

High-Speed Optical Binary Neural Network Accelerator Enabled by Nonvolatile MEMS Phase Shifters for Edge AI Applications

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Abstract—This paper presents a novel approach for implementing Binary Neural Networks (BNNs) utilizing nonvolatile optical phase shifters. These phase shifters employ a micro-electromechanical system (MEMS) tuning mechanism, which enables the adjustment of the refractive index and phase of the propagating mode. In this approach, the weights of the BNN can be controlled by applying electrical signals to the phase shifters. Moreover, due to the nonvolatile operation of these devices, the network's weights remain stable even when the electrical power source is cut off. The phases of the propagating modes, manipulated by the proposed phase shifters, determine the logic of the photonic circuit. The in-memory design of this device eliminates the need for network register banks, thereby significantly reducing resource usage, footprint, and power consumption. This approach offers much faster operation than other technologies, such as CMOS or spintronics, making it particularly appealing for edge artificial intelligence applications.

Index Terms—Binary neural network (BNN), microelectromechanical systems (MEMS), phase shifter, photonic integrated circuits.

I. INTRODUCTION

IN RECENT years, convolutional neural networks (CNNs) have achieved significant success across various domains, including image classification [1], [2], object recognition [3], and speech detection [4]. Standard CNN models employ 32-bit floating point operations, which demand substantial resources and produce high power consumption. Consequently, these models may not be well-suited for applications with resource constraints. Furthermore, in many cases, there is no need for the high accuracy that CNNs can deliver [5]. Therefore, researchers have proposed several methods to reduce the resources required for implementing these networks.

Parameter quantization is one of the most effective techniques to reduce resource consumption and memory capacity

in CNNs [6]. This approach involves representing neural network weights in lower-precision formats, such as integers or binary numbers [6].

Binary neural networks (BNNs) utilize binary weights. In BNNs, the computationally intensive convolutional multiplication operation is simplified to a logical XOR/XNOR operation, significantly lowering resource requirements [7]. Recently, extensive research has been dedicated to the hardware implementation of these networks [8]. By introducing innovative methods, such as in-memory devices, researchers have decreased the necessary resources, including the memory banks these networks utilize [9], [10]. However, the reliance on circuits based on CMOS technology still results in leakage currents and high power consumption within these networks [11], [12].

In recent years, the rise of silicon photonic platforms has significantly advanced the deployment of photonic integrated circuits. Utilizing optical signals as alternatives to electrical signals has reduced power consumption and enhanced the speed of these circuits. This advancement is particularly desirable for a range of applications, including neuromorphic computing and artificial intelligence [13], [14].

Photonic components employ various tuning mechanisms, including thermo-optical mechanisms and those based on plasma dispersion. Low optical losses, compact footprint, and acceptable speed characterize the thermo-optical mechanism. However, it comes with the drawback of high power consumption, which limits the ability to integrate a large number of photonic components on a single chip [15]. In contrast, the plasma dispersion mechanism excels in speed and size, while its power consumption is significantly lower than that of the thermo-optic method. However, it does experience considerable optical losses [16].

To mitigate these issues, electrostatic MEMS actuators can be employed [17]. These actuators interact with the evanescent field of the mode propagating through the waveguides, allowing for the adjustment of the effective refractive index of the mode. This method is highly advantageous for application in photonic integrated circuits, as it demonstrates exceptionally low power consumption and minimizes optical losses while offering suitable dimensions and operational speed. Furthermore, it exhibits compatibility with silicon photonic platforms, making it a pragmatic choice for advancing the field of integrated photonics [18], [19].

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This paper presents a photonic BNN hardware accelerator that utilizes an opto-electromechanical phase shifter as the primary component for executing logical XOR operations. The proposed device features two inputs: an optical signal originating from activation signals. At the same time, the second is an electrostatic input that fine-tunes the phase shift by the network weights. The output of this device is an optical signal that can be utilized to determine the optical activation signal for the subsequent layer.

Moreover, the proposed device incorporates a bistable configuration that allows it to maintain its last state even when the electrical power source is disconnected. As a result, the MEMS actuator exhibits non-volatile behavior, guaranteeing the device's consistent performance and reliability.

The remainder of this paper is organized as follows: Section II discusses the operating principles of the proposed photonic BNN and provides a detailed overview of the design of the employed MEMS actuator. Section III presents the numerical analyses and outlines the functional characteristics of the photonic hardware accelerator. Furthermore, Section IV provides a comparative study of the performance of the proposed MEMS device compared to the other recent contributions in this field.

II. THE OPERATION PRINCIPLES OF THE PROPOSED PHOTONIC BNN ACCELERATOR

A. XOR/XNOR-Based BNNs

BNNs employ single-bit representations for weights and activation data. In typical XOR/XNOR-based BNNs, the quantization process of weights and activations into binary values is facilitated through the application of a specific sign function as follows [20]:

$$\text{sign}(y) = \begin{cases} -1, & \text{if } y \geq 0 \\ +1, & \text{otherwise} \end{cases} \quad (1)$$

In these networks, the convolutional multiplication operation is substituted with the logical XOR/XNOR operator, followed by the application of a pop-count to the resulting output (Fig. 1). The resultant output is then stored in the register banks of the subsequent layer, serving as the activation for that layer. The utilization of single-bit storage for value representation and the transformation of convolution multiplication into logical XOR and XNOR operations lead to a substantial reduction in required resources, power consumption, and circuit delay [20].

B. Design of the Proposed Photonic MEMS Logic XOR Operator

The primary component of the BNN hardware accelerator is the XOR/XNOR logic operator. This paper presents a nonvolatile photonic XOR logic gate designed for BNN implementation. As illustrated in Fig. 2, the proposed device features an electrostatic MEMS actuator next to a straight waveguide that carries the propagating mode. The dimensions and physical parameters of this device are provided in Table I.

The MEMS actuator features a moving silicone component suspended by two stands. When an electrical tuning signal is

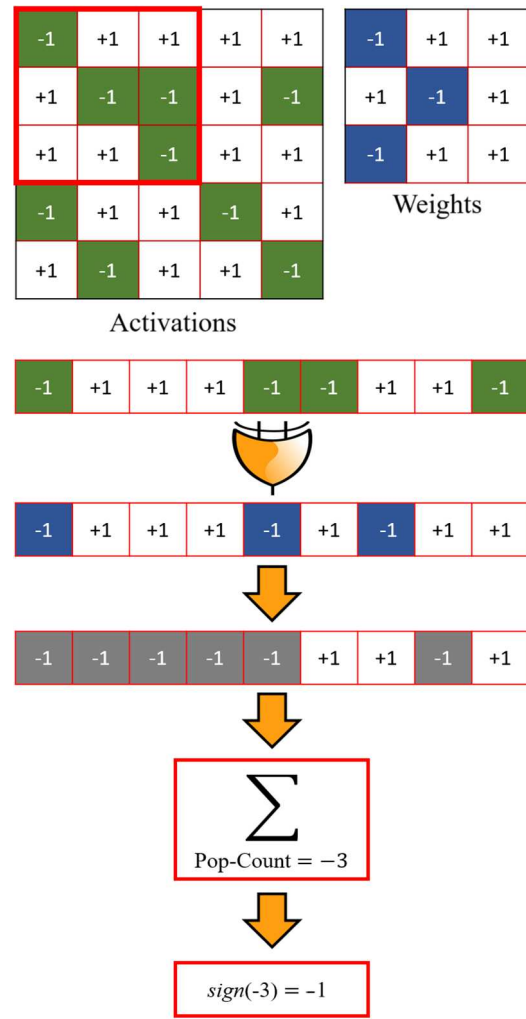


Fig. 1. The XOR operator in typical BNNs.

TABLE I
THE DIMENSIONS AND PHYSICAL PARAMETERS
OF THE PROPOSED MEMS ACTUATOR

Symbol	Parameter	Value
L_m	Length of moving part	25 (μm)
W_m	Width of the moving part	9 (μm)
th	Thickness of structure	1 (μm)
WW	Width of waveguide	0.35 (μm)
h_w	Height of waveguide	0.22 (μm)
L_{eff}	Length of shifting region	16 (μm)
L_s	Length of stands	10 (μm)
W_s	Width of stands	0.4 (μm)
V_{op}	Operating voltage	30 (V)
λ_{op}	Operating wavelength	1.55 (μm)
n_{Si}	Silicon refractive index at the wavelength of 1550 nm	3.48

applied to the moving part, the potential difference between the fixed excitation electrodes and the moving part results in its displacement.

This actuator incorporates angular stands, creating a bistable structure that retains its last mechanical state without a tuning signal. As a result, the distance between the waveguide and the

moving part remains consistent when the electrical source is disconnected. Thus, the proposed device exhibits non-volatile behavior.

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As depicted in Fig. 2-b, applying a High-voltage electrostatic signal (V_{cc}) to the moving part creates a potential difference between it and the grounded fixed excitation electrodes. This potential difference generates an electrostatic force that drives the moving part toward the straight waveguide. When the moving part approaches the waveguide, we refer to this condition as the S1 state.

When a Low-voltage tuning signal (GND) is applied to the moving part, a potential difference is created between the High-voltage fixed electrode and the moving part. This results in an electrostatic force acting in the opposite direction. If this electrostatic force surpasses a certain threshold, the moving part rapidly changes its position, moves away from the waveguide, and enters the S2 state. To return to the S1 state, a High-voltage tuning signal must be applied to the moving part, with its amplitude exceeding the threshold value; otherwise, the device will remain in the S2 state.

When the device is in the S1 state, the moving part's proximity to the waveguide allows it to interact with the evanescent field of the propagating mode. This interaction alters the refractive index of the mode, leading to a phase shift ($\Delta\phi$) of the mode passing through the waveguide according to:

$$\Delta\phi = \frac{2\pi L \Delta n_{eff}}{\lambda} \quad (2)$$

where L is the effective length of the phase shift region, Δn_{eff} is the effective refractive index change, and λ is the operating wavelength of the device.

In this approach, the length of the phase shift region is designed so that when the device is in the S1 state, a phase shift of $\Delta\phi = \pi$ is created compared to the S2 state.

The output phase (ϕ_o) of the optical mode exiting the MEMS-based optical phase shifter is influenced by three distinct components. The first component is the initial phase of the mode (ϕ_i) as it enters the phase-shifting region. The second component ($\Delta\phi$) is the phase shift induced by the electrostatic tuning mechanism of the MEMS device, which modifies the effective refractive index of the propagating mode through its interaction with the evanescent field of the waveguide. The third component ($\phi_{waveguide}$) arises from the natural phase accumulation due to light propagation along the waveguide over the interaction length. Consequently, the total output phase can be expressed as:

$$\phi_o = \phi_i + \Delta\phi + \phi_{waveguide} \quad (3)$$

When multiple MEMS-based optical phase shifters are arranged in series, the total phase shift at the output of the final stage can be accurately measured using an interferometric approach. This is achieved by employing two waveguides: one

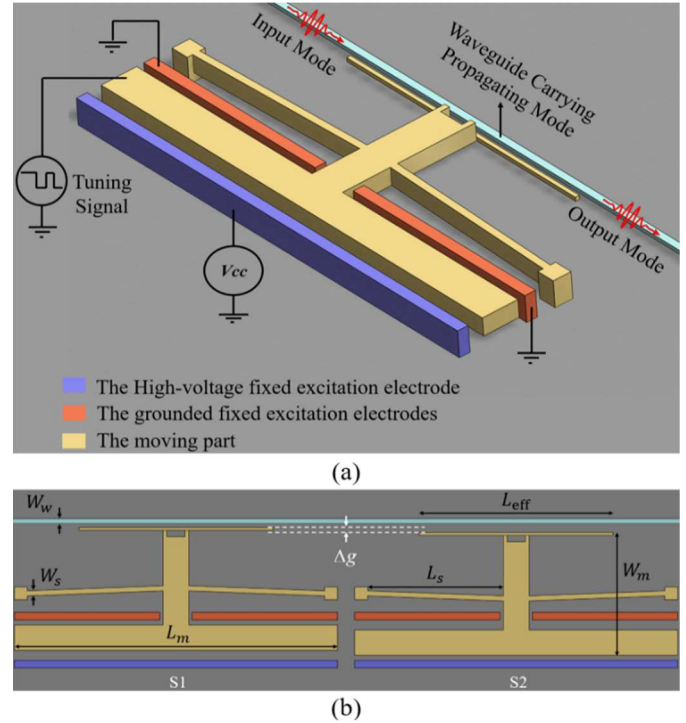


Fig. 2. (a) The design of the proposed MEMS actuator. (b) The displacement of the moving part of the actuator in S1 and S2 states.

that passes through the cascaded phase shifters and another that serves as a reference. The resulting interference pattern can determine the phase difference between these two paths. In this setup, the natural phase accumulation due to light propagation along the waveguides is effectively canceled as both the reference and signal paths experience the same propagation effects. Any initial phase contributions from prior natural propagation in earlier stages are also nullified. As a result, the interference pattern exclusively reflects the cumulative phase shifts introduced by the MEMS-based phase shifters across all cascaded stages. This technique allows for a precise and direct measurement of the intended phase shifts created by the phase shifters.

Based on the previous explanations, we can infer that the proposed device functions as a non-volatile bistable device featuring two inputs with different types. The first input is an electrical input (the tuning signal), and the second is an optical input (the phase of the incident mode). The electrical input is a DC signal that alternates between values of V_{cc} (High) and 0 (Low), while the optical input can be obtained by the incident mode phase that is either an odd (High) or even (Low) multiple of π .

To explain the operation of the proposed device, initially, we assume that the phase difference of the incident mode with the reference mode is an even multiple of π ($2n\pi$). In this scenario, when the electrical input signal is 0, the device is in the S2 state, resulting in the optical output mode having an even multiple of π phase difference with the reference mode. When the electrical input changes to V_{cc} , the device's state transitions to the S1 state, introducing an additional phase shift of π to the output mode. Consequently, the phase difference

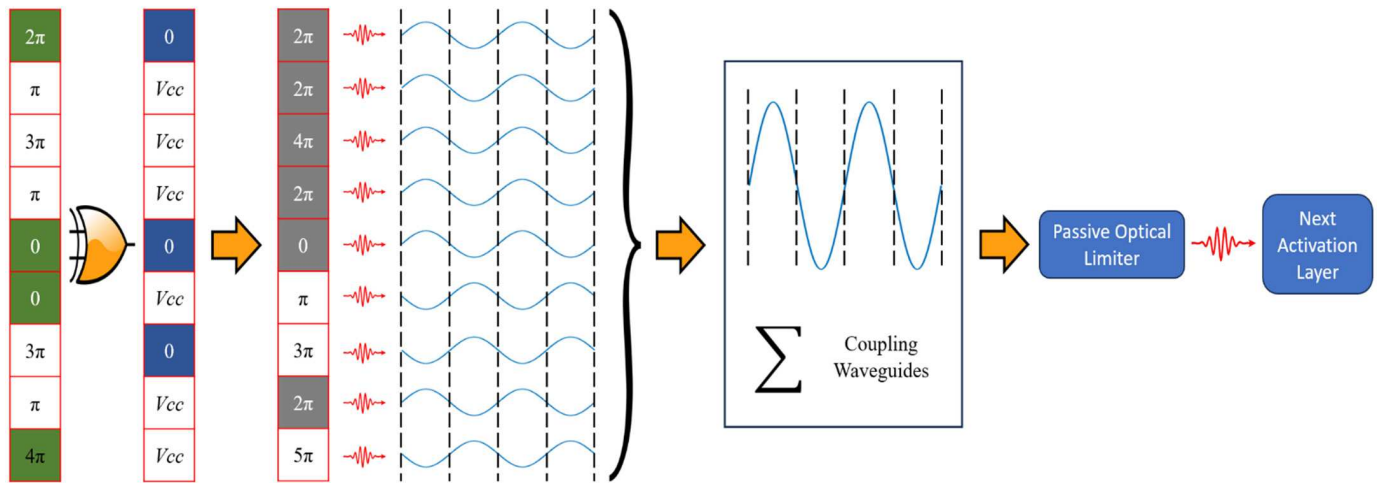


Fig. 3. The operation principles of the photonic BNN accelerator utilizing the proposed MEMS devices.

TABLE II
THE OPERATION OF THE PROPOSED LOGIC DEVICE BASED ON THE
ELECTRICAL AND OPTICAL INPUT SIGNALS

Optical Input	Electrical Input	Optical Output
$2n\pi$ (Low)	0 (Low)	$2n\pi$ (Low)
$2n\pi$ (Low)	V_{cc} (High)	$(2n+1)\pi$ (High)
$(2n+1)\pi$ (High)	0 (Low)	$(2n+1)\pi$ (High)
$(2n+1)\pi$ (High)	V_{cc} (High)	$2n\pi$ (Low)

between the output and reference modes becomes an odd multiple of π ($(2n+1)\pi$).

Similarly, when the optical input presents a phase difference of an odd multiple of π with the reference mode, the optical output will exhibit a phase difference of an odd (High) or even (Low) multiple of π with the reference mode, depending on whether the device receives Low or High electrical inputs, respectively. The proposed device's operation is summarized in Table II. As illustrated in this table, the function of the proposed device is equivalent to that of an XOR logic gate.

C. Implementation of the Photonic BNN Utilizing the Proposed MEMS Device

The proposed logic device can be employed in the implementation of photonic BNNs. This approach introduces activations from the preceding layer as photonic signals, serving as the photonic inputs to the proposed XOR gates. Simultaneously, the weights are applied as electrical signals to the electrical inputs of the devices.

Fig. 3 presents the binary convolution of an activation layer with a three-by-three filter that incorporates the network weights, as previously shown in Fig. 1. In this context, it is assumed that the activations exhibit varying phase differences with the reference mode (even or odd multiples of π). Also, the network weights are electrical signals with V_{cc} or 0 values.

In this scenario, photonic and electrical signals originating from the network's activations and weights are initially applied to the proposed logic XOR gates to generate the corresponding photonic output signals. If a High-voltage tuning signal (V_{cc})

is applied to any of the devices, an additional phase shift of π is introduced to the phase of the mode associated with that device. Subsequently, when all of the photonic output signals are coupled, a single photonic signal emerges from the constructive and destructive interference of the output signals of the XOR operators.

The resulting photonic signal will exhibit a phase difference of either an odd or even multiple of π with the reference mode. The intensity of this signal will be equal to or greater than the intensity of the output signals from the XOR gates. Moreover, suppose the number of signals that experience a phase shift of an even multiple of π exceeds those that undergo a phase shift of an odd multiple of π . In that case, the interference of the signals will result in the output mode having a phase difference of an even multiple of π relative to the reference mode. Otherwise, the output mode will have a phase difference of an odd multiple of π with the reference mode. These scenarios represent the output's logical state of 0 and 1, respectively.

Passive optical limiters regulate the intensity of this signal to utilize it as an activation value in the subsequent layer. It is worth noting that the coupling of the waveguides and the use of passive optical limiters in this method serve a function analogous to that of pop-count and sign functions in conventional BNN implementations.

D. Practical Implementation Framework

In a practical implementation scenario, the operation of the proposed photonic BNN accelerator begins with data acquisition from the environment using a sensing system such as an optical camera or photodetector array. The captured analog data is binarized using a preprocessing unit, such as a microcontroller, FPGA, or integrated logic, by applying a suitable thresholding or sign function. This process generates a binary representation of the input features that is compatible with the network architecture.

The binarized data is subsequently encoded into optical signals through phase modulation. In this encoding scheme, logical 0 and 1 are represented by optical signals having phase differences of even and odd multiples of π , respectively, with

respect to the reference optical mode. This modulation can be implemented using conventional optical phase modulators or directly via the proposed MEMS-based phase shifters. In the latter case, optical signals with the same phase as the reference mode are applied to the optical input ports of the proposed phase shifters, and electrical binarized signals (either 0 or V_{cc}) are applied to their tuning ports. Devices receiving a high tuning voltage induce a π phase shift in the output signal (corresponding to logic '1'), while those receiving a low signal produce no phase change (corresponding to logic '0').

Within the core processing stage, the encoded optical signals are fed into the photonic BNN implemented using nonvolatile MEMS-based photonic XOR gates. The network weights, previously binarized, are applied as static electrostatic inputs to the phase shifters, enabling all-optical execution of binary convolution operations. These weights are initially determined during the training phase of the BNN and then mapped onto the device through electrostatic inputs. However, due to the programmable nature of the MEMS actuators, these weights can be updated over time as new input data or learning scenarios are introduced, simply by modifying the tuning signals applied to each unit. The bistable configuration of the MEMS actuators ensures that the encoded weights remain stable even after power is removed.

It is important to note that the proposed MEMS structure is fully compatible with CMOS fabrication processes. This enables straightforward integration of the required metal routing layers and contact pads for electrical signal delivery. Similar electrical interfacing approaches are routinely employed in electrostatically actuated MEMS computing arrays, allowing scalable and reconfigurable hardware implementations [13], [18].

After computation, the output optical signals are processed using optical interferometers to compare their phase to the reference mode. The resulting interference pattern is converted into electrical signals using photodetectors to extract the final binary outputs. These binary outputs can either be used as inputs to the next layer in a multilayer BNN or interpreted by an electronic control system for real-time decision-making in Edge AI applications such as image recognition or smart sensing.

This framework highlights the feasibility of integrating the proposed photonic BNN architecture into complete and deployable AI hardware systems. A visual overview of this flow is provided in Fig. 4.

III. PERFORMANCE ANALYSIS OF THE PROPOSED MEMS DEVICE

This section presents the functional characteristics of the proposed MEMS device. The simulations are divided into two parts and performed using COMSOL Multiphysics, which are described in the following subsections.

A. Mechanical Analysis

Modifying the gap size between the moving part and the straight waveguide can adjust the network's weights. This gap size is influenced by the device's state, which is determined

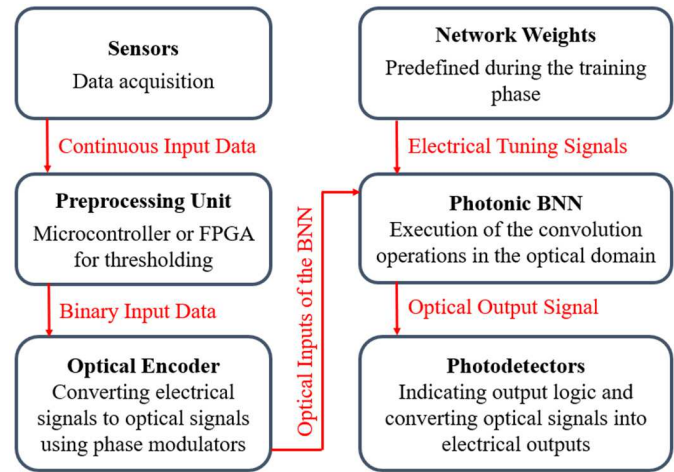


Fig. 4. The flowgraph of the device to the application framework.

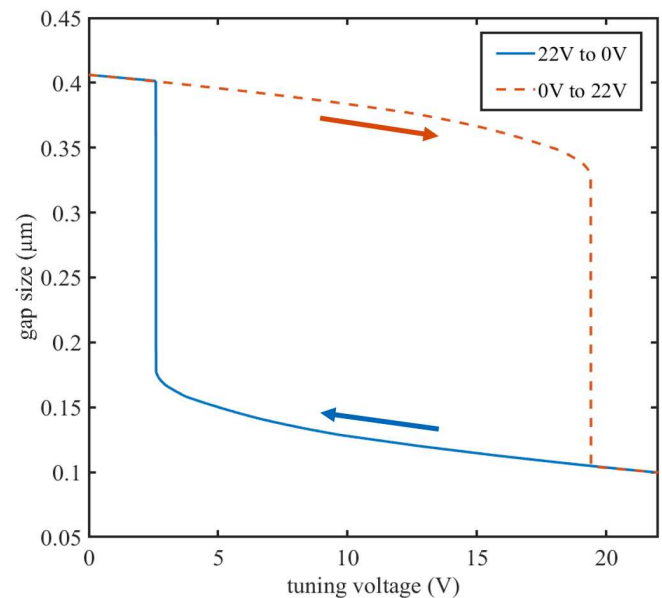


Fig. 5. The gap size between the moving component and the waveguide varies with changes in the voltage of the tuning signal.

by the electrical signal applied to the moving part. To alter the state of the proposed MEMS actuator, the amplitude of the force exerted through electrostatic excitation must exceed a certain threshold. Fig. 5 illustrates how the gap size between the moving part and the waveguide varies with changes in the voltage of the tuning signal.

Initially, it is assumed that the device is in the S2 state. As we gradually increase the voltage of the tuning signal from 0V, the moving part exhibits minimal displacement and resists movement until the voltage reaches 19.5V. The device abruptly transitions from the S2 to the S1 state, causing it to approach the waveguide. Conversely, when the device is in the S1 state, and the voltage is decreased from 22V, it suddenly transitions from the S1 state to the S2 state when the tuning signal voltage drops to 2.5V. Consequently, the minimum operating voltage for this device is determined to be 19.5V. To ensure proper operation, the recommended operating voltage is $V_{cc} = 22V$.

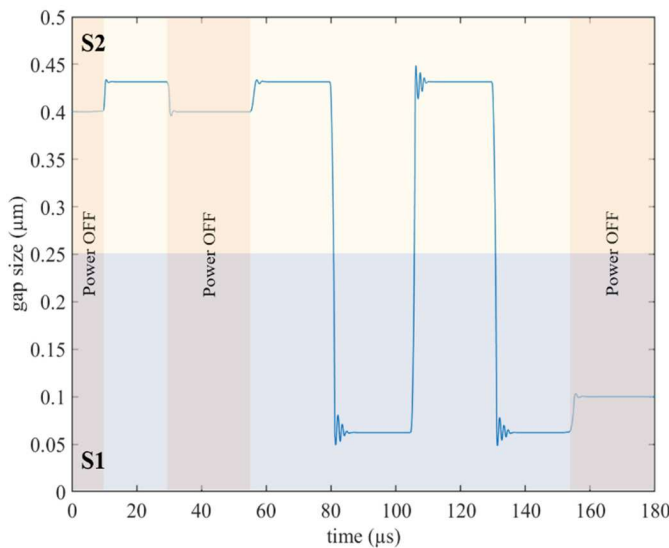


Fig. 6. The variation in gap size between the moving part and the waveguide over time is applied to the MEMS device as a tuning signal.

One of the key advantages of the proposed approach over all-optical circuits is the ability to adjust the weights after the physical implementation of the network. In all-optical photonic circuits, altering the network weights is not feasible. Once the waveguides and other optical components are implemented, the configuration of the circuit elements cannot be modified. In other types of photonic circuits that allow for weight adjustments, the thermo-optic mechanism is commonly employed, which results in significant power consumption. In contrast, the proposed method will enable changes to the BNN weights simply by applying the electrostatic tuning signals to the MEMS actuators.

Fig. 6 illustrates the variation in the gap size between the moving part and the waveguide over time as the tuning signal is applied to the MEMS device. It is notable that during certain intervals, the electrical source was disconnected. In these periods, the moving part remained in its current state (S1 or S2) but exhibited a slight retraction. This retraction occurs because when the tuning signal is applied, the electrostatic force exceeds the minimum threshold necessary for a state transition, causing the moving part to be pulled slightly beyond its equilibrium position. Once the signal is removed, this excess displacement relaxes, allowing the moving part to settle back into its steady state while maintaining its state. Disconnecting the tuning signal after adjusting the network weights is crucial to ensure precise positioning at gap sizes of 100 nm and 400 nm for the S1 and S2 states.

B. Optical Analysis

As shown in Fig. 7, when the gap size between the waveguide and the moving part is altered by applying a tuning signal to the MEMS actuator, the moving part interacts with the propagating mode's evanescent field.

Fig. 8 depicts the effective refractive index and phase shift of the propagating mode changes with the gap size variation between the moving part and the waveguide. When the device

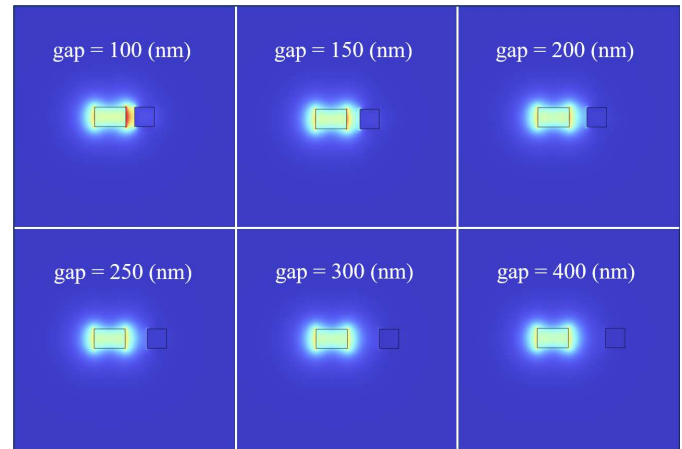


Fig. 7. The interaction of the moving part with the evanescent field of the propagating mode, with the variation of the gap size.

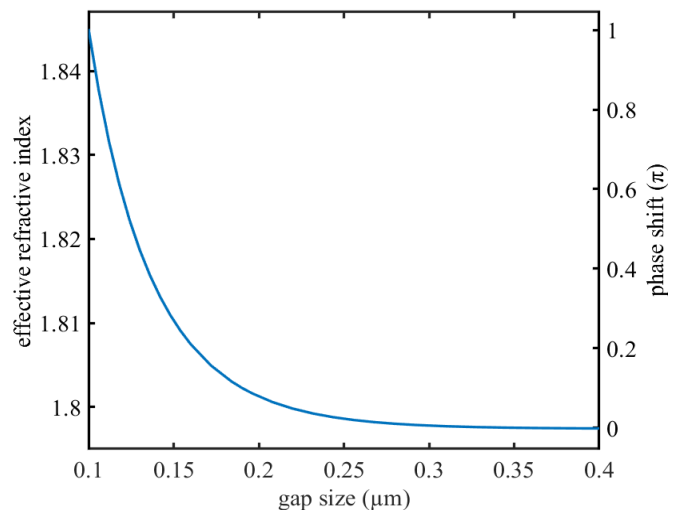


Fig. 8. The variation of the effective refractive index and phase shift of the propagating mode with the gap size change between the moving part and the waveguide.

is in the S2 state, the initial gap is 400nm, and the effective refractive index of the mode is 1.795. Upon transition to the S1 state, the gap size is adjusted to 100 nm, resulting in an effective refractive index of 1.845. Thus, changing the state of the MEMS actuator results in a phase shift of π for a phase shift length of 16 μm , according to (1).

IV. COMPARATIVE STUDY

The primary component of the proposed approach for implementing binary neural networks is a non-volatile XOR logic gate. Variations in electrostatic inputs lead to alterations in the phase of the passing mode. Thus, achieving optimal performance from the MEMS actuator to produce a sufficient phase shift over a shorter length can minimize the dimensions of each unit and, in turn, reduce the overall area of the network.

In Table III, the functional characteristics of the proposed device are compared with various optical phase shifters developed in recent years. This table underscores that many contributions, such as those reported in [21], [22], and [23],

TABLE III
FUNCTIONAL CHARACTERISTICS OF THE PROPOSED DEVICE IN
COMPARISON WITH RECENT CONTRIBUTIONS IN THIS FIELD

phase shifters	footprint (μm^2)	operating voltage (V)	L_π (μm)	nonvolatile
[21]	4500	10.7	17.2	No
[22]	2400	19	30	No
[23]	5400	17	105	No
[24]	1225	18	16	Yes
Proposed device	234	22	16	Yes

demonstrate volatile behavior. In this scenario, disconnecting the electrical source results in losing all weights within the network, necessitating a reconnection of electrical signals to all input ports for the network to resume operation. Conversely, non-volatile logic gates allow weight retention even when the electrical source is disconnected.

Moreover, the proposed structure attains the required phase shift over a shorter effective length than the devices shown in [21], [22], and [23], substantially reducing the footprint of each XOR gate. To highlight the scalability potential, it is worth noting that the proposed phase shifter achieves an approximate 80% reduction in footprint compared to [24], while preserving its nonvolatile and bistable behavior. This compactness enables high-density integration of a large number of photonic logic gates on a single chip, which is crucial for the realization of complex, low-cost Edge AI systems.

Alongside these benefits, the proposed device necessitates a higher operating voltage. Nevertheless, since the weights remain constant during the network's operation, the input electrostatic signals also remain unchanged. Consequently, in these static conditions, no electrical power is consumed. Thus, a higher operating voltage in this approach does not result in increased electrical power consumption.

The functional characteristics of the proposed design reveal that this innovative approach exhibits remarkable performance in implementing BNNs. This methodology holds substantial promise for significantly improving processing speeds while simultaneously reducing power consumption within these networks, which appeals to many Edge AI Applications.

V. CONCLUSION

BNNs offer a promising alternative to conventional CNNs in applications where ultra-high precision is not a strict requirement. In BNNs, the computationally expensive convolutional multiplications are replaced by efficient XOR operations followed by pop-count calculations, significantly reducing resource consumption, power dissipation, and processing delay. Additionally, integrating photonic circuits further lowers electrical power consumption and enhances computational speed. This paper presents an innovative approach for implementing optical BNNs using optical phase shifters with a MEMS-based tuning mechanism. In this framework, a novel electrostatically actuated MEMS device is designed to perform XOR operations through phase modulation of the propagating optical modes. This non-volatile device eliminates the need for conventional register banks in standard BNN architectures.

Furthermore, the proposed device is optimized in terms of footprint to improve integration capabilities. With outstanding performance characteristics, including a $16\mu\text{m}$ practical phase shift length, a 22V tuning voltage, and a compact $234\mu\text{m}^2$ footprint, this device is highly suitable for resource-constrained, power-efficient, and high-speed BNN implementations.

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