Comparison between black box and gray box strategies for configuration of feedforward waveguide meshes

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We compare the performance of the genetic algorithm (GA) and particle swarm optimization (PSO) methods in black box circuit configuration strategies in simulation and discuss the performance of both black box and gray box strategies by implementing a balanced power splitter on a 4-port feedforward waveguide mesh circuit.

Introduction

Like FPGAs in electronic integrated circuits, programmable photonic integrated circuits (PICs) can achieve multiple functions on the same chip [1]. To realize the expected versatile functions on the programmable PIC, proper configuration strategies and algorithms should be applied.

In this article, we demonstrate both experimentally and in simulation, both black box and gray box configuration strategies on a 4-port feedforward programmable photonic integrated circuit (PIC). As shown in Fig. 1, the photonic circuit consists of a forward-propagating waveguide mesh connecting six 2×2 unitary optical gates implemented as balanced Mach-Zehnder interferometers (MZIs) with two thermo-optic phase shifters each, and three additional phase shifters, with a total of 15 independent controls. The PIC was fabricated using the iSiPP50G silicon photonics platform by IMEC.

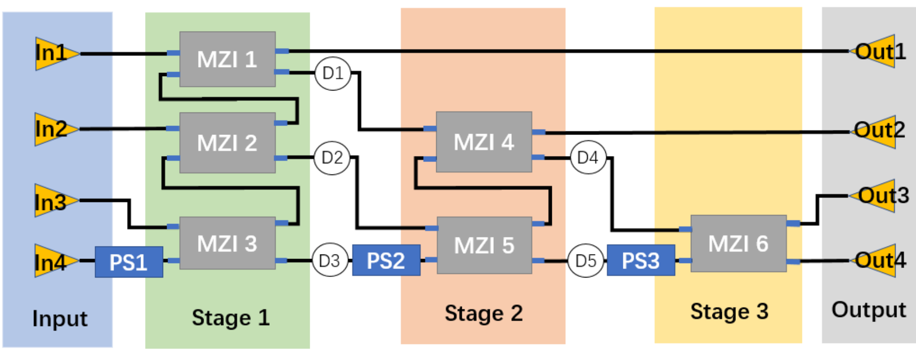

Figure 1: The schematic of the 4-port feedforward programmable PIC

Black box and gray box strategies

Both the black box and the gray box configuration strategies are based on computational optimization methods. While a black box strategy does not make any a-priori assumptions about the internal flow of light and the function of each tuning parameter, the gray box strategies require some information about the states of the intermediate stages between the inputs and the outputs.

In the black box configuration, the PIC configuration process is implemented as a global optimization process that searches for the optimized voltages applied on the thermo-optic phase controllers. For this, a cost function needs to be defined based on the difference between the optical outputs and their target values. One of the simplest definitions can be

$$cost = \sum_{i=1}^{4} \left| I_{out} - I_{target} \right| \tag{1}$$

By using global optimization methods, the PIC is configured to the targeted function by minimizing the cost function. Commonly used global optimization algorithms are the genetic algorithm (GA) [2] and particle swarm optimization (PSO) [3] methods.

The GA is a class of algorithms that simulate the natural selection process. In this process, the potential solution points of optimization are encoded into a generation of genes. The crossover, mutation and selection process of the genes make the optimization converge to a global optimum with the minimum cost function value. The crossover rate p_c and the mutation rate p_m play an important role in the convergence of the GA algorithm.

In the PSO algorithm, randomly generated particles in the swarm are distributed in the restricted optimization space. The global optimum searching process is achieved in the convergence of the particle positions in this swarm. The speed v_i of the i^{th} particle is decided by three contributions: the group optimum location p_g, the individual optimum location p_i and the particle inertia ωv_i. The corresponding parameters are c_1 as the social coefficient, c_2 as the cognitive coefficient and ω as the inertia factor.

In the gray box configuration, the individual MZIs are taken as small-scale black boxes, and the PIC is configured by the local control loops on each MZI. During this process, the topological structure of the programmable PIC is a-prior knowledge and internal optical flow is monitored at the intermediate stages of the PIC. For example, the four-beam combiner can be configured in the gray-box strategies by sequentially optimizing *MZI3, MZI2,* and *MZI1* to minimize the optical power monitored by *D3, D2,* and *D1.*

Simulation results of black box algorithms

The feedforward chip shown in Fig.1 can be represented by its transfer matrix, hence the simulation of the circuit is implemented by calculating the cascade of six MZI transfer matrices. The GA and PSO are implemented by using the *scikit-opt* package [4].

The hyperparameters in the global optimization algorithms, such as p_c and p_m in GA or ω, c_1 and c_2 in PSO, strongly affect the convergence of the optimization. To get a good convergence performance of the global optimization algorithms, the hyperparameters are selected by using the grid search method. In the grid search results, the optimized GA hyperparameters are the crossover rate $p_c = 0.7$, the mutation rate $p_m = 0.003$ with 40 genes in the generation, while for the PSO algorithm, the optimized hyperparameters are the inertia factor $\omega = 0.2$, the social coefficient $c_1 = 1.1$, the cognitive coefficient $c_2 = 0.4$ with 35 particles in the swarm.

With the optimized hyperparameters for both GA and PSO, 100 simulations are done to compare the performance of the GA and PSO in the black box configuration of a four-beam combiner and a 1-to-4 balanced beam splitter. The convergence curve of the GA and PSO in these two black box configurations are shown as follows,

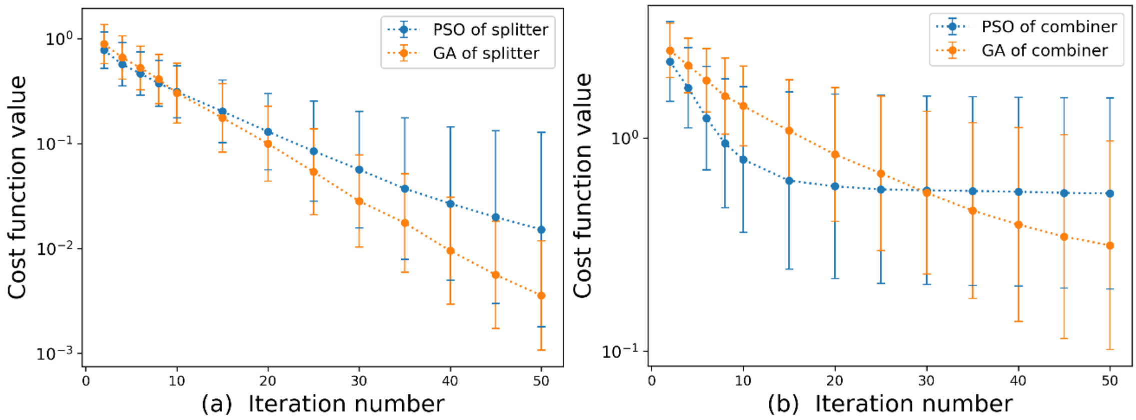

Figure 2: The convergence curves of the GA and PSO algorithm in the configuration of (a) a 1-to-4 balanced beam splitter and (b) a four-beam combiner

From Fig.2, the conclusion can be drawn that the PSO algorithm converges faster in the early iterations, but the GA has smaller cost function residuals after sufficiently long iteration times.

Experimental results of beam splitter configuration

The black box and gray box configuration are examined in the experiment through a feedback control loop. We use a NI PXIe-1073 tunable multichannel source to apply voltages on the phase shifters. The optical flows are monitored on-chip by Keithley 2400A source meters and measured through HP 8153A power meters at the output ports. The measured power data are feedback into the software-based configuration algorithm, and the algorithms control the phase shifters through the multichannel source.

For the 1-to-4 beam splitter configuration, the black-box PSO algorithm results are shown in Fig. 3(a). In the beginning, the particles in the swarm are randomly distributed in the solution space and search for the global optimum for the phase controllers on the PIC. After about 60 seconds, the PSO algorithm converges. The black box configuration experiments of the splitter by using the PSO algorithm are repeated 100 times, and statistics of the experimental results are shown in Fig. 3(b). It can converge in 20 iterations with 72% possibility and the configuration time consumed is less than two minutes.

For the gray box configuration strategy, the gradient descent (GD) algorithm is used in the local control loops for each MZI. For a 1-to-4 balanced beam splitter with the input port *In2*, firstly the phase shifters of *MZI2* are optimized locally to route all the optical power to *MZI1* by minimizing the optical power detected by *D1*, then the *MZI1*, *MZI4*, and *MZI6* are optimized sequentially to reach the targeted output power value. The experimental results of the gray box configuration for the beam splitter are shown in Fig. 3(c).

The cost value after the black box configuration is smaller than that of the gray box since the thermal crosstalk will degenerate the gray box configuration more than the black box configuration. While the configuration time of the gray box is smaller than that of the black box, since the black box configuration depends on the global optimization, while the gray box configuration only works on the local optimization loops.

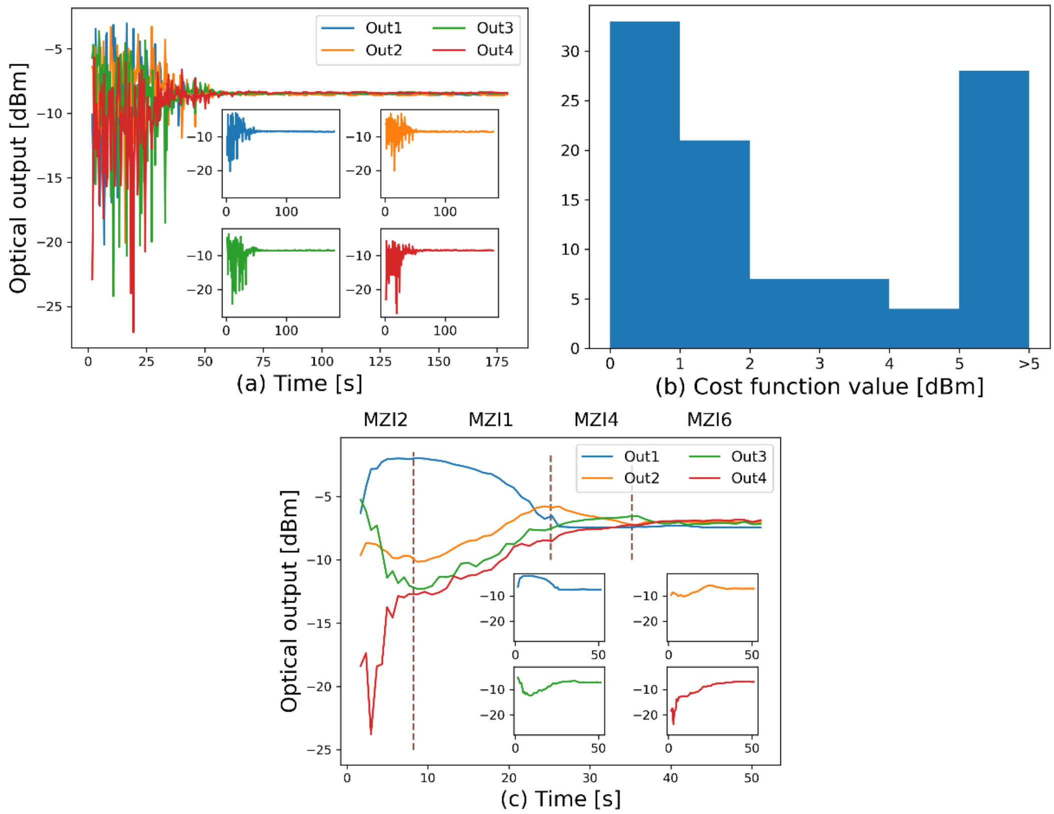

Figure 3: (a) The black-box configuration of 1-to-4 beam splitter by using the PSO algorithm. (b) The statistical results of the black box configuration in 100 experiments. (c) The gray-box configuration of the 1-to-4 beam splitter by using the GD algorithm.

Conclusion

In this article, we illustrate and discuss the black box and gray box strategies for the configuration of the feedforward PIC and compare the performance of the GA and PSO optimization algorithm in the black box configuration. The black box configuration takes advantage of a lower cost residual than the gray box configuration, while the gray box configuration converges faster.

Acknowledgments

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