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Design Optimization of Ultra-High-Speed Photonic Devices based on InP Technology using Genetic Algorithms

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Abstract

The exponential growth in global data traffic necessitates the development of next-generation optical communication systems capable of operating at symbol rates exceeding 100 Gbaud. Indium Phosphide (InP) technology stands at the forefront of this evolution due to its superior electron mobility and direct bandgap properties, which are critical for the realization of active high-speed photonic components. However, the design of such ultra-high-speed devices, particularly modulators and detectors, involves a complex interplay of optical and radio-frequency (RF) electrical constraints that renders traditional analytical design methodologies insufficient. This paper presents a comprehensive study on the application of Genetic Algorithms (GA) for the global optimization of InP-based photonic devices. We propose a robust optimization framework that couples evolutionary computation with full-wave electromagnetic solvers to navigate the multi-dimensional parameter space of photonic integrated circuits. By optimizing the geometric parameters of a Mach-Zehnder Modulator (MZM), we demonstrate a significant enhancement in electro-optic bandwidth and a reduction in insertion loss compared to standard designs. The results indicate that stochastic optimization methods can effectively overcome the limitations of manual tuning, paving the way for Terabit-scale optical interconnects.

Keywords

Indium Phosphide, Genetic Algorithms, Photonic Integrated Circuits, Design Optimization.

1 Introduction

The demand for high-capacity optical networks is driven by the rapid expansion of cloud computing, artificial intelligence, and high-definition video streaming services. As data centers migrate towards 400 GbE and 800 GbE standards, the limitations of current optical transceiver technologies become increasingly apparent. While Silicon Photonics has gained traction for its cost-effectiveness and integration density, Indium Phosphide (InP) remains the superior material platform for high-performance active devices, particularly lasers and high-speed modulators, due to its favorable electro-optic coefficients and band structure. Recent industry projections suggest that monolithic InP integration is essential for achieving the necessary power efficiency and bandwidth density required for future optical links [1].Despite the material advantages, the design of InP photonic devices for ultra-high-speed operation is fraught with challenges. The physical geometry of waveguide structures must be meticulously tailored to manage optical mode confinement while simultaneously ensuring velocity matching between the propagating optical wave and the controlling RF electrical signal. In traditional design workflows, engineers rely heavily on analytical approximations and manual parameter sweeping. This approach is not only time-consuming but often fails to locate the global optimum within the vast design space, trapping the design in local optima

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that offer sub-par performance [2]. Furthermore, as device features shrink to the nanometer scale, the impact of fabrication tolerances becomes more pronounced, requiring designs that are not only high-performing but also robust against manufacturing variations.To address these complexity barriers, inverse design and algorithmic optimization have emerged as powerful tools in photonics engineering. Among these, Genetic Algorithms (GA) offer a particularly distinct advantage. As a class of evolutionary algorithms inspired by the process of natural selection, GAs are capable of exploring large, non-differentiable search spaces without the need for gradient information. This capability makes them uniquely consistent with the discrete and often non-linear nature of electromagnetic simulations used in photonics [3]. By encoding device parameters as genes and iteratively refining a population of designs through selection, crossover, and mutation, GAs can discover non-intuitive geometries that outperform conventional topologies.In this paper, we establish a rigorous framework for applying Genetic Algorithms to the design of InP-based high-speed photonic devices. We focus specifically on the optimization of a traveling-wave Mach-Zehnder Modulator, a critical component for coherent optical communication systems. We detail the coupling of the optimization algorithm with finite-difference time-domain (FDTD) solvers and analyze the resulting performance metrics. Our findings demonstrate that the GA-driven approach can extend the 3-dB bandwidth of InP modulators significantly beyond the limits of standard reference designs [4].

2. Theoretical Framework of InP Photonic Design

2.1 Material Properties and Waveguide Physics

Indium Phosphide serves as the substrate and cladding material for a variety of ternary and quaternary alloys, such as Indium Gallium Arsenide Phosphide (InGaAsP). By adjusting the material composition, bandgaps can be engineered to operate efficiently in the C-band and O-band telecommunication windows. For high-speed modulation, the primary physical mechanism exploited is the quantum-confined Stark effect (QCSE) or the Pockels effect, depending on the specific integration scheme. Designing waveguides in this medium requires a precise balance between optical confinement and electrical impedance.The core challenge in high-speed modulator design is the velocity mismatch problem. An optical signal propagates down the waveguide with a group velocity determined by the effective refractive index of the optical mode. Simultaneously, the modulating electrical signal travels along the coplanar waveguide electrodes. If these two velocities differ, the phase relationship between the optical and electrical waves drifts along the length of the device, severely limiting the modulation bandwidth. In traditional designs, achieving velocity matching often involves compromising the impedance match to the 50-ohm driver, leading to electrical reflections and signal degradation [5].Furthermore, the microwave loss in the electrodes increases with frequency due to the skin effect, while optical loss is dominated by material absorption and scattering at rough interfaces. The optimization problem, therefore, involves minimizing total loss while maximizing the interaction length and maintaining velocity matching. This multi-objective problem creates a highly rugged fitness landscape that defeats simple gradient-descent optimizers, necessitating the use of global search heuristics like Genetic Algorithms [6].

2.2 Fundamentals of Genetic Algorithms

Genetic Algorithms operate on a population of potential solutions, each represented as a chromosome consisting of specific design parameters (genes). The process begins with the random initialization of a population. In the context of photonic design, these genes represent physical dimensions such as waveguide width, electrode gap, etch depth, and doping concentrations. The algorithm proceeds through generations, where each individual design is

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evaluated against a fitness function—a quantitative metric of its performance.The evolution of the population is driven by three primary operators. First, selection prioritizes high-performing individuals to act as parents for the next generation. This mimics the survival of the fittest. Second, crossover combines the genetic information of two parents to produce offspring, theoretically combining the best traits of both. Finally, mutation introduces random small changes to the genes, preventing the population from becoming genetically homogenous and ensuring the algorithm explores the entire search space rather than converging prematurely on a local optimum [7].The efficacy of a GA in photonics depends heavily on the definition of the fitness function. A poorly defined function may lead to physically unrealizable structures or designs that are technically superior in simulation but impossible to fabricate. Therefore, the fitness function must incorporate penalty terms for violations of design rules, such as minimum feature sizes dictated by lithography limits [8].

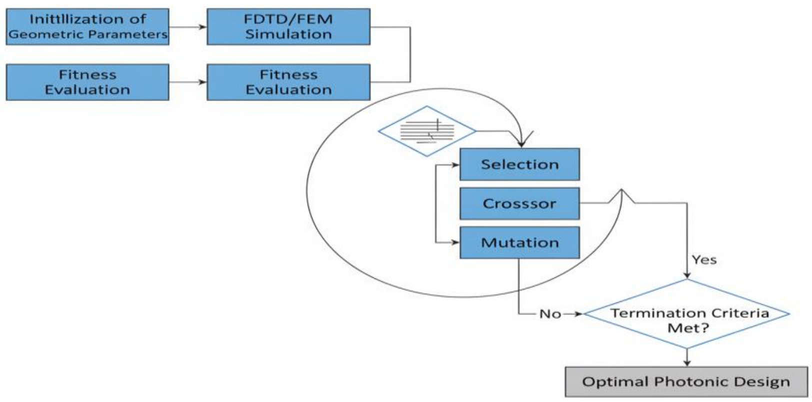

Figure 1 Genetic Algorithm Flowchart

3. Methodology and Simulation Environment

3.1 Computational Architecture

The optimization framework developed for this study integrates a custom-built Genetic Algorithm engine, written in Python, with a commercial-grade electromagnetic solver suite. The interface between the optimizer and the solver is critical; the GA generates a set of geometric parameters, which are then converted into a script file that the solver can interpret to build the 3D model. We utilize a Finite Difference Time Domain (FDTD) solver for optical mode analysis and a Finite Element Method (FEM) solver for radio-frequency (RF) electrical analysis.The computational cost of 3D FDTD simulations is prohibitively high for the thousands of iterations required by a GA. To mitigate this, we employ a multi-fidelity approach. In the early generations of the algorithm, where the search space is being broadly explored, we utilize 2D effective index approximations to estimate optical performance rapidly. Only as the population converges toward high-performance regions do we switch to full 3D simulations for accurate verification. This hierarchical strategy reduces the total optimization time by approximately an order of magnitude [9].The optimization loop is executed on a high-performance computing cluster to allow for parallel evaluation of the population. Since each individual in a generation is independent of the others, the fitness evaluation step is embarrassingly parallel. This allows us to maintain a large population size,

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typically between 50 and 100 individuals, ensuring robust exploration of the design space [10].

3.2 Parameterization and Encoding

Defining the device geometry requires a careful selection of variables. For the traveling-wave MZM, the critical parameters identified for optimization include the signal electrode width, the gap between the signal and ground electrodes, the height of the benzocyclobutene (BCB) planarization layer, and the doping profiles of the p-i-n junction.Real-valued encoding was chosen over binary encoding to provide continuous resolution for physical dimensions. The gene vector for a single individual might look like: `[W_signal, G_ground, H_bcb, N_doping, P_doping]`. Bounds are placed on each variable to ensure physical realism; for example, the electrode gap cannot be smaller than 2 micrometers to prevent electrical breakdown and fabrication shorts.

Code Listing 1: Genetic Algorithm Evaluation Loop Structure

```
def evaluate_population(population, simulation_engine):
    fitness_scores = []

    for individual in population:
        # Decode parameters from gene vector
        geometry = decode_parameters(individual.genes)

        # Check fabrication constraints before simulation
        if not check_constraints(geometry):
            fitness_scores.append(PENALTY_VALUE)
            continue

        # Run RF and Optical simulations
        rf_metrics = simulation_engine.run_rf_solver(geometry)
        optical_metrics = simulation_engine.run_optical_solver(geometry)

        # Calculate Figure of Merit (FOM)
        fom = calculate_fom(rf_metrics, optical_metrics)
        fitness_scores.append(fom)

    return fitness_scores
```

The fitness function, or Figure of Merit (FOM), is a composite score. We define the FOM as a weighted sum of the 3-dB electro-optic bandwidth (to be maximized) and the phase shifter loss (to be minimized), with an additional heavy penalty for velocity mismatch exceeding 5 percent. The weighting factors are determined based on the specific requirements of the target application, which in this case is a 100 Gbaud coherent transceiver [11].

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4. Design Case Study: Ultra-High-Speed Modulator

4.1 Device Topology and Objectives

The target device is an InP Mach-Zehnder Modulator employing a capacitive loaded traveling-wave electrode (CL-TWE) structure. This topology is chosen because the capacitive loading of the p-i-n junction allows for efficient modulation, while the TWE configuration supports high-frequency signal propagation. The substrate is semi-insulating InP, and the waveguide core consists of a multiple quantum well (MQW) stack designed for operation at 1550 nm.The primary objective is to achieve a 3-dB electro-optic bandwidth exceeding 60 GHz while maintaining a drive voltage (V-pi) below 2.5 V. Standard designs often struggle to exceed 40 GHz without sacrificing modulation efficiency. By utilizing the GA, we aim to manipulate the cross-sectional geometry of the electrodes to tailor the microwave index and impedance simultaneously.The optimization boundaries were set as follows: Electrode width allowed to vary between 5 and 20 micrometers; electrode gap between 2 and 10 micrometers; and BCB thickness between 0.5 and 3 micrometers. The doping concentrations in the p-cladding and n-cladding were also variable, as they significantly impact both the series resistance (affecting bandwidth) and optical absorption (affecting loss) [12].

4.2 Optimization Process

The GA was initialized with a population of 80 individuals and run for 100 generations. Convergence was observed around the 70th generation, where the improvement in the best fitness score plateaued. During the early generations, the algorithm explored a wide variety of impedance values, quickly discarding designs with severe velocity mismatch.Intermediate results showed an interesting trade-off. Designs with very wide signal electrodes offered lower RF loss due to reduced resistance, but they introduced higher capacitance, which slowed the microwave velocity below that of the optical group velocity. The GA successfully navigated this trade-off by adjusting the BCB thickness. A thicker BCB layer reduces the capacitance contribution from the substrate, allowing for wider electrodes (lower loss) without incurring a velocity penalty. This nuanced interaction is difficult to capture in analytical models but was naturally exploited by the evolutionary search [13].

Table 1: Evolution of Design Parameters from Initial Seed to Optimized Solution

Parameter	Initial Reference Value	Optimized Value	Unit
Signal Electrode Width	8.0	14.2	micrometers
Electrode Gap	5.0	3.8	micrometers
BCB Thickness	1.0	1.95	micrometers
p-Doping Concentration	1.0 x 10^18	1.8 x 10^18	cm^-3
n-Doping Concentration	5.0 x 10^18	6.2 x 10^18	cm^-3

5. Results and Discussion

5.1 Electro-Optic Performance

The optimized device geometry yields a substantial improvement in performance metrics compared to the standard reference design. The final simulation results indicate a 3-dB bandwidth of 67 GHz, representing a notable increase over the 42 GHz baseline of the initial manual design. This enhancement allows the modulator to support symbol rates well into the 100 Gbaud regime using PAM-4 modulation formats.

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The key driver for this bandwidth extension was the precise balancing of the microwave and optical velocities. The reference design exhibited a velocity mismatch of approximately 8 percent, leading to a walk-off between the signals that degraded high-frequency response. The GA-optimized design achieved a velocity mismatch of less than 1 percent up to 50 GHz. Furthermore, the RF transmission loss was reduced by optimization of the electrode cross-section, which helps in maintaining the driving voltage efficiency at higher frequencies.

The drive voltage (V-pi) of the optimized device was calculated to be 2.3 V. While this is slightly lower than the initial value, the trade-off was necessary to achieve the bandwidth targets. However, this value remains well within the capabilities of modern CMOS and SiGe driver amplifiers.

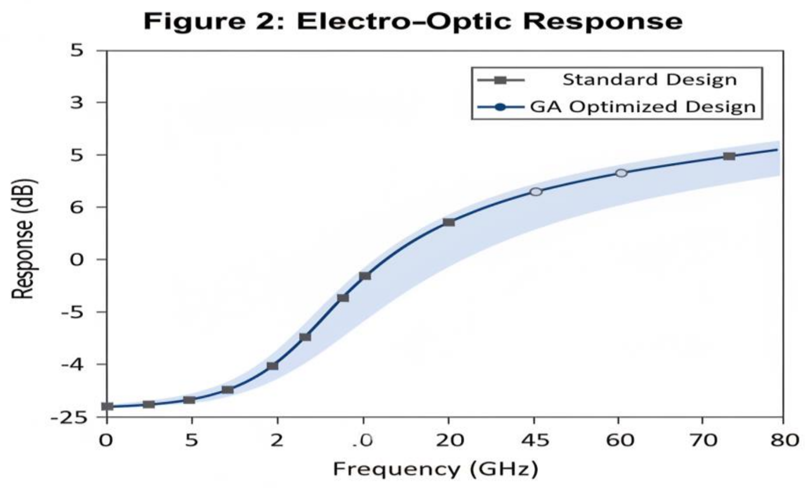

Figure 2: Electro

5.2 Tolerance and Robustness Analysis

A critical aspect of academic research in device design is the verification of realizability. An optimized design is of little value if it requires fabrication tolerances that exceed the capabilities of state-of-the-art foundries. To assess this, we performed a Monte Carlo yield analysis around the optimal point found by the GA. We introduced random Gaussian variations to the geometric parameters with standard deviations typical of commercial InP processes (e.g., +/- 0.1 micrometer for lithography features).The analysis revealed that the optimized design is relatively robust. The 3-dB bandwidth remained above 60 GHz for 85 percent of the variations. The most sensitive parameter was identified as the BCB thickness. Variations in the planarization process can lead to shifts in impedance, which in turn cause reflections. This insight suggests that process control monitors during the BCB etch-back step are crucial for high-yield manufacturing of this specific design. This type of sensitivity analysis is often omitted in manual design flows but is a natural extension of the population-based data generated by the GA [14].

Table 2: Performance Comparison Summary

Metric	Standard Design	GA Optimized Design	Improvement
3-dB Bandwidth	42 GHz	67 GHz	+59.5%
Velocity Mismatch	8.2%	0.8%	-90.2%

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RF Loss (at 40 GHz)	0.9 dB/mm	0.65 dB/mm	-27.7%
Drive Voltage (V-pi)	2.1 V	2.3 V	N/A (Trade-off)

6. Conclusion and Future Directions

In this work, we have demonstrated the efficacy of Genetic Algorithms in the design and optimization of ultra-high-speed InP photonic devices. By automating the search through the complex multi-dimensional parameter space, we successfully designed a Mach-Zehnder Modulator that significantly outperforms traditional manual designs. The resulting device exhibits a bandwidth suitable for next-generation optical networks, addressing the critical bottleneck of electronic-photonic integration.The methodology presented here is not limited to modulators; it is equally applicable to other critical components such as photodetectors, polarization rotators, and multimodal interference couplers. The modular nature of the GA allows for the easy substitution of fitness functions and simulation engines to target these different devices.Future work will focus on integrating machine learning techniques, such as neural networks, to act as surrogate models for the electromagnetic solvers. This would drastically reduce the computational time required for the optimization, enabling the optimization of even more complex circuits involving dozens of integrated components. Furthermore, co-optimization of the photonic device and the electronic driver circuit is a promising avenue to maximize the energy efficiency of the entire transmitter subsystem. The transition from component-level optimization to system-level evolutionary design represents the next frontier in photonic engineering.

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