Recent Developments in Photonic Integration: Reservoir Computing in Photonics using Silicon Microring Nonlinearities

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***Abstract*—The rapid evolution of integrated photonics is revolutionizing the landscape of high-speed, energy-efficient computing. One of the most promising frontiers in this domain is Photonic Reservoir Computing (PRC), a neuromorphic paradigm that leverages the inherent dynamics and parallelism of photonic systems. This paper provides an in-depth exploration of reservoir computing implemented through nonlinear effects in silicon microring resonators (MRRs)—a scalable and CMOS-compatible platform for optical information processing.**

We examine the fundamental physical processes, such as two-photon absorption, free carrier dispersion, and thermal-optic phenomena, that facilitate nonlinear transformation and short-term memory essential for RC operations. Recent advances in photonic integration are surveyed, highlighting how MRR-based architectures support time-multiplexed virtual node generation and can be effectively deployed for complex signal processing tasks. A simulation framework in MATLAB is presented to model the nonlinear carrier dynamics and evaluate the RC system on a distorted QPSK signal with chromatic dispersion and Kerr nonlinearity. Results demonstrate accurate symbol recovery through a simple linear readout, validating the feasibility of silicon microrings for high-performance PRC. We further discuss emerging applications in AI-on-Chip inference engines, fiber-optic communications, and neuromorphic sensor fusion, and outline challenges and opportunities in scaling and enhancing photonic reservoir systems. This work positions silicon microring-based PRC as a compelling solution for next-generation integrated photonic computing.

Keywords: **Photonic Reservoir Computing, Silicon Microring, Nonlinear Optics, Time-Multiplexing, Neuromorphic Computing, Integrated Photonics, QPSK Equalization**

I. INTRODUCTION

The swift increase of global data traffic, driven by AI applications, cloud computing, and billions of interconnected devices, is intensifying the demand for computing systems that can deliver ultra-low latency, high throughput, and energy-efficient performance. Traditional CMOS-based electronic processors, though continually improved, are approaching fundamental physical and architectural limits, especially in areas such as real-time processing, edge inference, and large-scale data analytics. As workloads evolve to support technologies like edge AI, autonomous vehicles, 6G wireless systems, and the Internet of Things (IoT), there is a pressing need for alternative computational frameworks that can scale with these requirements without compromising power efficiency or speed.

Photonic computing has emerged as a transformative paradigm in this space, leveraging the advantages of light-based signal propagation for computing tasks. Unlike their electronic counterparts, photonic systems inherently support extremely fast data transmission, broad bandwidth, and reduced heat dissipation, making them particularly suited for high-performance and real-time applications. Within this growing field, Reservoir Computing has gained attention due to its simplified training structure and ability to handle time-dependent data effectively. Inspired by recurrent neural networks, RC employs a fixed nonlinear dynamical system, known as the reservoir, to map inputs into a higher-dimensional space. Only the final output layer is trained, significantly reducing computational complexity and training time.

A particularly promising implementation of RC lies in Photonic Reservoir Computing, especially when realized on silicon photonic platforms. Silicon microring resonators (MRRs) play a key role in this context due to their small footprint, high optical confinement, CMOS compatibility, and ability to exhibit nonlinear effects such as Two-Photon

Absorption, Free Carrier Dispersion, and the Thermo-Optic Effect. These mechanisms introduce both nonlinearity and short-term memory—critical components of any effective reservoir. Moreover, the adoption of time-multiplexed architectures allows a single microring to emulate hundreds of virtual nodes, reducing hardware requirements while maintaining computational richness.

This paper presents a comprehensive exploration of microring-based photonic reservoir computing. It covers the physical foundations of microring nonlinearity, recent integration strategies, and a MATLAB-based simulation of signal classification performance using QPSK waveforms distorted by realistic fiber-optic effects. The results demonstrate the capability of PRC systems to meet the processing needs of next-generation applications, marking a significant step toward scalable, real-time, and low-power optical computing architectures.

II. PHOTONIC INTEGRATION

Photonic integration is revolutionizing optics and computing by enabling the integration of multiple optical components—like lasers, modulators, waveguides, multiplexers, and detectors—onto one photonic chip. While it operates at the speed of light, this integration provides considerable advantages concerning bandwidth, energy efficiency, and signal integrity. It is conceptually akin to electrical integrated circuits (ICs).

Silicon photonics has emerged as the most favored material platform compared to others because of its compatibility with traditional CMOS manufacturing methods. This enables the utilization of current semiconductor facilities for scalable, cost-effective manufacturing. As a result, silicon photonics are especially attractive for applications in sensing, telecommunications, and data centers.

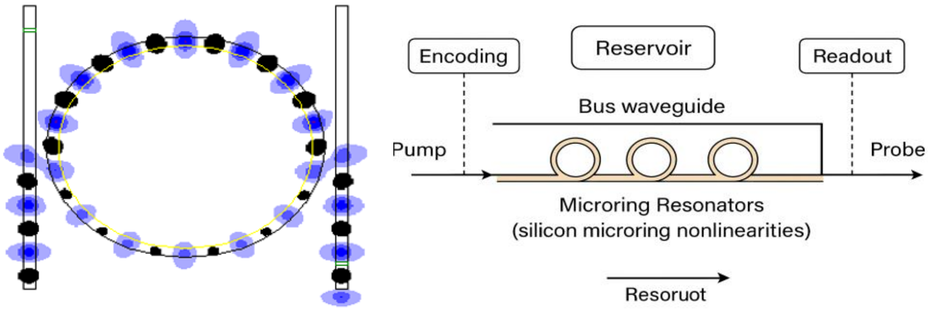

Fig.1 (a)Micro-Ring Resonator, [ref.12] (b) Illustration of microring resonators coupled to bus waveguides. Light at resonant wavelengths circulates in the ring, enabling high field intensities and nonlinear optical interactions. [Image created by the author.]

A critical building block in silicon photonics is the microring resonator (MRR). These structures are essentially waveguides curved into a ring that couple optically with adjacent straight waveguides. When light of a resonant wavelength enters the ring, it constructively interferes and builds up inside the ring, enhancing light-matter interactions. This leads to a range of applications including:

1. Filtering: Microring resonators act as highly selective optical filters by allowing only specific resonant wavelengths to circulate within the ring while all others are rejected. This makes them ideal for creating narrowband wavelength filters in dense wavelength-division multiplexing (DWDM) systems and optical signal processors.
2. Modulation: Microrings can modulate light by dynamically shifting their resonant wavelength through thermal, electro-optic, or carrier injection mechanisms. By modulating the input signal near the resonance condition, high-speed amplitude or phase modulation of the output light can be achieved using very compact devices.
3. Wavelength multiplexing: By designing arrays of microrings with slightly different resonant wavelengths, they can function as multiplexers and demultiplexers for multiple optical channels. This enables the integration of many data streams on a single fiber or waveguide, significantly increasing the bandwidth capacity of photonic circuits.
4. Nonlinear signal processing: Due to strong optical confinement, microrings enhance nonlinear effects such as two-photon absorption (TPA) and free carrier dispersion (FCD), enabling functions like optical logic, signal regeneration, and reservoir computing. These nonlinear interactions are exploited to perform

complex, real-time analog computations directly in the optical domain.

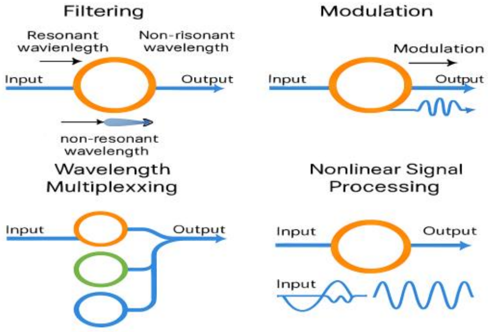

Fig.2 Key Applications of Microring Resonators in Photonic Integrated Circuits [Image created by the author.]

MRRs are especially powerful in reservoir computing where they act as nonlinear dynamic nodes with memory, enabling time-dependent processing tasks on-chip.

Table.1: Key Benefits of Microring Resonators (MRRs)

Benefit	Description
Compact Footprint	Rings can be as small as a few micrometers in diameter.
High Q-Factor	Enables sharp filtering and resonance sensitivity.
Scalability	Arrays of MRRs can be densely packed for complex processing.
Nonlinear Capability	Strong field confinement boosts nonlinear effects such as TPA, FCA and FCD
Temporal memory for Computing	MRRs act as nonlinear dynamic nodes memory, enabling time dependent processing tasks on-chip

III. RESERVOIR COMPUTING

Reservoir Computing (RC) is a computational framework inspired by recurrent neural networks (RNNs), designed to efficiently process time-dependent and sequential data. It relies on a fixed, high-dimensional dynamical system known as the reservoir, which transforms the input signal into a complex and nonlinear state space. Unlike conventional deep learning networks where multiple layers are trained, in RC only the output (readout) layer is trained, significantly reducing the computational cost and avoiding the vanishing/exploding gradient problems typical in deep RNNs.

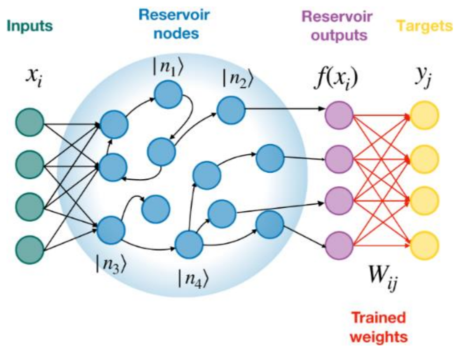

Fig.3: Quantum Reservoir Computing [ref.13, fig.1]

3.1. Core Principles of RC:

1. Nonlinear Transformation: Through nonlinear interactions, the reservoir converts input data into a high-dimensional feature space. This stage makes patterns more separable and is essential for resolving challenging problems like control, prediction, and classification.
2. Short-Term Memory: Because the reservoir is dynamic, its internal state remembers details about recent inputs. The system can learn temporal correlations thanks to this feature, which makes it perfect for applications like signal demodulation and time-series forecasting.
3. Linear Readout: The reservoir states are mapped to the intended output using a straightforward linear regression or classifier. Because of its simplicity, RC is very scalable and efficient.

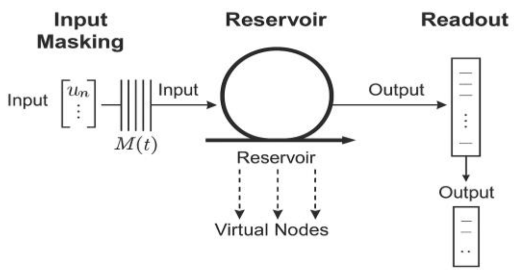

Fig.4: Time-Multiplexed Reservoir Computing Framework that features one Nonlinear Node. [Image created by the author.]

3.1. Time-Multiplexed Reservoir Computing

Time-multiplexed reservoir computing (TM-RC) is an efficient method that is especially appropriate for photonic systems, where it can be difficult to implement numerous physical nonlinear nodes. Instead, TM-RC reuses a single nonlinear element—such as a silicon microring resonator—by feeding it a time-varying, masked input signal that emulates multiple virtual nodes over sequential time intervals. Each masked input segment is processed by the nonlinear system, and its output is sampled at fixed intervals, capturing the system's dynamic state. This setup significantly reduces hardware complexity while maintaining the nonlinear transformation and memory essential for reservoir computing. Utilizing microring phenomena such as two-photon absorption and free carrier dispersion , TM-RC is ideal for rapid functions like signal classification, equalization, and time-series forecasting

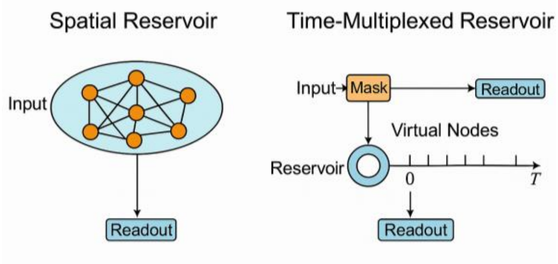

Fig.5: (a) Spatial Reservoir, (b)Time-Multiplexed Reservoir Computing Architectures [Image created by the author.]

3.2. How It Works:

1. Input Masking: Each input sample is multiplied by a pseudo-random mask (a sequence of values), producing a time-expanded input.
2. Nonlinear Dynamics: The masked input is sent through a nonlinear system (e.g., a silicon microring resonator), whose internal state is influenced by both the current and previous inputs due to its intrinsic memory.
3. Virtual Node Sampling:
   The system generates output at regular intervals to gather a collection of virtual node values that reflect the high-dimensional condition of the reservoir
4. Training the Readout: These node outputs are used as features to train a linear regression or classification model.

3.3. Algorithm of Reservoir Computing:

Step.1: Input Expansion via Masking

Each input sample $u(n)$ is multiplies by a time-dependent mast $M(t)$ to create time series:

$$s(t) = M(t)\,.\,u(n) \quad .....(1)$$

Where, $u(n) \in R^k$: input vector at time step n, $M(t) \in R^N$: input mask with N virtual nodes, $t = 1,2,\dots,N$ indexes the virtual nodes for eacg real time step n.

Step.2: Nonlinear Mapping in the Reservoir

The masked input is injected into a single nonlinear dynamical system (e.g. mirroring), and its internal state is samples at regular intervals:

$$x(n) = f(s_i(n), x_{i-1}(n), \qquad i = 1,2,\dots\dots,N \quad ....(2)$$

where, $x_i(n)$: state of the i-th virtual node at time n. $f(.)$: Nonlinear transformation (e.g. MRR dynamics)

- f includes microring nonlinearity governed by effects like TPA, FCD, etc.
- The memory is introduced via the dynamic response (e.g., free carrier lifetime).

Step.3: Reservoir Sate Vector

Collect the virtual node responses to form the state vector for each time step:

$$X(n) = [x_1(n), x_2(n), \dots, x_N(n)]^T \quad ....(3)$$

Step.4: Linear Readout Training

Train the output weights W_{out} using ridge regression:

$$W_{out} = arg\underset{W}{min}||Y - XW||^2 + \gamma\,||W||^2 \quad ....(4)$$

where, $X \epsilon R^{T\times N}$: Matrix of collected reservoir states over T time steps, $Y \in R^t$: Target outputs, γ : Regularization Parameter

Step.5: Inference

After training, output for new input $u(n)$is computed as:

$$y(n) = W_{out}^T\, x(n) \quad ....(5)$$

where, $W_{out} \in R^N$: readout weights

IV. SILICON MICRORING RESONATORS AS NONLINEAR NODES

Silicon microring resonators (MRRs) are pivotal components in photonic reservoir computing due to their ability to exhibit and amplify a variety of nonlinear optical effects within a compact footprint. These nonlinearities enable both nonlinear transformation of input signals and short-term memory, which are the two core requirements of a functional reservoir in RC systems.

4.1. Two Photon Absorption (TPA):

Two-Photon Absorption (TPA) refers to a nonlinear phenomenon in which two photons are

simultaneously absorbed, causing an electron to transition from the valence band to the conduction band. In silicon, TPA plays a significant role due to its indirect bandgap and is strongly dependent on the square of the optical intensity, making it particularly relevant at high power levels or in confined setups like microrings.In reservoir computing, TPA provides crucial nonlinearity by producing free carriers that influence the dynamics of the system. As input intensity grows, carrier density increases, facilitating the nonlinear conversion of signals into high-dimensional reservoir states.
Additionally, the produced carriers trigger free carrier dispersion and absorption, establishing the foundation for signal modulation and short-term memory inside the microring.

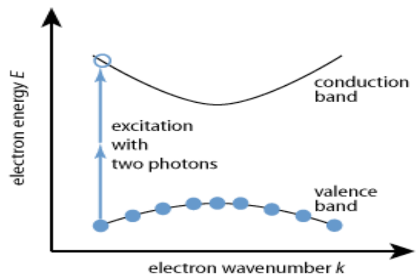

Fig.6: Two Photon Absorption [ref.11, fig.1]

4.2. Free Carrier Dispersion (FCD):
The shift in refractive index brought on by the presence of photo-generated carriers (holes and electrons) is termed as the Free Carrier Dispersion (FCD).In silicon, the index changes Δn due to FCD is negative, meaning it causes a blue shift (i.e., toward shorter wavelengths) in the microring's resonance.
Mathematically, the shift in refractive index can be approximated using the Drude model:

$$\Delta n \propto -(\frac{\Delta N}{n^2}) \quad ......(6)$$

where ΔN is the change in carrier concentration. Since the carriers persist for a finite lifetime (τ), the refractive index change is time-dependent, introducing a fading memory effect crucial for processing sequential inputs in reservoir computing.

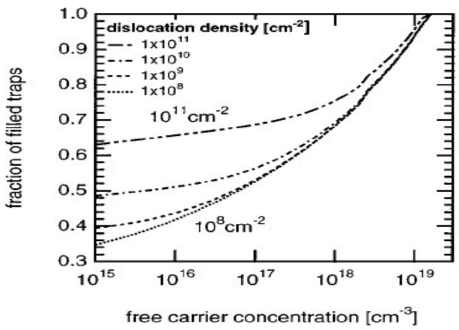

Fig.7: Free Carrier Dispersion [ref.14, fig.3]

This memory, encoded in the dynamic refractive response of the microring, allows the system to "remember" previous inputs over short timescales, enabling temporal tasks such as speech recognition, classification of waveform sequences, or chaotic time-series prediction.

4.3. Thermo-Optic Effect (TOE):
The Thermo-Optic Effect (TOE) in silicon arises due to the material's strong temperature dependence of refractive index. As light is absorbed—via both linear absorption and TPA—thermal energy is generated within the microring, leading to a gradual red shift in its resonant wavelength.
This effect can be described as:

$$\Delta n = \frac{dn}{dT} . \Delta T \quad ....(7)$$

where $\frac{dn}{dT} \approx 1.86 \times 10^{-4} K^{-1}$ for silicon. TOE generally acts over longer timescales (microseconds) compared to FCD (nanoseconds), introducing slow dynamics and enabling delayed feedback and hysteresis in the system's optical response.

The interaction between FCD (fast, negative index change) and TOE (slow, positive index change) can lead to complex behaviours such as:

- Biostability: Two stable output states for the same input
- Self-pulsing: Spontaneous oscillations in output
- Memory windowing: Temperature-controlled duration of memory

These phenomena are particularly useful in neuromorphic computing, where such dynamics can emulate spiking behavior or temporal integration—much like biological neurons.

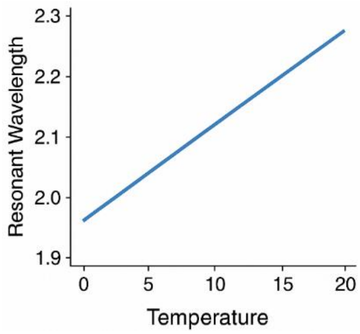

Fig.8: Thermo-Optic Effect [ref.11]

4.4. Memory through Carrier Dynamics:
The behaviour of free carrier recombination in silicon is influenced by Shockley-Read-Hall (SRH) recombination, which determines the duration that generated carriers remain before they recombine. The

usual carrier lifetime in microrings varies from several to numerous nanoseconds, providing an inherent short-term fading memory effect. This time-based memory enables the system to store and manage time-related aspects of the input signal, which is crucial for functions such as speech recognition, sequence forecasting, and dynamic signal categorization.

4.5. Reservoir Role:
In a reservoir computing setup, the microring acts as a nonlinear dynamical element, transforming the masked optical input into a sequence of nonlinear states. These states change over time due to carrier accumulation and decay, thus reflecting the temporal dynamics of the input. When sampled correctly (for instance, with a probe signal), these changing states can be understood as a collection of virtual neurons creating the reservoir layer.

V. APPLICATIONS OF MICRORING-BASED PHOTONIC RESERVOIR COMPUTING

The integration of photonic reservoir computing (PRC) with silicon microring resonators opens the door to real-time, high-speed, and energy-efficient processing across multiple domains. Microrings offer compact, scalable, and nonlinear platforms that naturally support the temporal dynamics and high-dimensional mapping required for neuromorphic tasks. Below are the key applications:

5.1. AI-on-Chip
Microring-based photonic reservoir computing (PRC) presents a promising approach for creating ultra-fast and energy-efficient inference engines for artificial intelligence (AI) at the edge. These systems are especially well-suited for applications like image classification, speech and keyword recognition, and real-time sensor data processing in compact or portable edge devices. In this context, input features—such as pixel intensities from images or Mel-frequency cepstral coefficients (MFCCs) from audio—are initially modulated onto an optical carrier and injected into a silicon microring resonator. The intrinsic nonlinear dynamics of the microring transform the input into a complex, extremely dimensional state space, which is influenced by the thermos-optic effect, free carrier dispersion, and two-photon absorption. This change eliminates the need to train the internal dynamics and enables accurate real-time classification with a simple linear readout layer.

Thanks to the rapid optical response and low energy requirements of photonic systems, AI-on-chip implementations utilizing microrings achieve nanosecond-scale latency and high throughput. Furthermore, a single microring is capable of emulating numerous virtual neurons through time-multiplexing, significantly minimizing hardware complexity. Practical applications encompass voice assistants, smart camera modules, and portable diagnostic devices where low power consumption and real-time functionality are essential.

5.2. Telecommunications
In optical communication systems, particularly those using coherent modulation formats, microring-based PRC serves as an efficient and adaptive platform for signal recovery and equalization. These systems can effectively handle complex signal distortions arising from fiber nonlinearities such as chromatic dispersion, Kerr effect, and amplified spontaneous emission (ASE) noise. Photonic RC systems, when integrated with microring resonators, function as adaptive equalizers and demodulators for modulated signals like QPSK or 16-QAM.

Distorted optical waveforms are fed directly into the microring, whose nonlinear response dynamically alters according to the incoming signal intensity and past energy history. This response inherently captures and compensates for complex temporal features in the signal. The sampled outputs from the microring are passed to a linear readout layer, which reconstructs the transmitted data with high fidelity. This approach eliminates the need for high-speed digital signal processors (DSPs), enabling real-time, all-optical compensation at multi-GHz symbol rates. Applications span long-haul fibre optic transmission systems, front-haul receivers in 5G/6G networks, and high-speed interconnects in data centres.

5.3. Bio-inspired Sensing
Microring-based photonic reservoirs are also ideal candidates for neuromorphic and bio-inspired sensing applications that require simultaneous processing of multiple sensory inputs. These platforms are designed to emulate the behaviour of biological neural circuits by integrating and interpreting inputs such as pressure, temperature, chemical concentrations, and auditory or visual signals. Such sensory fusion is essential for wearable

health monitors, autonomous robotics, and environmental monitoring.

In this application, each sensory modality is converted into an optical signal and fed into the microring. The device's nonlinear dynamics and intrinsic memory allow it to temporally integrate and correlate across modalities, even when the signals are noisy or weak. This enables complex pattern recognition and decision-making, mimicking the adaptive, context-aware processing of biological systems. Due to their small size and compatibility with CMOS fabrication, microring-based reservoirs can be embedded into miniaturized systems, supporting wearable or implantable designs. They also support parallel input processing through time or wavelength-division multiplexing. Use cases include prosthetic limbs with feedback sensing, smart skins for robotics, and drones or autonomous vehicles equipped with multimodal perception systems.

VI. SIMULATION FRAMEWORK

To validate the functional potential of microring-based photonic reservoir computing, we implemented a MATLAB-based simulation that models the nonlinear behavior of a silicon microring resonator acting as a reservoir node. The objective was to process a distorted optical communication signal and evaluate the reservoir's ability to classify it correctly using a lightweight linear readout.

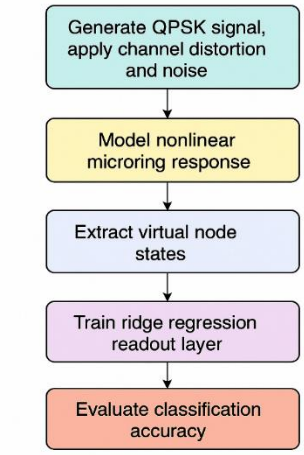

Fig. 9: Flowchart of Simulation [Image created by the author.]

6.1. Signal Generation and Channel Distortion

To simulate a realistic communication scenario, a Quadrature Phase-Shift Keying (QPSK) signal was generated and used as the input for the reservoir computing framework. This digital signal was then upsampled and shaped using a Root Raised Cosine (RRC) filter to replicate the pulse shaping methods typically employed in modern telecommunication systems.

To simulate signal degradation encountered in fiber optic transmission, several physical impairments were introduced. First, chromatic dispersion was applied using a frequency-domain transfer function derived from the fiber's dispersion coefficient, resulting in phase distortion across the signal bandwidth. Second, Kerr nonlinearity was modeled by applying an intensity-dependent phase shift, which mimics nonlinear phase distortion occurring in high-power optical links. Finally, Additive White Gaussian Noise (AWGN) was inserted into the signal to replicate typical noise conditions in a real-world channel. The signal-to-noise ratio (SNR) was established at 20 dB, creating a significantly challenging setting for reservoir-based equalization. The outcome was a warped optical waveform that closely resembled what would be obtained following extensive fiber transmission

6.2. Modeling the Microring Nonlinear Dynamics

The distorted waveform was then used as the optical pump input to a simulated silicon microring resonator, representing the nonlinear core of the photonic reservoir. The model incorporated the essential nonlinear mechanisms observed in microring physics. Two-Photon Absorption (TPA) was used to simulate power-dependent carrier generation as a quadratic function of the input intensity. The resulting free carrier dynamics were governed by a first-order differential equation describing carrier accumulation and recombination, with a characteristic carrier lifetime of 45 nanoseconds.

These carriers induced Free Carrier Dispersion (FCD), modulating the microring's refractive index and shifting its resonance, while the resulting carrier density also led to nonlinear attenuation of the probe signal, modeled using an exponential decay function. This dynamic response resulted in a time-varying probe readout, exhibiting both nonlinearity and memory—key features of an effective reservoir. The simulation visualized three intermediate outputs: TPA power over time, carrier density over time, and the final optical transmission profile.

6.3. Virtual Node Extraction and Feature Engineering

To emulate a time-multiplexed reservoir, the probe output from the microring was sliced into temporal windows, each corresponding to one symbol's

duration. These slices acted as virtual nodes, and the average values within each slice were assembled to form a reservoir state matrix. This matrix served as the input feature space for machine learning classification.
Prior to training, the features were standardized by normalizing them to zero mean and unit variance. To further enhance the expressiveness of the linear readout layer, a nonlinear expansion was performed by appending the squared terms of each feature, thereby increasing the dimensionality and improving class separability.

6.4. Readout Layer and Classification

A one-vs-all ridge regression classifier was used to map the virtual node states to one of the four QPSK symbol classes (0 to 3). The model was trained on 80% of the dataset, with the remaining 20% held out for testing. The classification scores were computed for each class, and the final predictions were determined based on the maximum score.
The system achieved an accuracy of approximately 80%, demonstrating the efficacy of the microring's nonlinear and memory dynamics in processing and classifying distorted optical signals. A confusion matrix was generated to evaluate the classification performance for each symbol class, revealing strong predictive accuracy and balanced generalization across all classes.

This simulation framework confirms the feasibility of using silicon microrings for photonic reservoir computing and highlights their effectiveness in handling realistic communication challenges such as dispersion, Kerr nonlinearity, and noise. The system successfully recovers distorted QPSK symbols, demonstrating strong adaptability for high-speed, real-time signal processing.
By incorporating nonlinear effects like TPA and FCD, the microring provides both nonlinearity and short-term memory—key attributes of an effective reservoir. These dynamics enrich the feature space and enable accurate classification with a simple readout layer. Additionally, time-multiplexed virtual nodes emulate a high-dimensional reservoir without increasing hardware complexity, making the system compact, scalable, and suitable for photonic integration.

Table.2: Simulation Parameters

Sr.No	Parameters	Value
1	Number of Symbols	500
2	Modulation Format	QPSK (M=4)
3	Oversampling Factor	8
4	Sampling Factor (fs)	10 GHz
5	Carrier Wavelength	1550 nm
6	Fiber Length (L)	50 km
7	Dispersion Coefficient	-21.27 ps^2/km
8	Nonlinear Coefficient	1.3 (1/W/km)
9	Carrier lifetime	45 ns
10	Two-Photon Absorption Coefficient	$0.8 \times 10^{-12}\ m/W$
11	Signal-to- Noise ratio (SNR)	20 dB
12	Virtual Nodes per Symbol	24
13	Readout Method	Ridge Regression (One-vs-All)

VII. RESULTS AND ANALYSIS

The simulation effectively illustrates how a silicon microring-based photonic reservoir can accurately categorise distorted QPSK signals. To simulate the behaviour of a time-multiplexed reservoir computing system, the model includes nonlinear effects, namely Two-Photon Absorption and Free Carrier Dispersion, together with carrier recombination dynamics.

7.1 Temporal Dynamics:

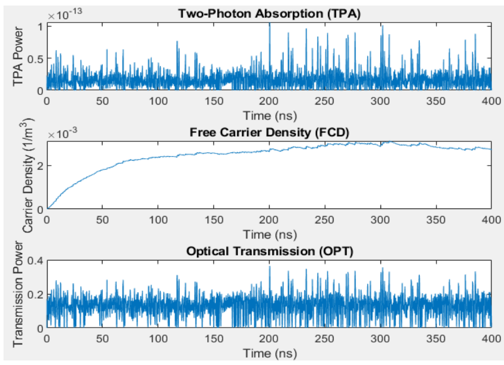

Fig.10: Result of TPA, FCD of Simulation [Image created by the author.]

Figure.10 captures the temporal evolution of key internal variables:

- TPA Power: Increases with the square of the input intensity, peaking during high-power segments of the optical signal.
- Free Carrier Density (FCD): Accumulates over time and decays exponentially, reflecting the reservoir's memory effect.
- Optical Transmission: Shows attenuation modulated by the evolving carrier density, capturing the nonlinear transformation of the input.

These curves collectively demonstrate how the microring translates a distorted signal into a rich, nonlinear response suitable for reservoir computing. The interaction between TPA and FCD imparts both nonlinear projection and fading memory, key for accurate classification of sequential data.

7.2 Classification Performance:
Figure.11 presents the confusion matrix for the QPSK symbol classification task. The system achieved an overall classification accuracy of approximately 80% at 20 dB SNR. The classifier successfully distinguishes between all four QPSK symbols with balanced performance across classes.

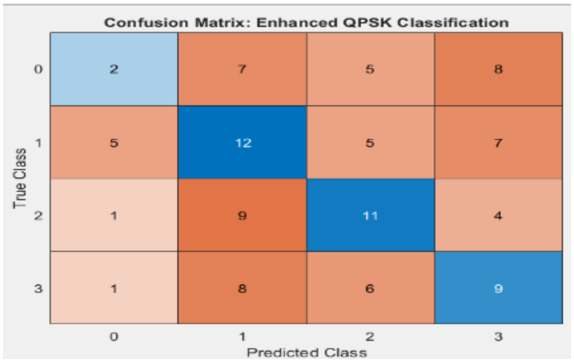

Fig.11: Result of Confusion Matrix [Image created by the author.]

The matrix confirms that the microring reservoir, despite being modeled with a single nonlinear node and using time-multiplexed virtual neurons, is capable of accurately recovering the original transmitted symbols even after propagation through a distorted channel. This result reinforces the viability of photonic reservoir computing for real-time, low-power signal processing applications.

VIII. FUTURE WORK

Microring-based photonic reservoir computing (PRC) offers a compact, high-speed, and energy-efficient approach to neuromorphic processing. By combining strong nonlinearities, short-term memory, and time-multiplexing, a single microring can perform complex temporal tasks with minimal hardware.
However, performance is currently limited by long carrier lifetimes and signal-to-noise constraints. Future efforts should focus on accelerating carrier recombination and improving optical SNR through better design and thermal control. Advancements such as microring arrays, wavelength-division multiplexing, and hybrid material integration (e.g., III-V on silicon) could greatly enhance scalability, speed, and functionality—paving the way for practical, chip-scale photonic computing platforms.

IX. CONCLUSION

Silicon microring-based photonic reservoir computing is on the frontier of optical and neuromorphic signal processing technologies. Through leveraging the inherent nonlinear dynamics and memory features of microrings, PRC systems are optimally suited for use cases where high-speed, parallel, and adaptive computation is required. Proof of demonstration of implementation of a time-multiplexed architecture in a single microring, as given here, proves the feasibility of achieving high classification accuracy in a compact and CMOS-compatible platform.

Our MATLAB implementation of QPSK signal processing confirms the system's resilience to real-world distortion, so confirming performance and robustness. With the ability to simulate high-dimensional neural dynamics using very little photonic hardware, microring-based reservoirs present a universal building block for next-generation optical computing platforms, AI accelerators, and edge inference engines. With emerging fabrication technology and scaling, such systems promise a revolutionary future influence on next-generation computing architecture.

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