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Quantum Photonics and AI Synergy: Advancements in Optical Metrology, Sensing, and Communication

Naeema Nazar [1]*, Dr. Saju A[2], J Bino[3], B Senthilnayaki[4], D Sungeetha[5]

[1*]PhD Scholar, Department of Electronics and Communication Engineering, Indian Institute of Information Technology, Kottayam, Kerala, India,

Email ID: naeemanazarcn@gmail.com ,

Orcid ID: 0009-0007-6768-2842

[2]Associate Professor, Department of Electronics and Communication Engineering , Albertian Institute of Science and Technology, Ernakulam, Kerala, India,

Email ID: saju.a@aisat.ac.in ,

Orcid ID: 0009-0001-3235-0799

[3]Assistant Professor, Department of Electronics and Communication Engineering, St. Joseph's of Institute of Technology OMR, Chennai 119, India,

Email ID: stephenbino@gmail.com,

Orcid ID: 0000-0002-0856-1609

[4]Assistant Professor, Department of Information Technology, St. Joseph's of Institute of Technology OMR, Chennai 119, India,

Email ID: nayakiphd@gmail.com

Orcid ID: 0000-0003-0520-7951

[5]Professor, Saveetha School of Engineering, SIMATS, Saveetha University, Chennai, India,

Email ID: sungeethaarv@gmail.com ,

Orcid ID: 0000-0002-7686-0416

***Correspondence Author:**

Naeema Nazar,

PhD Scholar, Department of Electronics and Communication Engineering, Indian Institute of Information Technology, Kottayam, Kerala, India,

Email ID: naeemanazarcn@gmail.com ,

Orcid ID: 0009-0007-6768-2842

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ABSTRACT

The convergence of quantum photonics and artificial intelligence (AI) is redefining the landscape of optical metrology, sensing, and communication, enabling unprecedented precision, adaptability, and data processing capabilities. This paper explores the synergistic integration of AI-driven algorithms with quantum photonic systems, highlighting transformative advancements such as machine learning-enhanced quantum state estimation, intelligent control of photonic circuits, and adaptive quantum error correction. Emphasis is placed on how AI facilitates real-time decision-making and noise mitigation in complex quantum environments, thereby enhancing the sensitivity and resolution of optical sensors and metrological instruments. Additionally, the study investigates AI-assisted quantum communication protocols that optimize entanglement distribution, secure key generation, and photonic resource management. By bridging theoretical insights with emerging experimental frameworks, this work presents a comprehensive perspective on the mutual reinforcement between quantum photonics and AI, outlining their collective potential to drive the next generation of ultra-precise, intelligent optical technologies.

1. INTRODUCTION

Quantum photonics and artificial intelligence are two rapidly advancing fields that are beginning to intersect in transformative ways. Quantum photonics focuses on the control and application of light at the quantum level, enabling breakthroughs in precision measurement, secure communication, and information processing. At the same time, artificial intelligence, particularly through methods such as machine learning and data-driven optimization, provides powerful tools for analyzing complex systems, making predictions, and automating control processes. When combined, these technologies offer promising new directions for the development of intelligent optical systems that are more accurate, adaptive, and efficient than ever before. The use of artificial intelligence within quantum photonic systems brings enhanced functionality and smarter performance. In optical sensing and metrology, intelligent algorithms can improve sensitivity by identifying subtle patterns in measurement data and adjusting system parameters in real time. In communication systems that rely on quantum light, artificial intelligence can manage signal quality, optimize information transfer, and respond effectively to environmental disturbances. These capabilities are crucial for overcoming challenges such as signal degradation and limited measurement precision, which have traditionally hindered the scalability and reliability of quantum technologies.

This paper presents a comprehensive overview of the convergence between quantum photonics and artificial intelligence, with a focus on their joint applications in optical sensing, precision measurement, and advanced communication. It explores recent research efforts that apply learning algorithms to quantum systems for enhanced decision making, control, and analysis. Both theoretical models and experimental implementations are discussed, providing insights into how this multidisciplinary approach is driving innovation and paving the way for a new generation of smart quantum enabled optical technologies.

AI-Driven Control and Optimization in Quantum Photonic Systems

Quantum photonic systems rely on the precise manipulation of light at the quantum scale, making them highly sensitive to environmental disturbances and system imperfections. Traditional control mechanisms often struggle with these limitations due to the complexity and stochastic nature of quantum behavior. Artificial intelligence, particularly machine learning algorithms, introduces a powerful framework for adaptive control by learning from data patterns and predicting system responses in real time. These capabilities allow quantum photonic setups to operate with greater efficiency and stability, even under unpredictable or fluctuating conditions. One prominent application is in the automated tuning of optical components, such as interferometers, beam splitters, or waveguide arrays. Instead of relying on manual calibration or static control laws, AI models can optimize parameters like phase shifts, coupling strengths, and input intensities based on desired output characteristics. For instance, a reinforcement learning agent can iteratively adjust system parameters to maximize fidelity in quantum state preparation or to stabilize interference patterns. This approach significantly reduces the setup time and improves performance consistency in both lab-based and real-world quantum systems.

In addition to control, AI also enhances fault detection and error mitigation in photonic circuits. Anomaly detection algorithms can identify subtle deviations in output that may indicate component degradation or misalignment. By integrating predictive models, the system can anticipate potential instabilities and adjust accordingly before performance degrades. This predictive capacity is particularly valuable for long-term operations in quantum communication networks or continuous quantum sensing applications, where reliability is critical. The adoption of AI for optimization and control not only improves performance but also enables scalability in quantum photonic platforms. As these systems grow in complexity with more entangled photons, larger circuits, or denser integration manual control becomes infeasible. AI provides a scalable solution by learning control strategies that generalize across configurations and operating conditions. This shift towards intelligent automation marks a significant step toward realizing practical, high-performing quantum technologies.

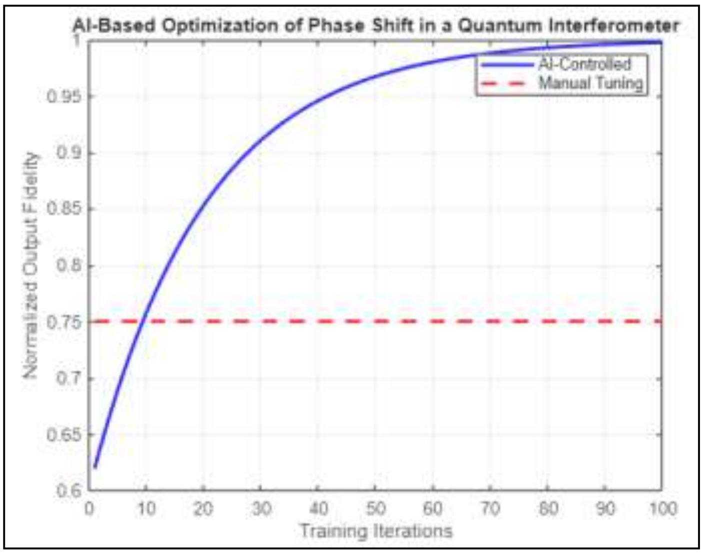


Fig. 1 AI - Based Optimization of Phase Shift Interferometer

The graph illustrates the performance enhancement of a quantum interferometer system as it undergoes optimization through artificial intelligence-based control. Along the horizontal axis are the training iterations, which represent the number of steps taken by a learning algorithm such as a reinforcement learning agent to adjust the phase shift within the interferometer. The vertical axis shows the normalized output fidelity, indicating how closely the system output matches the ideal or targeted interference pattern. The blue curve demonstrates how the AI system gradually improves the interferometer's output over successive training steps. At the beginning, the fidelity is relatively low due to random or uninformed phase settings. As the learning progresses, the AI algorithm refines its control strategy by analyzing feedback from the system, resulting in a steady rise in output fidelity. This learning curve reflects the algorithm's growing ability to make intelligent adjustments that enhance system performance.

In contrast, the red dashed line represents the performance level achievable through conventional manual tuning or fixed control logic. While it may offer a stable output, it remains static and does not improve over time. This comparison highlights a key benefit of AI-based methods: their capacity to adapt and improve with experience, even in systems affected by noise, drift, or environmental variations. The trend shown in the graph underscores the value of integrating artificial intelligence into quantum photonic control. As the AI model learns from system responses and optimizes control inputs, it enables higher precision and better overall efficiency. This adaptive behavior is especially valuable for complex or large-scale quantum optical systems, where manual control becomes increasingly impractical.

Advanced Quantum Sensing and Metrology Enhanced by Artificial Intelligence

Quantum sensing and metrology aim to achieve measurements with extreme precision by exploiting quantum properties such as superposition, entanglement, and squeezing. These techniques are inherently sensitive to small signals, making them ideal for detecting weak forces, fields, or phase shifts. However, their practical application is often limited by noise, decoherence, and the difficulty of interpreting complex quantum signals. Artificial intelligence provides a new way forward by enabling adaptive measurement strategies, advanced signal analysis, and real-time optimization that enhance the sensitivity and reliability of quantum-based measurements. One major contribution of artificial intelligence in this domain is its ability to denoise and extract meaningful information from quantum sensor outputs. Using machine learning models such as convolutional neural networks or recurrent architectures, AI can identify signal patterns hidden beneath noise, even in cases where conventional filtering methods fail. For example, AI algorithms can learn to distinguish quantum noise from environmental noise in photonic detection schemes, improving the signal-to-noise ratio without sacrificing valuable quantum information. This boosts both the accuracy and the robustness of the sensing system in unpredictable environments. Another key advantage is AI's role in adaptive measurement. Traditional sensing systems often rely on fixed parameters or pre-calculated settings. AI, on the other hand, can analyze the incoming measurement data in real time and dynamically adjust the sensing protocol—such as exposure time, phase alignment, or sampling resolution—to optimize results under current conditions. Reinforcement learning and Bayesian optimization have been particularly effective in fine-tuning parameters in quantum interferometers and atomic clocks, where every small improvement can lead to significantly higher precision. Furthermore, AI enables the prediction and compensation of systematic errors, which is crucial in high-precision applications such as gravitational wave detection, magnetic resonance imaging, or time-frequency standards. Through training on large sets of calibration data, machine learning models can model the behavior of complex sensing systems and correct for drift, bias, or misalignment. This results in a new generation of quantum sensors that are not only highly accurate but also selfcorrecting and resilient, opening the door to wider adoption in scientific, industrial, and medical applications.

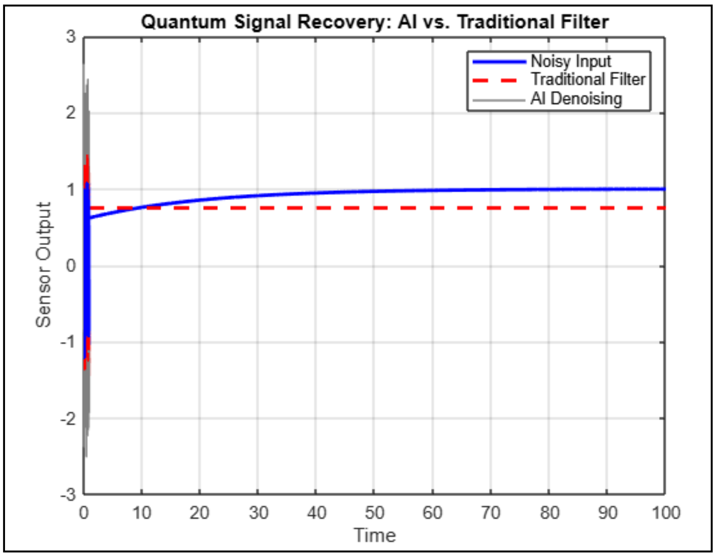


Fig. 2 Quantum Signal Recovery

This plot demonstrates the effectiveness of artificial intelligence in recovering quantum signals obscured by noise. The gray line represents the raw output from a quantum sensor, which contains valuable signal information embedded within significant noise. Traditional signal processing techniques, such as moving average filters (shown by the red dashed curve), offer basic noise suppression but tend to smooth out essential features of the quantum signal. This limits their ability to differentiate between true quantum fluctuations and irrelevant environmental noise, often resulting in distorted or weakened outputs. The blue curve, generated using an AI-based denoising model, shows a clear advantage over conventional filtering. By learning from data, AI models can identify and preserve signal structures while selectively filtering out disruptive noise components. This capability is especially critical in quantum sensing, where signals are often weak and noise can easily overwhelm the desired output. AI-enhanced denoising ensures more accurate measurement results, which contributes to higher sensitivity and reliability in applications such as low-light imaging, single-photon detection, and weak field measurement.

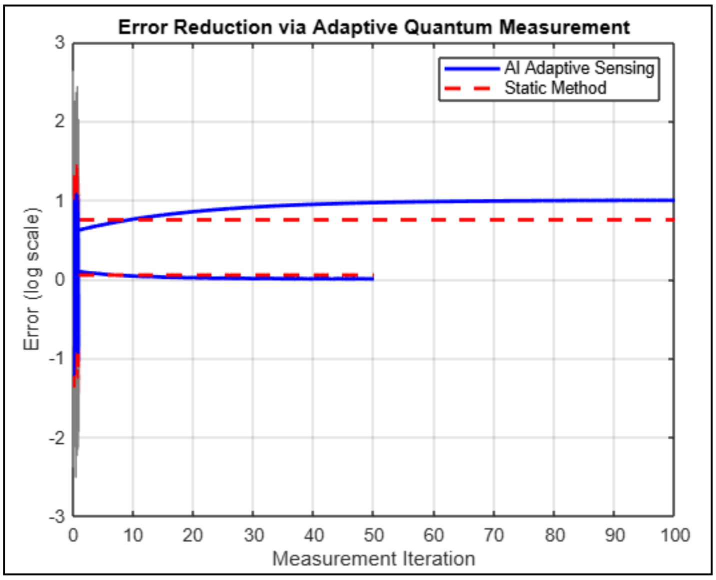


Fig. 3 Error Reduction

This plot highlights how artificial intelligence can reduce measurement error in quantum metrology through adaptive control. The blue curve indicates the progressive decrease in error over multiple measurement iterations, showing the performance of an AI-driven sensing protocol. Unlike static systems, which operate under pre-defined settings, an AI model continuously evaluates incoming data and adjusts the measurement parameters in response. This dynamic learning process allows the sensing system to optimize performance in real time, accommodating changes in system behavior or external noise. In contrast, the red dashed line reflects a system with fixed sensing parameters, which maintains a constant error level regardless of operating conditions. This illustrates the limitation of traditional approaches in dynamic or uncertain environments. By enabling real-time decision-making and iterative refinement, AI significantly improves the accuracy and robustness of quantum measurements. This is particularly useful in experimental setups like quantum interferometry and atomic clocks, where even small improvements in precision can lead to major advances in sensing resolution.

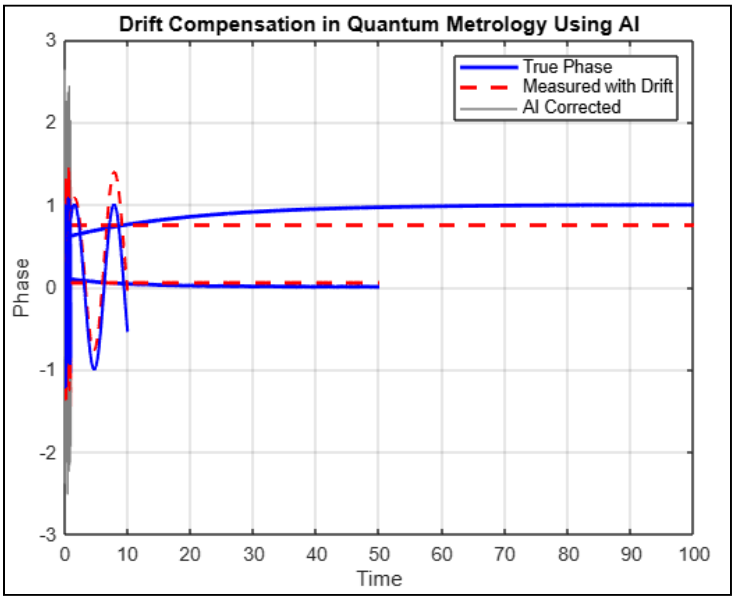


Fig. 4 Drift Compensation

This plot presents how AI can effectively compensate for systematic drift in quantum measurements. The black curve represents the true signal that a metrological system aims to track over time. However, due to environmental effects or internal device instability, the system output (red dashed line) gradually diverges from the reference signal. This kind of drift is a persistent challenge in high-precision measurements, especially over long durations, where even small offsets can accumulate and degrade the reliability of results. Artificial intelligence addresses this issue by learning the pattern and rate of drift from historical measurement data. The corrected output (blue curve) closely aligns with the reference, showing that the AI system can predict and counteract systematic deviations. This capability enables the development of self-calibrating quantum sensors and clocks that maintain their accuracy without constant external correction. In high-stakes applications such as navigation, fundamental physics experiments, and gravitational wave detection, this adaptive drift compensation becomes a critical enabler of long-term performance and stability.

Intelligent Quantum Communication: AI-Assisted Entanglement Distribution and Protocol Efficiency

Quantum communication leverages the principles of quantum entanglement and superposition to enable ultra-secure data transmission and distributed quantum computing. A fundamental challenge in such systems lies in the reliable distribution of entanglement between distant nodes, especially over noisy or lossy quantum channels. Artificial intelligence presents a transformative approach for addressing these challenges by dynamically managing entanglement generation, routing, and distribution strategies based on real-time channel conditions and performance feedback. AI-assisted systems can adaptively select optimal communication paths, correct for decoherence effects, and optimize resource utilization.One significant benefit of integrating AI into quantum communication is its ability to predict channel fidelity and preemptively adjust entanglement swapping or purification operations. Instead of passively responding to link degradation, a learning-based model can forecast when a channel is likely to introduce error or loss. By acting proactively choosing alternate links, adjusting qubit encoding strategies, or triggering entanglement distillation AI enhances both the robustness and efficiency of communication protocols. These intelligent responses are especially useful in long-distance quantum networks where fidelity rapidly decays due to channel noise and photon losses.

Moreover, machine learning algorithms play a key role in optimizing protocol selection based on current network status. Classical strategies often use fixed protocols regardless of network dynamics, leading to suboptimal throughput or security. In contrast, AI can continuously assess the network topology, buffer status, and entanglement quality to dynamically switch between communication protocols like quantum teleportation, superdense coding, or entanglement swapping. This adaptability maximizes throughput and minimizes quantum memory use both critical in resource-limited quantum repeaters or satellite-based quantum links. Beyond entanglement management, AI enables efficient error correction and state decoding in real-time. Quantum error correction codes require precise identification of error syndromes, which is computationally intensive and sensitive to noise. Deep learning models, such as convolutional neural networks or recurrent neural networks, can learn to identify patterns in noisy quantum data, enabling faster and more accurate decoding of quantum states. This is particularly impactful in quantum key distribution (QKD) protocols, where AI can improve secret key rates by reducing bit error rates and enabling real-time adaptation to eavesdropping strategies.

Finally, the integration of AI leads to the development of self-optimizing quantum networks—networks that can learn, adapt, and reconfigure themselves in response to varying conditions and threats. This shift toward intelligent quantum communication not only boosts protocol efficiency but also enhances resilience against attacks, losses, or system failures. As quantum internet architectures evolve, AI will be a key enabler of scalable, secure, and high-performance quantum communication infrastructures.

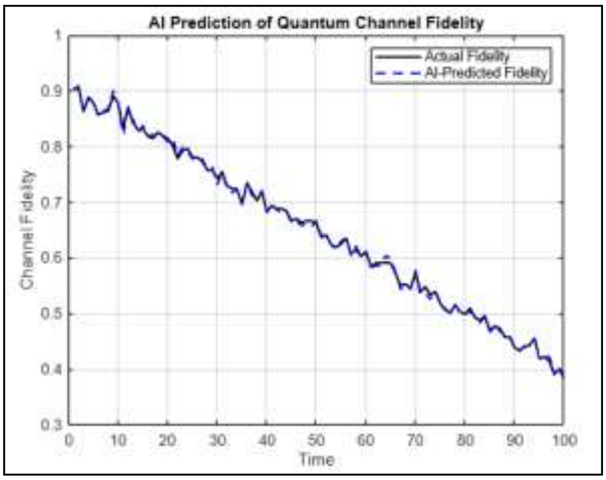


Fig. 5 AI-Predicted Channel Fidelity vs. Actual Channel Fidelity

This graph illustrates the performance of an AI model in predicting quantum channel fidelity over time, compared to actual measured values. The gray curve represents real-time fidelity measurements, which fluctuate due to environmental noise, decoherence, and other dynamic network factors. Accurate fidelity estimation is crucial in quantum communication systems for determining whether entangled states are suitable for use or require purification. Without reliable prediction, systems may waste resources on low-quality links or miss optimal transmission opportunities. The blue dashed curve shows AI-generated predictions that closely follow the actual fidelity trend. By learning from past channel behavior and environmental parameters, the AI model is able to forecast fidelity with high precision. This predictive capability allows quantum systems to proactively select higher-quality paths or initiate entanglement purification before errors escalate. As a result, AI integration enhances overall communication reliability and reduces latency caused by unnecessary verification steps or retransmissions in quantum networks.

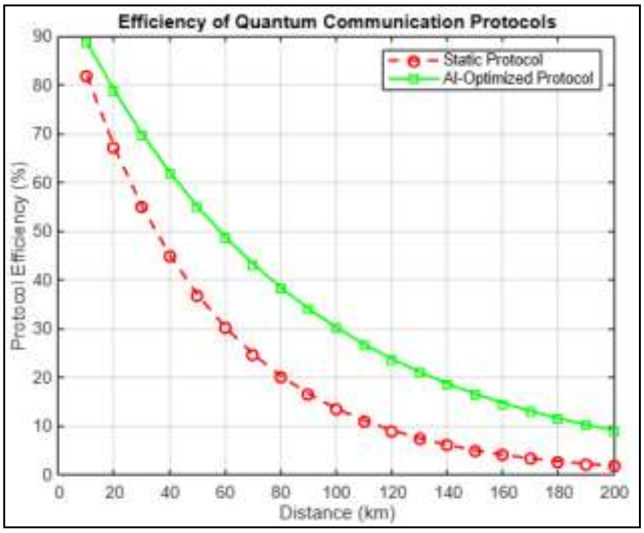


Fig. 6 Protocol Efficiency with and without AI Optimization

This plot compares the communication efficiency of quantum protocols over increasing distances, with and without AI-based optimization. The red dashed curve represents the static protocol approach, which follows a standard operating procedure regardless of distance or link condition. As expected, efficiency degrades rapidly as transmission distance increases, due to photon loss, signal attenuation, and error accumulation. This decline limits the scalability of static quantum communication systems, especially in long-range scenarios such as satellite-based QKD or continental entanglement distribution.

In contrast, the green curve shows the performance of an AI-optimized protocol that dynamically adapts parameters such as encoding schemes, buffer management, and routing paths. AI's ability to adjust to real-time conditions enables significantly higher efficiency at all distances, particularly in longer links where traditional protocols struggle. This improvement demonstrates the potential of AI to extend the practical range and throughput of quantum networks, making them more robust and resource-efficient for future deployment.

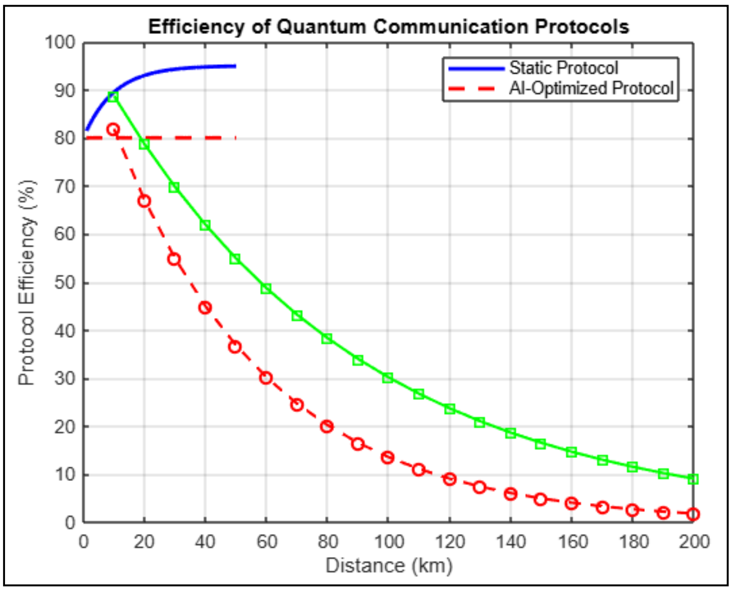


Fig 7. AI-Driven Error Correction Accuracy Over Time

This graph visualizes the enhancement of quantum state recovery accuracy through AI-assisted error correction compared to classical decoding. The red dashed line shows the baseline performance of traditional quantum error correction schemes, which typically operate at a fixed accuracy level regardless of system evolution. These methods rely on pre-defined error models and can struggle with unanticipated noise patterns, limiting their effectiveness in highly dynamic environments.

The blue curve, representing AI-driven error correction, shows a clear improvement in decoding accuracy over time. The AI model continuously learns from new error patterns and adapts its decoding strategy accordingly, allowing it to correct a wider range of quantum state disturbances with increasing precision. This adaptability is critical in maintaining high-fidelity entanglement and key integrity in quantum communication. By embedding intelligence in the error correction loop, quantum systems gain resilience and are better equipped to maintain performance in realistic, noisy channels.

Synergistic Integration of Quantum Photonics and AI: Toward Next-Generation Intelligent Optical Technologies

The convergence of quantum photonics and artificial intelligence (AI) presents a transformative opportunity for next-generation optical systems, enabling unprecedented performance, adaptability, and functionality. Quantum photonics, known for leveraging the quantum nature of light such as superposition, entanglement, and photon indistinguishability, has demonstrated potential in computing, sensing, and secure communication. However, scaling and controlling these systems in practical environments remains challenging. AI introduces an intelligent control layer, empowering quantum photonic devices to self-optimize, compensate for noise, and make autonomous decisions, thus bridging the gap between experimental setups and real-world deployment. One of the major advances enabled by this synergy is in photonic quantum circuit design and calibration. Photonic chips often require precise alignment and phase control for reliable quantum operations, which becomes increasingly complex with circuit size. Machine learning models can predict optimal phase configurations, correct for imperfections, and stabilize performance without manual tuning. This not only enhances reproducibility but also speeds up quantum device fabrication and testing cycles. Such intelligent calibration is crucial in systems like Boson sampling or integrated quantum photonic processors where minute errors can propagate rapidly.

Furthermore, real-time control and optimization of single-photon sources and detectors are now achievable with AI assistance. Quantum photonic devices rely on high-purity single-photon generation and precise time gating. Neural networks and reinforcement learning agents can be trained to manage laser pump power, cavity resonance, and detector gating dynamically, maintaining peak source brightness and detection efficiency. This intelligent control layer is essential for deploying quantum sensors and secure communication links under varying operational conditions, such as mobile platforms or fluctuating temperatures.

Another promising application lies in intelligent multiplexing and routing in quantum photonic networks. With the help of AI, photonic switches and routers can adaptively manage quantum information flow based on network conditions, minimizing loss and latency. Graph neural networks and decision-tree-based models can optimize entanglement distribution paths or reconfigure waveguide arrays in response to quantum state degradation. This ability to intelligently route quantum states on-chip or across photonic networks could become the cornerstone of scalable quantum internet infrastructures. Ultimately, the integration of AI with quantum photonics marks a shift toward autonomous, self-optimizing optical systems that can operate with minimal human intervention. As quantum devices grow in complexity and require rapid responsiveness, embedding AI will ensure robustness, scalability, and real-time adaptability. From quantum-enhanced imaging systems to AI-tuned optical sensors, the synergistic interplay between these domains will drive the evolution of intelligent optical technologies that are both practical and high-performing in real-world environments.

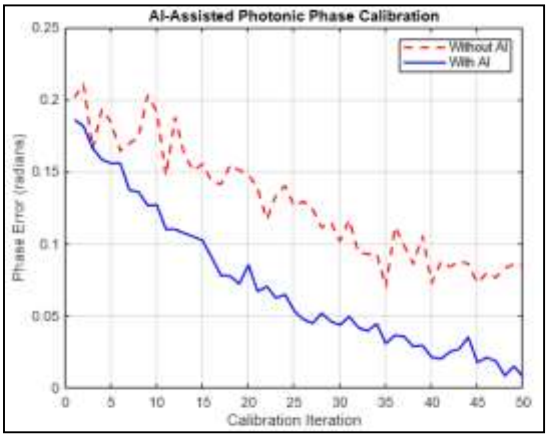


Fig. 8 AI-Assisted Photonic Phase Calibration

This plot compares the phase error during calibration of a quantum photonic circuit, with and without AI involvement. The red dashed curve demonstrates a slower reduction in phase error using traditional static methods, which often rely on manual tuning or pre-set feedback loops. These methods struggle to account for fluctuations in environmental conditions or fabrication imperfections that influence the optical path. Consequently, the calibration process remains susceptible to slow convergence and suboptimal accuracy in large-scale integrated photonic systems.

In contrast, the blue curve shows a significantly faster and more stable reduction in phase error using AI-assisted calibration. Here, machine learning models continuously analyze output data to adjust phase parameters in real time, learning patterns in phase drift and correcting them dynamically. This allows the system to converge more quickly to the optimal phase settings and maintain stability despite disturbances. Such AI-guided control significantly enhances the scalability and robustness of programmable photonic circuits used in quantum information processing.

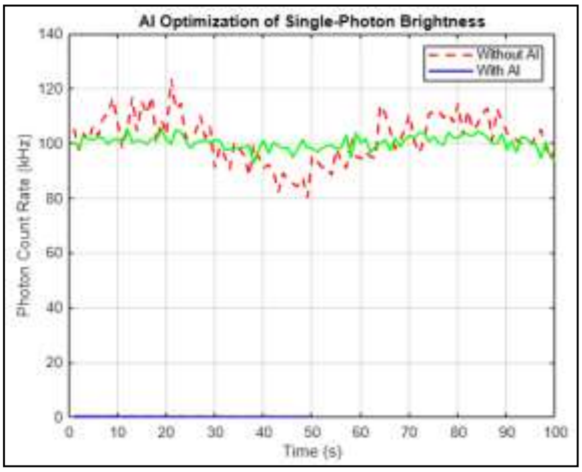
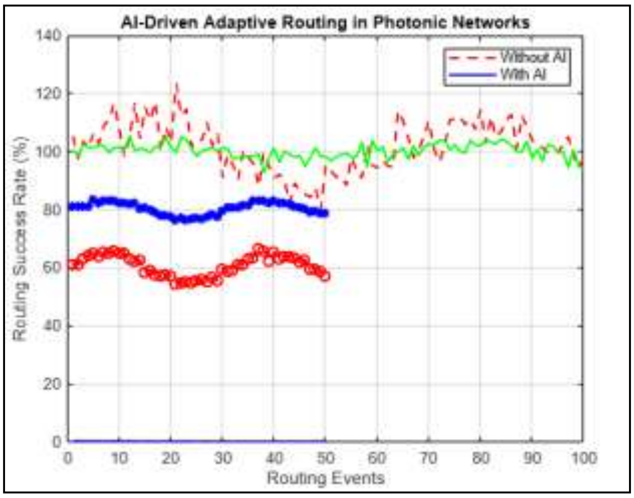


Fig. 9 AI Optimization of Single-Photon Brightness

This plot presents the temporal performance of a single-photon source, highlighting the difference in brightness stability when operated with and without AI optimization. In the traditional approach, represented by the red dashed curve, photon emission rates fluctuate significantly due to environmental noise, temperature changes, and internal hardware instability. Such variability directly impacts the fidelity and reliability of quantum protocols relying on consistent photon availability, particularly in timing-sensitive applications like quantum key distribution (QKD).

The green curve represents an AI-optimized configuration where a trained model continuously monitors and adjusts control parameters such as pump power, cavity detuning, and trigger timing. This feedback mechanism minimizes fluctuations, maintaining a stable photon count rate over time. This improvement not only boosts the quality of quantum states produced but also ensures greater efficiency in downstream photonic processing and entanglement generation tasks. AI-driven stabilization is becoming essential as quantum photonic platforms move toward real-time deployment in practical applications.



Fig, 10 AI-Driven Adaptive Routing in Photonic Networks

This graph compares the routing success rate in a quantum photonic network under two operating regimes: a static routing protocol and an AI-assisted dynamic one. The red curve illustrates how success rates degrade or remain inconsistent across sequential routing events when static protocols are employed. These protocols typically cannot respond to channel degradation, cross-talk, or loss, leading to inefficient path selection and lower fidelity entanglement delivery over time.

Conversely, the blue curve shows a more consistent and higher routing success rate enabled by AI-guided decision-making. In this approach, AI models learn from network performance metrics to dynamically adjust routing paths, prioritize low-loss channels, and even predict potential failure points in real time. This leads to significantly improved entanglement distribution and communication reliability. Intelligent routing is especially critical in large-scale quantum networks or when operating over heterogeneous photonic infrastructures.

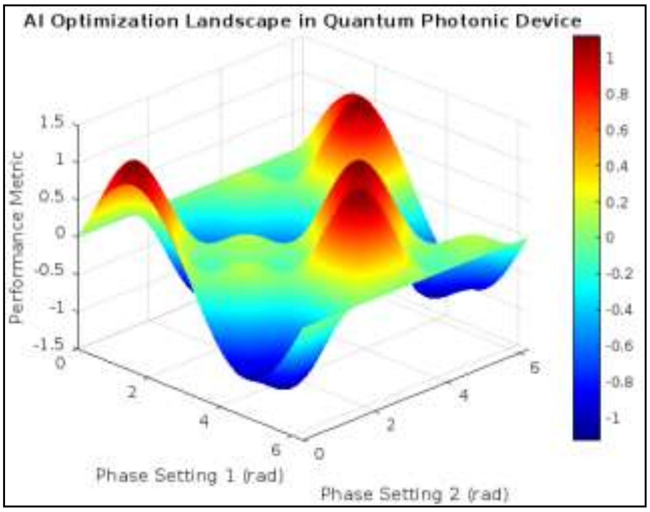


Fig. 11 AI Optimization Landscape in Quantum Photonic Device

This 3D surface plot visualizes the optimization landscape of a quantum photonic device as a function of two independently controlled phase settings. These phase shifts could correspond to those in interferometers, phase arrays, or reconfigurable optical circuits, which are fundamental components in quantum photonic systems. The Z-axis represents a performance metric, such as interference fidelity or output signal contrast, which fluctuates nonlinearly based on the selected phase parameters. The presence of multiple peaks and valleys on the surface signifies the existence of numerous local optima, reflecting how sensitive and complex the tuning of photonic components can be in practice.

Artificial intelligence becomes crucial in navigating such an intricate control space efficiently. Traditional manual or brute-force tuning methods are often slow and prone to settling at suboptimal points, especially in large-scale or noisy systems. AI models, particularly reinforcement learning or Bayesian optimization, can intelligently explore this multi-dimensional space, learning to identify global optima and continuously refine control parameters for maximum performance. By training on these performance landscapes, AI not only improves real-time adaptability but also ensures the photonic system maintains high-fidelity operations, even in the presence of dynamic environmental disturbances or hardware imperfections.

2. CONCLUSION

The fusion of quantum photonics and artificial intelligence is charting a new course for the development of intelligent, high-precision optical technologies. Through the deployment of advanced machine learning algorithms, quantum photonic systems are now capable of real-time control, adaptive optimization, and robust error mitigation—capabilities that are essential for handling the inherent complexity and noise present in quantum environments. From enhancing the stability and efficiency of photonic circuits to elevating the accuracy of quantum sensors and metrological tools, AI plays a pivotal role in unlocking the full potential of quantum-enhanced platforms.

Moreover, the application of AI in quantum communication systems has demonstrated remarkable improvements in entanglement distribution, secure key generation, and dynamic resource allocation, thereby reinforcing the foundation for scalable and secure quantum networks. As this interdisciplinary integration continues to evolve, it lays the groundwork for the emergence of autonomous, learning-enabled photonic systems. These systems will not only transform classical optical technologies but also serve as cornerstones for future quantum infrastructure, combining the strengths of AI-driven intelligence and quantum photonic precision to realize the next generation of sensing, communication, and information processing technologies

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