The reflection loss ( $R$ ) of the HV is not included in the prediction as it can be calculated easily from (2) and it also simplified our regression task as well.

$$T_1 + T_2 + R = 1 \tag{2}$$

The dataset was randomly split between the train and test sets using a stratified sampling method, to a ratio of 80:20. No standardization or normalization operation was performed on the dataset after splitting, as preprocessing did not increase our model performance. We also performed a 5-fold Cross-validation with 3 repeats. However, the results of the repeated  $k$ -Fold Cross-Validation were found to be the same as a single train-test split. Therefore, we have only reported the results of a single split. The train test split was done using the  $R$  package *splitTools*.

**B. IMPLEMENTATION DETAILS**

The LM was implemented using base  $\mathbb{R}$ .  $T_1$  and  $T_2$  were predicted using the 400 HV inputs. The linear equations of LM are

$$Y_{T_1} = \beta_{0T_1} + X \cdot \beta_{T_1} \tag{3}$$

$$Y_{T_2} = \beta_{0T_2} + X \cdot \beta_{T_2} \tag{4}$$

where,  $Y_{T_1}$ ,  $Y_{T_2}$  represent the predicted transmittance and  $\beta_{0T_1}$  and  $\beta_{0T_2}$  indicate the intercept terms for  $T_1$  and  $T_2$  respectively.  $X$  along with  $\beta_{T_1}$  and  $\beta_{T_2}$  are 400-length single

**TABLE 3. Forward modeling performance of LM and ANN.**

	$T_1$		$T_2$	
	LM	ANN	LM	ANN
RMSE	0.0075	0.0103 $\pm$ 0.002	0.0076	0.0115 $\pm$ 0.003
RMSPE (%)	0.0167	0.0229 $\pm$ 0.004	0.0162	0.0244 $\pm$ 0.006
MAE	0.0059	0.0082 $\pm$ 0.002	0.0059	0.0093 $\pm$ 0.003
MAEPE (%)	0.0131	0.0181 $\pm$ 0.004	0.0127	0.0197 $\pm$ 0.006

vectors that contain all HV inputs and all the corresponding coefficients to the HV positions respectively.

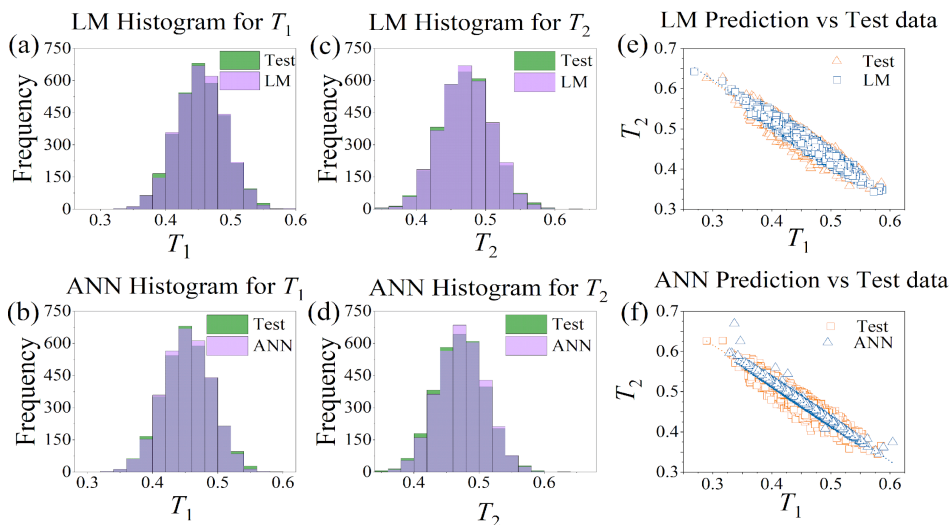
The ANN was implemented in Keras, where a shallow network was used for the prediction purpose that consisted of only 2 hidden layers.

As input, 400 HV positions were used. Our output consisted of 2 neurons, each predicting  $T_1$  and  $T_2$  respectively. We used the He uniform initialization [34] to initialize our hidden layers. Both *sigmoid* and *tanh* were found to be a viable option as activation function, where, *sigmoid* took longer to train compared to *tanh*. However, we used *ReLU* (Rectified Linear Unit) as our activation function as it converged the fastest compared to *sigmoid* and *tanh*.

We did not use any input normalization (*BatchNorm*) for our hidden layers [35] as it did not increase the model performance. We used *Adam* [36] as our optimizer with a fixed Learning Rate (LR) of 0.005 and epsilon of 0.0003. The model was trained for 25 epochs with a batch size of 100. Also, 20% of our training set was used as a validation set.

**C. FORWARD MODELING PERFORMANCE**

The forward modeling performances of the models are given in Table 3, where  $\pm$  indicates the standard deviation. To validate our ANN results, we use 10 different random seeds. The LM performed marginally better for both  $T_1$  and  $T_2$  prediction



**FIGURE 7. Comparison of LM and ANN predictions. (a), (c) is the overlay of Test and LM predicted  $T_1$  and  $T_2$ , (e) is fitting of LM predicted  $T_1$  vs  $T_2$  on Test  $T_1$  vs  $T_2$ . (b), (d) is the overlay of Test and ANN predicted  $T_1$  and  $T_2$  (f) is fitting of LM predicted  $T_1$  vs  $T_2$  on Test  $T_1$  vs  $T_2$ .**

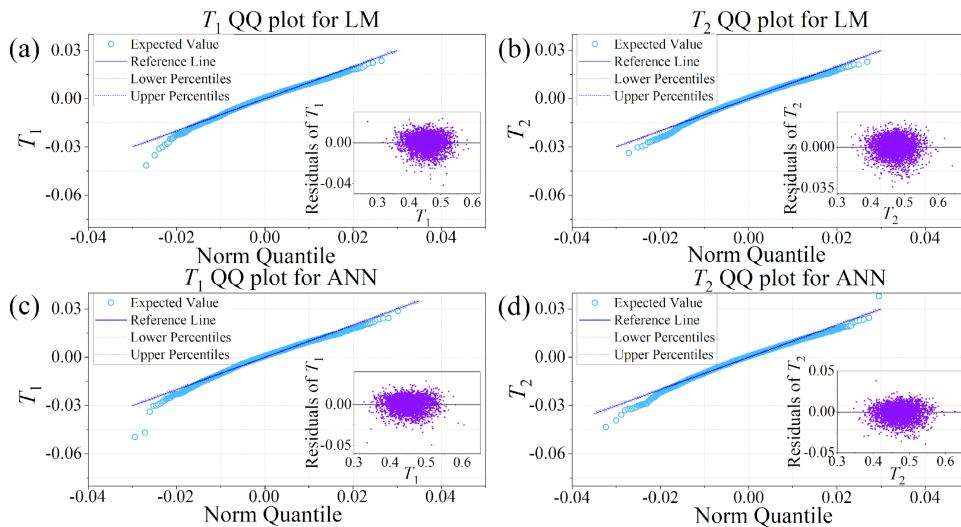


FIGURE 8. QQ plot of residuals and residual vs fitted plots (inset) for LM and ANN.

compared to the ANN. Fig. 7 shows the comparison between test vs predicted results.

While predicting  $T_1$  in Fig. 7(a) and 7(b), both LM and ANN had an error on the mean region (0.44-0.46) of the test set. However, the ANN made more errors around the mean (0.40 to 0.44 and 0.46 to 0.48) compared to the LM, by predicting more values as per count frequency than the test set. Similar behavior can be observed in LM for  $T_1$  prediction (0.46 to 0.48). The same trend for errors is observed in Fig. 7(c) and 7(d), from both LM and ANN. However, for  $T_2$ , both models made errors mostly around the mean. Again, as seen for  $T_1$  the ANN made more errors due to more prediction as per count frequency. From Fig. 7(e) and 7(f), we can see that the predicted values of the LM have more variance compared to the ANN predictions respectively.

Fig. 8 shows the QQ plot for our prediction residuals and the residual vs fitted plot for LM (Fig. 8(a)- (b)) and ANN (Fig. 8(c)-(d)). From the QQ plot, we can see that compared to LM the prediction residuals for ANN deviate more in the lower quantile for  $T_1$  and in the upper quantile for  $T_2$ . We found that a residual of  $\pm 0.02$  for both  $T_1$  and  $T_2$  kept our SR error under 5%, which can be observed in the residual vs fitted plot.

We also visualized the structure of our device, with the coefficients of the hole vector positions of our LM in Fig 9. The brighter regions mean that these coefficient values are more influential in the prediction of respective transmittance, given there is a hole in that region. This can be interpreted as the importance of hole vector position in a configuration.

From Fig. 9, the most significant areas are found to be at the source edges, which agrees with our observation from FDTD simulations in Fig. 6. Interestingly, the upper port ( $T_1$ ) gets more influenced by the lower edge of the source, and vice versa for the lower port ( $T_2$ ). This is because the light from the source edge that lies diagonally to the output port has to

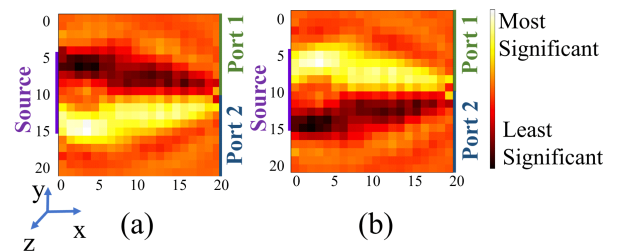


FIGURE 9. The structure of the photonic power splitter with the coefficients of the LM is a  $20 \times 20$  matrix, where each  $1 \times 1$  index corresponds to the coefficients. This representation also shows the importance of HV with respect to the coefficients for both (a)  $T_1$  and (b)  $T_2$ .

cover a further distance than the closer one. Therefore, adding any obstacles (holes) into the longer path will create more disturbance than the shorter one.

We found that the LM performed marginally better compared to the ANN in the single transmittance prediction. We believe this is due to the nature of the forward modeling problem. ANNs seem to slightly overfit the problem which in terms reduces their prediction quality compared to LM. We believe using single-layer ANNs with regularizations should solve this issue.

From this analysis, we verify that it is possible to do forward modeling using a single wavelength response. For most DL-based inverse modeling, meaning predicting a topology for a target optical response [37]–[41], broadband spectrum is required. It is to note that, to construct an inverse model, forward modeling solutions are crucial building blocks for tandem networks [37], [42], [43] and iterative methods [22], [44]–[46]. Hence, we solely focus on the forward modeling here and inverse design remains beyond the scope of this study. We also believe that our dataset can be used for inverse modeling for Generative model-based

solutions like variants of Generative Adversarial Network (GAN) [38] and Variational Autoencoder (VAE) [37], [39].

#### IV. CONCLUSION

A  $1 \times 2$  compact footprint of  $2 \mu\text{m} \times 2 \mu\text{m}$  power splitter offering an arbitrary splitting ratio in the popular optical communication spectrum around  $1.55 \mu\text{m}$  has been proposed. To obtain a wide span of transmittance values particularly from 0.75 to 0.95, a random pattern of holes was etched onto the silicon substrate and 16,000 unique designs are generated for the study. Dimension of the holes are optimized ensuring minimum reflection losses and the effect of different materials have also been investigated. It is observed that the  $\text{Si}_3\text{N}_4$ -Si combination offers the highest and most stable transmittance response making it the least sensitive to fabrication uncertainties. To be specific, 96% of structures with  $\text{Si}_3\text{N}_4$  holes show minimum transmission of 90% compared to 26% of structures with  $\text{SiO}_2$  holes. The coupling ratio between the two output ports is M:N, where M and N vary from 1 to 5. achieved for 3 different dielectric materials:  $\text{SiO}_2$ ,  $\text{Al}_2\text{O}_3$ , and  $\text{Si}_3\text{N}_4$ . Modal analysis indicates that better transmittance is evident for TE mode at  $1.55 \mu\text{m}$ . Machine learning has also been adopted to accurately predict the transmittances of any possible design of the structure. Both LM and ANN have been incorporated for this forward model. However, LM shows better accuracy in terms of RMSE value of only 0.84%. The model clearly shows that the hole vectors in the lower half of the splitter make a higher contribution in the transmittance of the upper port and vice versa. To the best of the author's knowledge, such comprehensive analysis has not been reported yet, which can pave the way for realizing compact and efficient photonic power splitters. The data used in this work are freely available for any future analysis.

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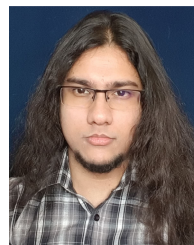
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