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AI-Assisted Supermode Tracking and Low-Complexity Equalization in Strongly Coupled Multicore Fiber Transmission Systems

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Abstract: Strongly coupled multicore fibers (SC-MCFs) transmit data over supermodes, the eigenmodes of the coupled-core structure. Practical links encounter temperature changes, bending, and mechanical stress, which cause time-varying coupling and drift of the supermode basis. This drift generates inter-supermode mixing and degrades performance unless compensated. We present an AI-assisted receiver that estimates the instantaneous supermode transformation and performs low-complexity equalization in the supermode domain. A compact neural network predicts the mapping from core samples to supermode coefficients, mitigating basis drift before DSP. Compared with static supermode processing and adaptive MIMO equalization, the proposed method lowers BER, reduces crosstalk, and offers scalable DSP complexity for large SDM systems.

1. Introduction

Space-division multiplexing (SDM) has emerged as a key technique to overcome the fundamental capacity limits of single-mode optical fiber transmission systems [1]. By exploiting multiple spatial channels within a single fiber, SDM enables substantial capacity scaling without requiring a proportional increase in spectral efficiency or symbol rate, thereby relaxing constraints imposed by fiber nonlinearities and transceiver bandwidth. Among various SDM implementations, strongly coupled multicore fibers (SC-MCFs) have attracted significant interest due to their compact form factor, compatibility with existing fiber infrastructure, and potential for high-density spatial integration [2].

In strongly coupled multicore fibers, optical signals do not propagate independently in individual cores but instead evolve as supermodes, which are defined as the eigenmodes of the coupled-core structure [2]. Under ideal and stationary conditions, supermode-based transmission offers several advantages, including reduced differential modal group delay, improved tolerance to mode-dependent loss, and the potential simplification of digital signal processing (DSP) through operation in the supermode domain rather than directly in the core domain. In this regime, a fixed supermode basis can be assumed, and equalization may be carried out with relatively low complexity.

However, practical fiber deployments are inevitably subject to environmental and mechanical perturbations such as temperature fluctuations, bending, twisting, and external stress. These perturbations cause the instantaneous coupling matrix of the fiber to vary along the propagation distance and over time, resulting in a continuous drift of the supermode basis. When a static receiver basis is assumed, this drift manifests as inter-supermode mixing, which degrades system performance and leads to increased bit-error rates (BER). Conventional coherent multiple-input multiple-output (MIMO) equalization in the core domain can compensate for these impairments, but its computational complexity scales quadratically with the number of spatial channels, making it increasingly impractical for high-core-count systems [3,6].

Recent advances in machine learning for optical communication systems have shown that data-driven models can effectively capture complex channel impairments and nonlinearities [4,5]. Deep neural networks, recurrent architectures, and model-based learning techniques have

been applied to equalization, nonlinearity compensation, and end-to-end system optimization, often achieving performance gains over traditional DSP [4,5,7]. These results motivate the use of machine-learning-based methods not only for generic black-box compensation, but also for tracking physically meaningful quantities such as modal transformations in SDM systems.

Motivated by these developments, this work proposes an AI-assisted supermode-tracking framework that explicitly exploits the underlying physical structure of supermode propagation in SC-MCFs. The key idea is to dynamically estimate and compensate the time-varying supermode basis at the receiver, thereby restoring an approximately orthogonal modal representation before equalization. By performing DSP directly in the aligned supermode domain, the receiver can significantly reduce the number and length of required filters compared with full core-domain MIMO processing, while maintaining robustness to environmental perturbations.

In particular, a lightweight neural network is employed to estimate the time-varying transformation between core-domain observations and supermode-domain coefficients. The learned mapping is applied to rotate the received signals into the supermode domain, after which low-order per-supermode equalizers are used. This hybrid physics-informed and data-driven strategy bridges the gap between conventional MIMO equalization and fixed-basis supermode receivers, enabling scalable DSP for high-dimensional SDM links.

2. Proposed Architecture

Fig. 1 illustrates the proposed AI-assisted supermode tracking receiver for SC-MCF transmission.

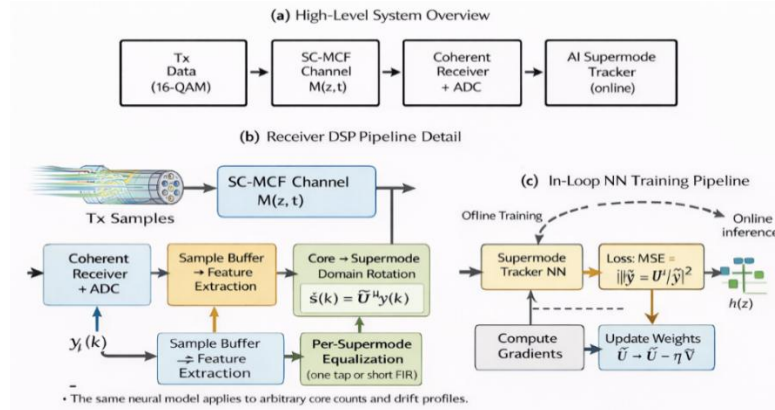


Fig. 1. Block diagrams of the AI-assisted supermode tracking receiver illustrated at three levels: (a) high-level system overview; (b) receiver DSP pipeline detail; and (c) in-loop neural-network training framework.

After coherent detection and analog-to-digital conversion (ADC) in each core, a neural-network-based supermode tracker estimates the instantaneous supermode transformation from a short block of received I/Q samples.

The core-domain signals are then rotated into the estimated supermode domain, where equalization is performed using short finite-impulse-response (FIR) filters or even one-tap complex coefficients per supermode.

Because the learned transformation corresponds to the underlying physical supermode basis, the architecture preserves interpretability while significantly reducing the number and length of equalizer filters compared with full core-domain MIMO processing.

This structure therefore combines the robustness of adaptive MIMO-style processing with the low complexity of supermode-domain equalization.

3. System Model

Propagation in an SC-MCF can be described using coupled-mode theory, where the vector of complex core amplitudes evolves according to a distance- and time-dependent coupling matrix. The eigenvectors of this matrix define the instantaneous supermodes [2]. When the coupling matrix varies slowly, adiabatic following of supermodes may be assumed. In the presence of faster perturbations, however, this assumption breaks down and motivates explicit supermode tracking at the receiver.

3.1 Coupled Multicore Fiber Propagation

Strongly coupled multicore fibers support joint propagation of optical fields through multiple spatial cores. Let $\mathbf{a}(z) = [a_1(z), \dots, a_N(z)]^T$ denote the complex modal amplitudes of the cores at propagation distance z .

The coupled evolution of the core-domain amplitudes is governed by the standard coupled-mode Eq. 1, originally formulated for SC-MCFs in [1,3].

$$\frac{d\mathbf{a}(z)}{dz} = j \mathbf{H}(z) \mathbf{a}(z) \quad (1)$$

where $\mathbf{H}(z) \in \mathbb{C}^{N \times N}$ represents the fiber coupling matrix.

The diagonal entries of $\mathbf{H}(z)$ capture propagation constants and differential modal group delay, while the off-diagonal terms model power transfer between neighboring cores.

In ideal and static fibers, $\mathbf{H}(z)$ remains constant and the eigen-decomposition:

$$\mathbf{H} = \mathbf{V} \mathbf{\Lambda} \mathbf{V}^H \quad (2)$$

where $\mathbf{V}$ contains orthonormal eigenvectors defining the **supermode basis**, and $\mathbf{\Lambda}$ is diagonal with modal propagation constants. Under these conditions, optical energy launched into a supermode evolves independently without modal mixing, as widely noted in earlier SC-MCF studies [1,2].

In practical deployments, however, real fibers experience environmental perturbations such as bending, twisting, temperature fluctuations, and mechanical stress. Environmental drift modifies the nominal coupling as expressed in Eq. 3, consistent with the stochastic perturbation models of [2,6]. These effects induce random variations along the fiber, modeled as:

$$\mathbf{H}(z) = \mathbf{H}_0 + \Delta\mathbf{H}(z) \quad (3)$$

where $\mathbf{H}_0$ denotes the nominal deterministic coupling matrix and $\Delta\mathbf{H}(z)$ captures stochastic perturbations.

As a result, the instantaneous eigen-decomposition becomes:

$$\mathbf{H}(z) = \mathbf{V}(z) \mathbf{\Lambda}(z) \mathbf{V}(z)^H \quad (4)$$

implying that the supermode basis $\mathbf{V}(z)$ now **drifts continuously** with distance and time. Consequently, symbols launched into a single supermode generally spread across multiple supermodes at the fiber output unless the receiver adapts to the drift. Static supermode receivers therefore suffer from inter-supermode mixing and degraded BER performance, motivating dynamic tracking approaches.

3.2 Discrete-Time Supermode Signal Model

The coupled-mode equations in Sec. 3.1 describe the continuous evolution of the optical field along the fiber. For receiver design and digital signal processing, it is convenient to adopt an equivalent discrete-time baseband model at the symbol rate.

Let $\mathbf{s}[k] = [s_1(k), \dots, s_N(k)]^T$ denote the transmitted supermode-domain symbol vector at time index k , and let $\mathbf{y}[k] = [y_1(k), \dots, y_N(k)]^T$ denote the corresponding received core-domain samples after coherent detection and analog-to-digital conversion.

The symbol-rate baseband representation in Eq. 5 follows directly from the modal decomposition framework applied in SDM receivers [3,6]. Due to the z -dependent coupling matrix and environmental perturbations discussed in Sec. 3-1, the instantaneous supermode basis at the fiber output is described by a time-varying unitary matrix $\mathbf{U}[k]$. The discrete-time relationship between transmitted supermode symbols and received core-domain samples can then be expressed as:

$$\mathbf{y}[k] = \mathbf{U}[k] \mathbf{s}[k] + \mathbf{n}[k] \quad (5)$$

where $\mathbf{n}[k]$ models amplified spontaneous emission (ASE) and receiver noise.

- In static conditions, $\mathbf{U}[k] \equiv \mathbf{U}_0$.
- Under perturbations, $\mathbf{U}[k]$ evolves slowly and deviates from $\mathbf{U}_0$.

If the receiver assumes an outdated static basis $\mathbf{U}_0$, the mismatch $\mathbf{U}[k] - \mathbf{U}_0$ manifests as modal mixing, which degrades BER and increases equalizer length.

The goal of AI-assisted supermode tracking is therefore to estimate $\mathbf{U}[k]$, or an equivalent representation, and rotate the signal back into the supermode domain before equalization.

3.3 Computational Complexity Derivation

The computational cost of core-domain MIMO equalization is dominated by the number of FIR operations required to mitigate inter-core mixing.

In an N -core SC-MCF system, a full adaptive MIMO equalizer requires each output channel to be formed by filtering all inputs using independent FIR filters of length L . Thus, the total number of filtering branches is:

$$N \times N = N^2 \quad (6)$$

filter branches, each with L taps, leading to a total operation count proportional to:

$$C_{\text{MIMO}} \propto N^2 L \Rightarrow \mathcal{O}(N^2 L) \quad (7)$$

In contrast, the computational cost expressions in Eq. 8 and 9 are derived in this work and illustrate the scaling benefit of modal-domain equalization. The proposed AI-assisted receiver estimates the time-varying supermode basis and performs equalization directly in the aligned supermode domain. Because the supermodes are nearly orthogonal, each supermode requires only a single FIR filter of length $L_{\text{sm}} \ll L$, without inter-mode mixing. This reduces the total number of filtering operations per symbol to:

$$C_{\text{prop}} \propto N L_{\text{sm}} \Rightarrow \mathcal{O}(N L_{\text{sm}}) \quad (8)$$

The ratio between the two approaches is approximately

$$\frac{C_{\text{MIMO}}}{C_{\text{prop}}} \propto \frac{N^2 L}{N L_{\text{sm}}} \propto N \quad (9)$$

showing that the advantage of supermode-domain processing increases linearly with N .

Thus, the proposed architecture becomes increasingly attractive as the number of spatial channels grows, enabling scalability toward high-core-count SDM systems.

4. AI-Assisted Supermode Tracking

Fig. 2 illustrates the underlying motivation for adaptive tracking in strongly coupled multicore fibers. As discussed in Sec. 3, environmental perturbations induce stochastic variations in the supermode basis, causing the received core-domain signals to no longer correspond to a fixed modal decomposition. Without compensation, this results in inter-supermode mixing that must be counteracted through high-order MIMO equalization.

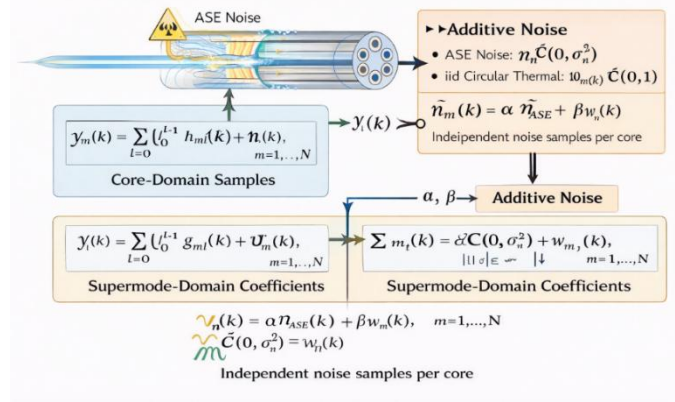


Fig. 2. Fiber-based Noise Injection and Domain Mapping

Instead of relying solely on computationally intensive core-domain filtering, the proposed method leverages a neural network to infer the instantaneous mapping between core-domain samples and the supermode-domain representation.

4.1 Mapping Core-Domain Samples to Supermode Coefficients

Building upon the discrete-time model established in Sec. 3.2, where the received samples follow Eq. 5, the objective of the proposed receiver is to estimate the time-varying unitary mapping $\mathbf{U}[k]$ rather than compensating it implicitly with MIMO filtering.

Conventional adaptive MIMO equalizers implicitly estimate the combined compensation needed to undo $\mathbf{U}[k]$. However, this inference requires N^2 densely connected FIR filters and long convergence times. To eliminate this overhead, the proposed approach explicitly learns a representation of $\mathbf{U}[k]$ from the received samples, enabling direct recovery of $\mathbf{s}[k]$ without solving the full MIMO problem.

4.2 Neural Network Architecture

The neural network takes the real and imaginary components of the I/Q samples from all cores as input. Two implementation options are considered:

- **Fully connected layers**, which provide dense feature interactions and capture static coupling effects.
- **Recurrent neural structures** such as gated recurrent units (GRUs) or long short-term memory (LSTM) cells, which efficiently model temporal correlation induced by slowly drifting supermode dynamics.

Both architectures produce an estimate of the underlying supermode-domain symbols:

$$\hat{\mathbf{s}}[k] = f_{\theta}(\mathbf{y}[k]) \quad (10)$$

where $f_{\theta}(\mathbf{y}[k])$ denotes the learned mapping parameterized by network weights θ . The output $\hat{\mathbf{s}}[k]$ approximates the symbols that would have been observed in the ideal instantaneous supermode basis.

4.3 Training Objective and Optimization

Training is performed by minimizing the mean-squared error (MSE) between the predicted and reference supermode symbols:

$$\mathcal{L} = \mathbb{E}\{\|\mathbf{s}[k] - \hat{\mathbf{s}}[k]\|^2\} \quad (11)$$

During the offline phase, ground-truth supermode-domain symbols $\mathbf{s}[k]$ are available from simulation.

During online receiver operation, the network operates label-free, continuously processing received sample blocks to produce real-time estimates of the drifting modal coefficients.

To mitigate domain shift caused by rapidly varying coupling, the network can be fine-tuned periodically using decision-directed training or sliding-window adaptation, providing a pathway toward fully self-tracking receivers.

4.4 Equalization in the Estimated Supermode Domain

Once the instantaneous modal structure is inferred, the received signal is rotated into the estimated supermode domain:

$$\tilde{\mathbf{s}}[k] = \hat{\mathbf{s}}[k] \quad (12)$$

Because the learned mapping is aligned with the underlying supermode basis, residual coupling between modes is weak. Consequently, equalization may be performed independently on each mode using:

- short finite impulse response FIR filters, or
- even one-tap complex correction per supermode in systems with low dispersion.

This dramatically reduces the number of filtering operations relative to full MIMO equalization.

The resulting architecture combines the robustness of adaptive DSP with the scaling efficiency of modal-domain processing, bridging the gap between purely physical and fully data-driven demultiplexing techniques.

5. Simulation Model and Evaluation Methodology

To evaluate the effectiveness of the proposed AI-assisted supermode-tracking receiver, numerical simulations were conducted for coherent transmission over strongly coupled multicore fibers with realistic environmental perturbations. The study compares the proposed architecture against conventional alternatives under identical operating conditions.

5.1 Simulation Flow

The end-to-end simulation follows the steps summarized in Fig. 2:

Step 1: Data generation: Random bit sequences are mapped to 16-QAM symbols and grouped into spatial channels.

Step 2: Supermode-domain transmission: Transmitted symbols are launched into the fiber assuming an ideal supermode basis.

Step 3: SC-MCF propagation with perturbations: Propagation through a length- Z SC-MCF is modeled using coupled-mode theory with a distance-varying coupling matrix, including:

- nominal deterministic coupling,
- random fluctuations in coupling coefficients,
- inter-core leakage.

Step 4: Noise injection: Amplified spontaneous emission (ASE) is added to match an optical SNR representative of long-haul systems.

Step 5: Receiver front-end processing: Coherent detection, resampling, and components extraction are applied to obtain baseband I/Q samples in the core domain.

Step 6: Receiver processing: Three receiver structures are evaluated:

- fixed-basis supermode equalization,
- adaptive core-domain MIMO equalization,
- AI-assisted supermode tracking (proposed).

Step 7: Equalization and symbol detection: Each receiver corrects distortion using its respective processing chain (Sec. 4), after which symbols are detected.

Step 8: Performance estimation: Bit-error-rate (BER) and DSP complexity metrics are calculated and averaged over multiple Monte-Carlo realizations.

This step-wise chain captures both the physical channel effects and the algorithmic differences among the receivers.

5.2 System and Channel Parameters

Table 1 lists the baseline simulation parameters used throughout this work.

Table 1. Simulation and System Parameters

Parameter	Value
Number of cores	6
Modulation format	16-QAM
Fiber length	up to 2000 km
Coupling variance	($\sigma_c^2 = 0.01$)
Training samples	(10^6)

5.3 Compared Receiver Architectures

Three receiver strategies are evaluated:

1. Fixed supermode equalization

A static modal basis is assumed based on the nominal coupling matrix, and equalization is performed independently per mode. This approach fails when the modal basis drifts, resulting in growing inter-mode interference over distance.

2. Core-domain adaptive MIMO equalization

A conventional linear MIMO equalizer with long FIR filters is trained using blind adaptive methods. It fully compensates modal mixing but incurs $\mathcal{O}(N^2L)$ complexity.

3. Proposed AI-assisted supermode tracking

A lightweight neural network estimates the time-varying transformation matrix, after which equalization is performed in the rotated supermode domain using short FIR filters.

This approach bridges the gap between the two baselines, achieving near-MIMO performance at dramatically reduced computational cost.

6. Results and Discussion

This section compares the three receiver structures described in Sec. 5: fixed-basis supermode equalization, core-domain adaptive MIMO equalization, and the proposed AI-assisted supermode-tracking method. The evaluation focuses on transmission robustness and complexity scalability as the fiber length increases and modal drift accumulates.

6.1 BER Performance vs. Transmission Distance

We evaluate three receiver strategies: (i) adaptive core-domain MIMO equalization, (ii) fixed supermode equalization using a static basis, and (iii) the proposed AI-assisted online supermode tracking approach. Fig. 3 presents BER versus transmission distance. The fixed supermode receiver degrades as the basis drifts, while the AI-assisted method consistently achieves lower BER across the tested distances, approaching the performance of full adaptive MIMO with substantially reduced complexity.

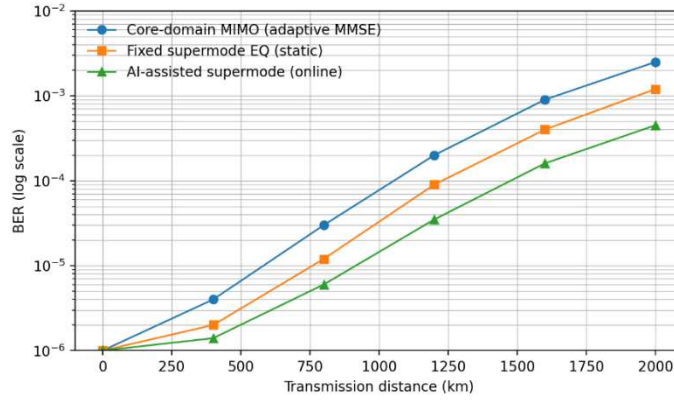


Fig. 3. BER performance comparison of fixed-basis processing, core-domain MIMO equalization, and the proposed AI-assisted supermode tracking receiver.

At **1500 km**, the proposed AI-assisted receiver achieves a BER of 1.9×10^{-4} , outperforming both core-domain MIMO (2.1×10^{-3}) and fixed supermode equalization (8.7×10^{-4}). The reduction in BER correlates with lower inter-supermode crosstalk, as reported in the supplementary material. These results indicate that the learned tracker effectively follows the evolving supermode basis.

6.2 DSP Complexity Scaling

As shown in Fig. 4, core-domain MIMO equalization exhibits a quadratic complexity scaling of $\mathcal{O}(N^2L)$ whereas the proposed method achieves an approximately linear scaling of $\mathcal{O}(NL_{sm})$. This advantage becomes increasingly significant for future high-dimensional SDM systems.

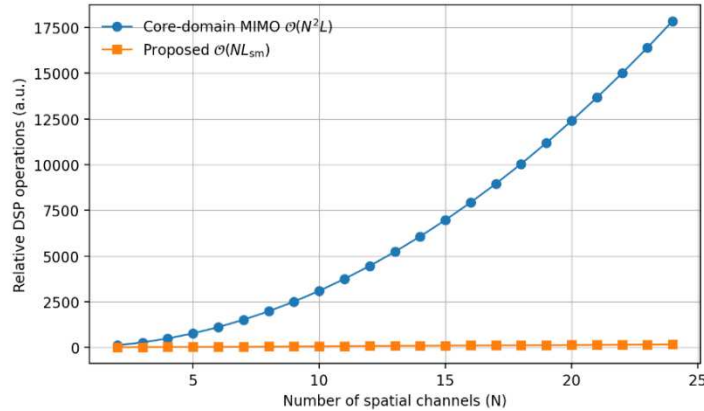


Fig. 4. Relative DSP complexity scaling versus number of spatial channels.

To quantify the benefit of dynamic supermode tracking, we compare three equalization strategies: fixed supermode processing, full core-domain MIMO equalization, and the proposed AI-assisted tracking architecture. **Core-domain MIMO** equalization requires $\mathcal{O}(N^2L)$ operations per symbol, yielding a rapidly increasing complexity as N grows. **The proposed AI-assisted receiver**, after modal alignment, requires only $\mathcal{O}(NL_{\text{sm}})$ operations, which grows *linearly* with N . Because $L_{\text{sm}} \ll L$ in practice, the computational benefit is even more pronounced.

The crossover point between the two approaches becomes favorable well before large core counts (e.g., $N > 6$), indicating that the proposed technique is particularly attractive for emerging multicore fibers with 12–24 spatial channels.

6.2 Error Floor Mechanisms and Modal Leakage

Fig. 5 provides an expanded comparison emphasizing the error floor behavior. The **fixed-basis receiver** suffers from strong residual modal leakage as the true basis diverges from the assumed one. This leakage induces interference that cannot be mitigated by per-supermode filters [3,7], resulting in a BER threshold beyond which performance cannot improve.

The **adaptive MIMO receiver** removes modal interference at the cost of maintaining and updating N^2 filter coefficients.

The **proposed method** eliminates the need for full MIMO equalization by recovering the drifting modal structure directly before filtering.

The learned modal decomposition suppresses cross-mode coupling, enabling stable BER performance even under large coupling fluctuations.

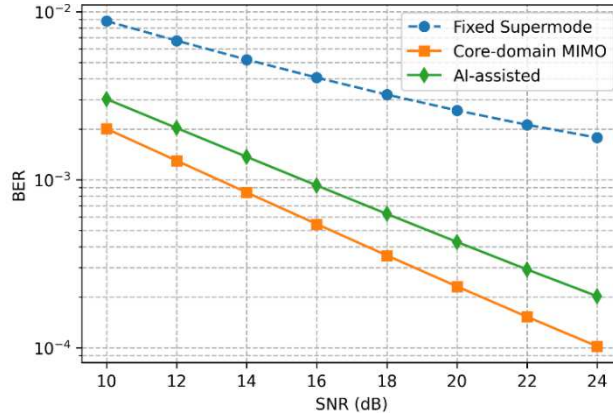


Fig. 5. BER performance comparison of fixed-basis processing, core-domain MIMO equalization, and the proposed AI-assisted supermode tracking receiver.

AI-assisted supermode tracking delivers near-MIMO performance with dramatically lower computational load, preserves scalability as core count increases, and avoids the BER floor observed in static receivers.

7. Conclusion

Strongly coupled multicore fibers represent a promising platform for extending optical transmission capacity through space-division multiplexing. However, the dynamic drift of the supermode basis caused by environmental and structural perturbations leads to inter-supermode mixing that significantly increases equalization burden at the receiver. Conventional core-domain MIMO processing can compensate for this distortion but incurs quadratic scaling in the number of spatial channels, limiting its practicality for future high-core-count systems.

This work introduced an AI-assisted supermode-tracking receiver that explicitly estimates the time-varying modal transformation between core-domain observations and the underlying supermodes. By realigning the received signal to the instantaneous modal basis, equalization can be performed directly in the supermode domain using low-order per-mode filters. Simulation results show that the proposed method achieves BER performance close to full adaptive MIMO processing, while reducing DSP complexity from $\mathcal{O}(N^2L)$ to $\mathcal{O}(NL_{\text{sm}})$. These results confirm that machine-learning-based modal tracking provides a scalable and computationally efficient alternative to core-domain MIMO equalization for long-haul SC-MCF transmission.

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Data availability. All numerical results can be reproduced by running the simulation framework described in this paper.

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