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► To cite this version:

Maurício Gomes de Queiroz, Raphael Cardoso, Paul Jimenez, Mohab Abdalla, Ian O'Connor, et al.. Power Reduction in Photonic Meshes by MZI Optimization. *Frontiers in Optics, Optica*, Oct 2023, Tacoma (Washington), United States. pp.JW4A.7, 10.1364/FIO.2023.JW4A.7 . hal-04361296

HAL Id: hal-04361296

<https://hal.science/hal-04361296>

Submitted on 11 Jan 2024

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Power Reduction in Photonic Meshes by MZI Optimization

Maurício Gomes de Queiroz,^{1,*} Raphael Cardoso,¹ Paul Jimenez,¹
Mohab Abdalla,^{1,2} Ian O'Connor,¹ Alberto Bosio,¹ Fabio Pavanella^{1,3}

¹ Univ. Lyon - CNRS, École Centrale de Lyon, INSA Lyon, Université Claude Bernard Lyon 1, CPE Lyon - INL,
UMR5270 - Écully, F-69134, France,

² School of Engineering, RMIT University, Melbourne, VIC 3000, Australia

³ Univ. Grenoble Alpes, Univ. Savoie Mont Blanc, CNRS, Grenoble INP, IMEP-LAHC, 38000, Grenoble, France

*mauricio.gomes@ec-lyon.fr

Abstract: Here, we investigate power reduction techniques for meshes of Mach Zehnder Interferometers (MZI), used for photonic matrix multiplications. We also propose a novel bottom-up algorithm that optimally lowers the applied phase shift in each MZI. © 2023 The Author(s)

1. Introduction

Neuromorphic approaches are particularly suitable where computing resources are limited, and energy-efficient hardware is necessary [1]. In this context, emerging technologies show opportunities for improved efficiency: Photonic Neural Networks (PNNs), for example, use optical signals to perform computations, taking advantage of several properties of light which enable, e.g., high parallelization, low latency, and low power consumption [2].

Matrix multiplications, alongside activation functions, form the basis of PNNs and can be implemented using interferometers that modify and combine different inputs. A 2×2 unitary matrix multiplication is performed by a single MZI, as illustrated in Fig. 1a, and scaling up can be achieved by arranging several MZIs into meshes [3]. The specific operation performed is determined by adjusting the interferometers' phase shifters.

In addition to the number of components, a mesh's power requirement is also proportional to its average applied phase shift [4], therefore, lowering it can directly improve static power consumption. Current strategies achieve such reduction by applying top-down pruning techniques, in large-scale meshes [5]. However, to our knowledge, no bottom-up approaches, i.e., starting from the MZI (which are also convenient for small meshes), have been investigated yet.

In this work, we analyze the MZI at a device-level to obtain closed-form expressions that describe how to lower its mean applied phase shift while, at the same time, remaining as close as possible to its expected operation. Then, based on these expressions, we explore how MZI meshes behave under phase shift reductions and what benefits can be achieved by adopting the approach proposed in this paper.

2. Single MZI and Mesh Optimization

Consider a single MZI, a mesh of size $N = 2$, performing a 2×2 matrix multiplication U (see Fig. 1a), where

$$U(\theta, \phi) = ie^{i\theta} \begin{bmatrix} e^{i(\phi)} \sin(\theta) & \cos(\theta) \\ e^{i(\phi)} \cos(\theta) & -\sin(\theta) \end{bmatrix}. \quad (1)$$

Displacing the phase shifts ϕ and 2θ by δ_ϕ and $\delta_{2\theta}$, we change U to a modified matrix \tilde{U} . To assess the impact of these changes, we calculate the fidelity F between U and \tilde{U} . Ranging from 0 to 1, $F(U, \tilde{U}) = |\text{Tr}(\tilde{U}^\dagger U)|^2/N^2$ reaches its maximum only if $U = \tilde{U}$, and thus provides a measure of the similarity between them. In such case,

$$F(\delta_{2\theta}, \delta_\phi) = \left| \cos^2\left(\frac{\delta_{2\theta}}{2}\right) \cos^2\left(\frac{\delta_\phi}{2}\right) \right|^2. \quad (2)$$

Therefore, the impact of an overall displacement δ on the fidelity depends on how it is distributed between the phase shifters, and can result in an optimal fidelity loss if an appropriate strategy is adopted. Let δ be distributed between the two phase shifters according to a ratio r , such that

$$\begin{cases} \delta_{2\theta} = & r\delta \\ \delta_\phi = & (1-r)\delta \end{cases}, \quad (3)$$

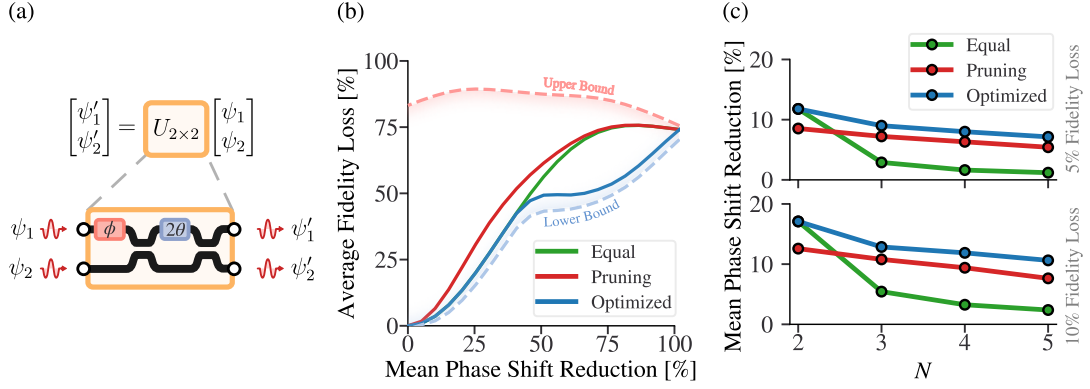


Fig. 1. (a) A schematic of an MZI. (b) Average fidelity loss $1 - F(U, \tilde{U})$ over the parameter space $(2\theta, \phi)$ for various reductions, following the strategy: lowering the values of the phase shifters equally as much as possible (equal); reducing the lowest-valued phase shifter to zero first (pruning); distributing the reductions as to find the MZI's global maximum for fidelity, as proposed here (optimized). (c) Mean phase shift reduction for 5% and 10% fidelity loss, at different mesh sizes N .

then we can calculate how to best allocate it as to maximize fidelity. Note that r is only bounded by the domain of applied phase shifts, i.e., for a positive δ , we have that $2\theta - \delta_{2\theta} \in [0, \pi]$ and $\phi - \delta_\phi \in [0, 2\pi]$. It follows from Eq. (2) that the fidelity's global maximum occurs either at the domain's limits of r or at a local maximum

$$r_{\max} = \frac{1}{2} + \frac{n\pi}{\delta}, n \in \{-1, 0, 1\}. \quad (4)$$

We propose to best distribute δ , in an MZI, by choosing the value of r that maximizes fidelity when evaluated at these points. Any change in the phase shifters is still met with a loss in fidelity, since we stray from the operation originally performed. We investigate this trade-off by looking at an MZI whose mean applied phase shift is lowered from an initial value E to \tilde{E} . Fig. 1b shows how different strategies achieve this reduction, expressed as $1 - (\tilde{E}/E)$.

The best way to obtain up to 40% reductions (the strategy approaching the lower bound) is to equally lower the phase shifters' phase. As expected, Eq. (4) tells us that $r = 1/2$ can be a global maximum for fidelity, although it not always is. Higher reductions are best achieved by carefully choosing r . The lower (upper) bound was determined by evaluating all phase shift combinations resulting in a mean $\tilde{E} \pm 0.01$, and then selecting the one that minimizes (maximizes) fidelity as the boundary. This results in slight deviations due to defining an acceptable threshold, seen here as an offset between the lower boundary and the optimized curve in Fig. 1b.

We also investigate bigger meshes, which can have their mean applied phase shift lowered by first distributing δ among the MZIs, and then individually finding the best r for each one of them. We model this as a single objective optimization problem, solved by a genetic algorithm. Our findings indicate that the different reduction approaches yield similar behavior for larger meshes. Given their context of application and how much fidelity loss is acceptable, we explore the power savings we can obtain for 5% and 10% fidelity loss in Fig. 1c.

3. Conclusions

In this study, we investigated the trade-off between mean applied phase shift and fidelity, while also proposing an effective approach to reduce the mean applied phase shift in both individual MZIs and MZI meshes. This approach ensures the highest fidelity trade-off for a single MZI, and when applied to meshes of MZIs using genetic algorithms, it outperforms the other explored strategies.

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