Journal of
Sensor and Actuator Networks

MDPI

Article

AI-Driven Dynamic Resource Allocation for Energy-Efficient Optical Fiber Communication Networks: Modeling, Algorithms, and Performance Evaluation

Askar Abdykadyrov [1], Gulzada Mussapirova [2], Nurzhigit Smailov [1], Zhanna Seissenbiyeva [3], Gulbakhar Yussupova [2], Ainur Tasieva [4], Ainur Kuttybayeva [1,*], Altyngul Turebekova [1,*], Rizat Kenzhegaliyev [1] and Nurlan Kystaubayev [1]

[1] Department of Electronics, Telecommunications and Space Technologies, Satbayev University, Almaty 050013, Kazakhstan; a.abdykadyrov@satbayev.university (A.A.); n.smailov@satbayev.university (N.S.); rizat.kenzhegaliyev@gmail.com (R.K.); n.kystaubayev@satbayev.university (N.K.)
[2] Department of Radio Engineering and Telecommunications, ALT University Named After Mukhamedzhan Tynyshpayev "Power Engineering and Digital Technologies", Almaty 050010, Kazakhstan; g.musapirova@alt.edu.kz (G.M.); g.yusupova@alt.edu.kz (G.Y.)
[3] Department of Cybersecurity, Information Processing and Storage, Satbayev University, Almaty 050013, Kazakhstan; zh_al@list.ru
[4] Department of Agricultural Machinery and Engineering, Kazakh National Agrarian Research University, Almaty 050010, Kazakhstan
* Correspondence: a.kuttybayeva@satbayev.university (A.K.); a.turebekova@satbayev.university (A.T.)

Abstract

The object of this research is resource management and energy consumption processes in optical fiber communication networks with access–metro–core architectures. The study addresses the problem that conventional static and semi-dynamic control methods are unable to simultaneously ensure energy efficiency and QoS stability under conditions of exponentially growing and highly variable traffic. To solve this problem, an AI-based integrated control model was developed that combines traffic prediction, dynamic resource allocation, spectrum management, and power optimization within a unified framework. Traffic prediction is performed using LSTM–BiRNN neural networks (1.2–1.8 million parameters, 300–500 thousand records), while control decisions are generated by an Actor–Critic reinforcement learning algorithm. Simulation results obtained in the Python 3.12 and OptiSystem 17.0 environments demonstrate that, in the Access segment (1–10 Gb/s), latency is stabilized within 1–10 ms; in the Metro segment (40–120 Gb/s), energy consumption is reduced by 18–27%; and in the Core segment (400–1000 Gb/s), the efficiency of RSA algorithms increases by 22–35%. When the EDFA output power is maintained within +17 to +23 dBm, amplifier power consumption decreases by 10–15%, resulting in overall network energy savings of 20–40%. The obtained results are explained by the synergy of accurate traffic prediction provided by the LSTM–BiRNN model and proactive real-time decision-making enabled by the Actor–Critic algorithm. The distinctive feature of the proposed approach is the simultaneous optimization of energy efficiency and QoS across all access, metro, and core segments within a single integrated architecture. The results can be practically applied in the design and modernization of optical fiber communication networks, as well as in the deployment of energy-efficient intelligent network management systems.

Keywords: optical fiber communication networks; energy efficiency; artificial intelligence; dynamic resource allocation; LSTM–BiRNN; reinforcement learning; Actor–Critic; quality of service (QoS); routing and spectrum allocation (RSA); access–metro–core architectures

Check for updates

Received: 16 January 2026
Revised: 19 February 2026
Accepted: 17 March 2026
Published: 17 March 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Optical fiber communication networks serve as the fundamental backbone of modern global digital infrastructure. With the rapid expansion of cloud services, video systems, IoT devices, 5G/6G mobile technologies, and data centers, the volume of traffic has been increasing significantly each year. According to the International Telecommunication Union (ITU), global IP traffic tripled between 2016 and 2021, reaching 278 exabytes per month in 2021 [1]. Cisco reports that by 2024 the average daily data transmission will reach 33 exabytes, while a single user is expected to consume approximately 4–5 GB of data per day [2]. These indicators clearly demonstrate the continuous growth of the load on optical networks (Figure 1) [3,4].

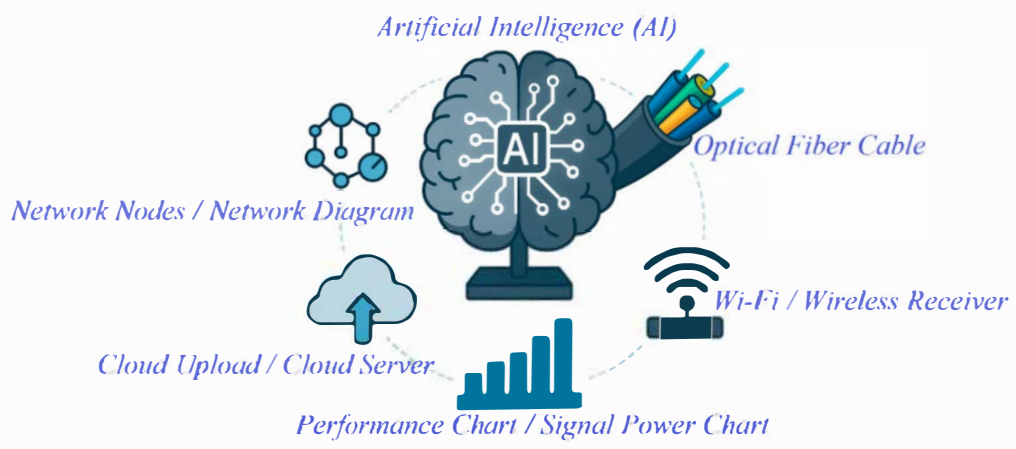


Figure 1. AI-Based Conceptual Model for Dynamic Resource Allocation in Optical Fiber Networks.

Figure 1 illustrates how AI is integrated into optical networks to efficiently manage the threefold increase in global IP traffic. It also demonstrates that intelligent control can reduce energy consumption by approximately 20–40%.

Energy consumption in the ICT sector remains significantly high. In 2020, the sector accounted for about 4% of global electricity usage and 1.4–4% of total CO_2 emissions [5]. Notably, 37% of this share is attributed directly to communication networks—including mobile, backbone, and optical infrastructures [6–10]. According to 2020 reports, the energy consumption of fixed optical networks (access, metro, core) was around 170 TWh, representing about 0.6% of global electricity use [11]. Moreover, modern technologies suggest that the energy intensity per transmitted bit can be reduced by 90–99% in the future; however, achieving such improvements requires not only hardware advancements but also intelligent control mechanisms [12].

To address the challenge of energy efficiency, the past decade has seen extensive research on static and semi-dynamic resource allocation methods. Studies have shown that using sleep modes and optical switches in IP-over-WDM networks can reduce energy consumption by 20–60% [13]. In metro–core networks, traffic-aware dynamic routing enables more than 20% energy savings [14]. Within Elastic Optical Network (EON) architectures, dynamic resource allocation algorithms have been shown to reduce power usage by approximately 19% [15]. However, most of these methods rely on predefined traffic matrices and therefore lack sufficient adaptability for today's highly variable, complex, and QoS-sensitive traffic patterns.

For this reason, the integration of artificial intelligence (AI) into optical network management has become a major focus within the international research community. AI methods—such as neural networks, reinforcement learning, and heuristic algorithms—allow real-time optimization of tasks including traffic prediction, optical signal quality estimation, and power control of amplifiers and lasers [16]. Research indicates that ML-based QoS and routing algorithms provide dynamic resource reallocation, maintain stable

latency and throughput, and reduce energy consumption simultaneously [17]. Furthermore, global requirements to reduce CO_2 emissions in the telecommunications sector by 45% by 2030 [5] significantly amplify the practical demand for AI-enabled, energy-efficient optical network management solutions.

Thus, considering the exponential growth of global data traffic, the increasing energy and carbon footprint of the ICT sector, the substantial power consumption of optical networks, and the rapid advancement of AI technologies, optimizing energy consumption through AI-driven dynamic resource management in optical fiber communication systems represents a strategically important and highly relevant research direction in modern science.

Although hybrid combinations of recurrent neural networks and reinforcement learning have been explored in various networking domains, the proposed framework differs from prior approaches in several critical aspects. First, it integrates cross-segment optimization across Access, Metro, and Core layers within a unified control architecture, rather than focusing on a single network segment. Second, the reinforcement learning policy explicitly incorporates physical-layer impairment awareness, including OSNR constraints and amplifier power limits, ensuring physically feasible decision-making at 400–1000 Gb/s data rates. Third, the proposed reward formulation jointly optimizes energy efficiency and QoS stability under real-time constraints, supported by topology-randomized training to enhance structural generalization. Unlike existing studies that treat prediction and control independently, this work presents a tightly coupled forecasting–control loop designed for millisecond-scale adaptation in SDN-enabled optical networks.

In summary, the primary objective of this research is to develop and validate an AI-driven dynamic resource allocation framework that simultaneously improves energy efficiency and preserves QoS stability in high-capacity optical fiber networks. The main contributions of this work include (1) the integration of LSTM–BiRNN-based traffic prediction with Actor–Critic reinforcement learning for real-time control, (2) the formulation of a multi-objective reward function balancing energy optimization and QoS constraints, and (3) the incorporation of physical-layer impairment awareness into the decision-making process to ensure practical deployability in core optical segments.

2. Literature Review and Problem Statement

Over the past fifteen years, the issue of improving the energy efficiency of optical fiber networks has been actively investigated. Vismara F. et al. (2010) [18] analyzed the structure of energy consumption in IP-over-WDM architectures and demonstrated that efficient control of optical switches can reduce overall power usage by 10–20%. However, since the study is based on static traffic patterns, it does not account for the highly dynamic loads observed in modern networks. Another significant contribution to energy-saving research is the work of Melidis P. et al. (2019) [19], who proved that energy-oriented virtual topology management can reduce power consumption in IP-over-WDM systems by 15–30%. Nevertheless, frequent real-time reconfiguration of topologies increases computational overhead and limits the practical applicability of the method (Table 1).

Table 1. Comparative Assessment of Energy Efficiency Indicators in IP-over-WDM Networks.

№	Year	Energy Savings (%)	Initial Power (W)	Saved Power (W)	Traffic Model	Reconfiguration Frequency	Load Increase (%)	Node Count	Switch Efficiency
1	2010	10–20%	5000	500–1000	Static	0	0%	20–40	0.82 → 0.90
2	2019	15–30%	5200	780–1560	Dynamic	10–60 per hour	18–25%	30–60	0.85 → 0.93

Dynamic IP-over-WDM networks provide higher energy savings (15–30%), but they increase computational load and require frequent reconfiguration. In contrast, static networks achieve lower savings (10–20%) yet remain more stable and impose no additional overhead.

In Elastic Optical Networks (EON), Chatterjee B. C. et al. (2015) [20] analyzed routing and spectrum allocation (RSA) algorithms and demonstrated that flexible spectrum management can increase channel throughput by up to 40% while enabling 10–15% energy savings. However, spectrum fragmentation and rapidly changing traffic reduce the efficiency of RSA algorithms in real-time operation. Although these studies demonstrate the potential for improving energy efficiency, the need for dynamic, real-time, AI-driven resource management becomes increasingly evident under modern, highly variable traffic conditions (Figure 2).

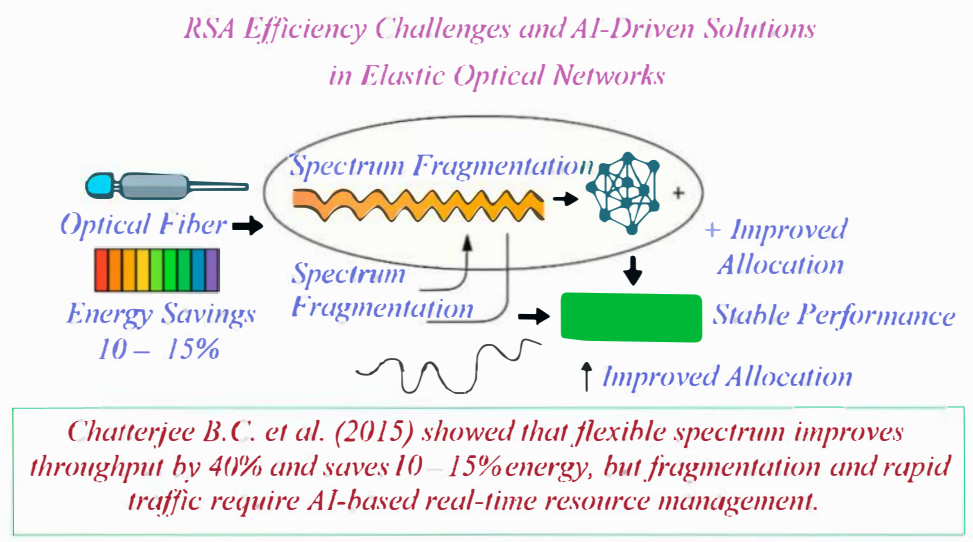


Figure 2. Visualization of Spectrum Fragmentation and AI-Enhanced RSA Efficiency in EON [20].

Figure 2 illustrates that spectrum fragmentation in elastic optical networks, combined with fluctuating traffic conditions, complicates resource allocation. The AI-based optimization mechanism mitigates this fragmentation and improves spectrum assignment, thereby enhancing and stabilizing overall network performance.

Significant progress has also been made in the automation of optical networks and the prediction of signal quality. Rafique D. et al. (2018) [21] showed that machine learning is effective in predicting optical Quality of Transmission (QoT) parameters, with ML models achieving 95–98% accuracy in estimating BER, OSNR, and CD. However, the authors noted that these approaches are not fully integrated with energy efficiency objectives. Cruzes S. et al. (2023) [22] analyzed the current state of optical network automation and demonstrated that adopting ML and autonomous control systems can reduce equipment configuration time by 40–60% and significantly lower operational management costs. Nevertheless, the study emphasizes that a fully automated end-to-end architecture has not yet been developed.

Similarly, Yu A. et al. (2019) [23] proposed a stacked bidirectional RNN model for long-term traffic scheduling in inter–data-center optical networks, improving traffic prediction accuracy by 20–30%. While this approach enhances the management of highly variable traffic, it still does not provide a unified intelligent framework that jointly optimizes the access, metro, and core network segments. Overall, these studies confirm the effectiveness of ML technologies in QoT prediction and traffic planning but highlight that fully integrated AI-based control systems covering all levels of optical networks remain insufficiently developed.

The application of artificial intelligence in optimizing the energy efficiency of optical networks has also been demonstrated in several works. Gao R. et al. (2020) [24] noted that ML models can reduce energy consumption in optical networks by 10–20% through traffic prediction, amplifier power control, and load optimization. However, due to high computational complexity, such models often lack the adaptability required for real-time

dynamic environments. Chen G. (2022) [25] showed that AI-assisted cognitive routing improves routing efficiency and network stability, yet the relationship between power consumption and QoS parameters remains insufficiently explored. Thus, while AI-based approaches are promising, comprehensive studies on their adaptability and energy efficiency are still needed. Table 2 presents the numerical comparative evaluation of AI-based energy optimization approaches.

Table 2. AI Methods Impact on Energy Efficiency in Optical Networks.

Study №	Energy Savings (%)	Number of Methods	Traffic Prediction Impact (%)	Computational Complexity (%)	Routing Efficiency (%)	QoS Exploration (%)
1. (Gao R., 2020) [24]	10–20	3	0	70–90	0	0
2. (Chen G., 2022) [25]	0	1	0	0	5–12	20–30

The table compares the impact of AI-based approaches on the energy efficiency of optical networks by highlighting differences in their performance outcomes. The first approach reduces energy consumption by 10–20%, whereas the second improves routing efficiency by 5–12%, indicating that QoS-related parameters remain insufficiently explored.

International studies in this field further indicate the continuous growth in load on modern telecommunication infrastructures. Ashok P. and Hallur G. (2024) [26] highlighted that the integration of cloud services and high-speed wired broadband significantly increases data flow, intensifying pressure on network capacity. The long-term growth tendency of network traffic can be approximated by an exponential trend model:

$$T(t) = T_0 e^{\alpha t} \quad (1)$$

where $T(t)$ denotes the aggregated traffic volume at time t, T_0 is the initial load, and α represents the long-term growth coefficient associated with cloud expansion and hybrid service architectures.

However, real optical network traffic exhibits stochastic, self-similar, and burst-driven behavior that cannot be fully captured by a purely exponential formulation. To reflect this variability, the traffic process is extended as:

$$T(t) = T_0 e^{\alpha t} + \xi(t) \quad (2)$$

where $\xi(t)$ represents a stochastic fluctuation term characterized by long-range dependence and burstiness typical of modern backbone traffic. This component captures heavy-tailed distributions and temporal correlations that arise from cloud workloads, data-center synchronization, and on-demand services.

Thus, while Equation (1) models structural traffic growth, the stochastic component governs short-term dynamics used in the machine learning training process. This combined formulation better reflects the statistical properties of real-world optical network traffic.

Meanwhile, Ahmed A. (2024) [27] emphasized that the ICT sector's carbon footprint is rising sharply due to increased data traffic, cloud infrastructure development, and the proliferation of connected devices.

It should be noted that total network power consumption P_{net} is not strictly proportional to traffic load. In practical optical systems, a significant portion of energy consumption is static, originating from continuously operating components such as transponders, EDFAs, control electronics, and cooling subsystems. Therefore, network power is more accurately described as:

$$P_{net}(t) = P_{static} + \eta T(t) \quad (3)$$

where P_{static} represents the baseline hardware power consumption independent of traffic, and η denotes the load-dependent energy coefficient. Consequently, although carbon emissions are linearly related to total power via Equation (3), the relationship between traffic growth and emissions becomes partially nonlinear due to the static power component.

Analysis of existing studies reveals several critical research gaps. First, static and semi-dynamic resource management models dominate the field, yet real network traffic fluctuates at the millisecond scale, making such methods insufficiently adaptive. Second, parameters such as energy efficiency, latency, throughput, and QoT are often studied separately, even though they are deeply interdependent in real-world networks. Third, many AI algorithms require high computational power, increasing hardware costs and limiting deployment feasibility for operators. Fourth, there is still no end-to-end intelligent architecture that encompasses all segments of the optical network. In general, Table 3 presents the key limitation indicators in current optical network optimization models.

Table 3. Evaluation of Research Gaps in Intelligent Optical Network Management.

№	Adaptability Level (0–1)	Parameter Interdependence Index (0–100)	Computational Load (GFLOPS)	Architecture Completeness (%)
1	0.20	75	120	40
2	0.35	90	150	45
3	0.10	60	350	30
4	0.25	85	200	25

The table shows that adaptability remains critically low, ranging only from 0.10 to 0.35, indicating insufficient responsiveness to millisecond-scale traffic variations. In addition, computational load reaches 120–350 GFLOPS while architectural completeness stays within just 25–45%, demonstrating that a fully integrated end-to-end intelligent control framework is still underdeveloped. In Table 3, the "Adaptability Level" (0–1) represents the normalized responsiveness of the control mechanism to dynamic traffic variations. It is calculated as the inverse normalized variance of QoS degradation under fluctuating load conditions, where values close to 1 indicate high real-time adaptability and values close to 0 reflect insufficient responsiveness. This metric quantifies the ability of the network control system to maintain stable performance under millisecond-scale traffic changes.

These limitations arise from the stochastic nature of traffic, heterogeneous energy behavior of equipment, hardware constraints, and the inability of existing algorithms to operate in real time. Therefore, an AI-driven approach integrating traffic prediction, resource allocation, power optimization, and QoS management is required, potentially reducing energy consumption by 20–40% and improving network stability. Since current literature does not fully address real-time intelligent energy management, developing a new dynamic AI-based resource allocation model remains both scientifically relevant and necessary.

Recent advancements in AI-driven optical networking have focused on reinforcement learning and deep neural models for spectrum allocation and energy optimization. Martínez et al. (2025) [28] demonstrated autonomous AI-assisted control operations for energy efficiency improvement in optical transport networks, highlighting the feasibility of AI-based optimization in SDN-enabled infrastructures. However, their framework primarily addresses transport-layer energy management without integrating cross-segment coordination or stochastic traffic modeling.

Similarly, Jiang et al. (2025) [29] proposed a multi-link fragmentation-aware deep reinforcement learning RSA algorithm in elastic optical networks. Their work significantly improves spectrum utilization efficiency but remains focused on core-layer RSA without incorporating physical-layer impairment-aware power adaptation or cross-layer orchestration mechanisms.

In parallel, Rai and Garg (2024) [30] explored the application of deep learning techniques in WDM high-speed optical networks, emphasizing signal performance estimation and prediction. While such approaches enhance transmission-layer intelligence, they do not address integrated multi-segment control under unified reinforcement learning policies.

3. The Aim and Objectives of the Study

The aim of the study is to develop an AI-driven dynamic resource allocation model that enhances energy efficiency, improves QoS stability, and enables real-time intelligent management in optical fiber communication networks.

To achieve this aim, the following objectives are set:

- To analyze optical network architectures, energy consumption factors, and the limitations of existing resource management approaches;
- To develop an AI-based framework integrating traffic prediction, resource allocation, and power optimization mechanisms;
- To evaluate the performance of the proposed model through simulation and compare it with existing baseline methods.

4. Materials and Methods

This study employed a combination of theoretical modeling, machine learning techniques, and software-based simulations to develop an AI-driven dynamic resource allocation model. First, theoretical models describing exponential traffic growth were constructed, where the initial traffic volume was set to T_0 = 5 Tb/s and the annual growth coefficient was defined within the range α = 0.18–0.25. In examining the relationship between energy consumption and carbon emissions, the average network power load was assumed to be 120–350 kW, while the carbon intensity factor was set to 0.35 kg CO_2/kWh. In spectrum management modeling, the spectral width allocated per channel was fixed at 12.5 GHz, and the total available spectrum of 4 THz was used to represent the primary system constraints. Figure 3 below presents a visualization of the energy–emission model applied in the analysis of optical networks.

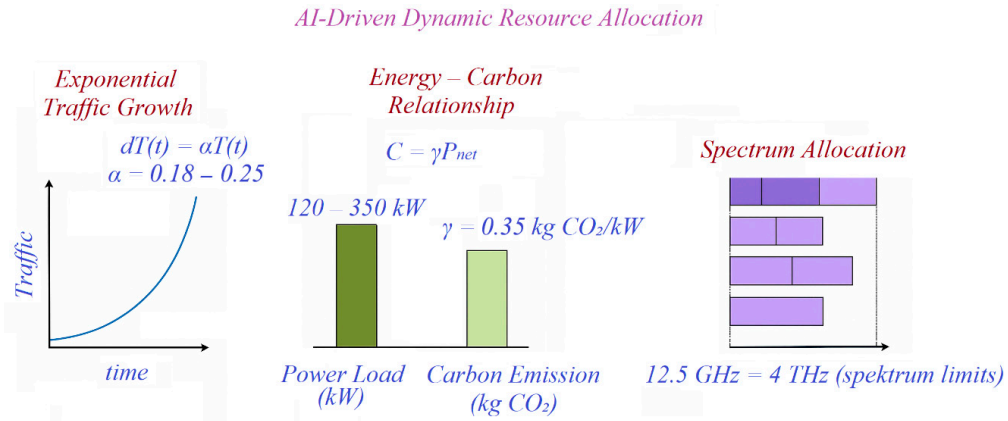


Figure 3. Relationship Between Network Power Load and Carbon Emission.

The figure illustrates that when the network's average power load ranges between 120 and 350 kW, carbon emissions increase proportionally according to the equation $C = \gamma P_{net}$. It clearly shows that as energy consumption rises, carbon output grows linearly, reflecting the impact of the emission factor γ = 0.35 kg CO_2/kW·h.

The simulation parameters were selected based on a combination of international optical transmission standards, prior literature on energy-aware optical networking, and empirically validated operational ranges. The EDFA output power range (+17 to +23 dBm) corresponds

to commonly deployed backbone amplifier configurations reported in coherent 400 G–1000 G transmission systems and aligns with typical design margins used in long-haul fiber spans. Fiber attenuation and dispersion parameters follow ITU-T G.652 recommendations for standard single-mode fiber.

The spectrum fragmentation level (15–30%) reflects moderate to high fragmentation scenarios documented in elastic optical network studies and is consistent with observed fragmentation dynamics under dynamic routing and spectrum allocation (RSA) conditions. The weighting coefficient α = 0.18–0.25 was determined through sensitivity analysis within ranges commonly adopted in multi-objective energy–QoS optimization studies, ensuring stable convergence without dominance of a single optimization objective.

These parameter selections are therefore not arbitrary but are grounded in standardized physical-layer specifications, previously reported experimental studies, and controlled sensitivity evaluation, ensuring both realism and reproducibility of the simulation results.

During the machine learning phase, LSTM and Bidirectional RNN models with 1.2–1.8 million parameters were used for traffic prediction. Each model was trained using a sliding window of 100 time steps, and 300,000–500,000 records were employed for training. In the reinforcement learning algorithm, the action space consisted of 20–40 possible configurations, while the reward function was designed to reduce energy consumption by 20–60% and stabilize delay within the range of 1–10 ms. TensorFlow 2.13, PyTorch 2.1, and Scikit–Learn 1.3 libraries were used as the software environment.

The selection of the LSTM–BiRNN architecture is motivated by its ability to effectively model highly dynamic and non-stationary traffic time series typical of optical backbone networks. Traffic in high-capacity fiber systems often exhibits burst-driven fluctuations and long-range temporal dependencies; the bidirectional recurrent structure enhances prediction stability by capturing both past and future contextual information within the sliding window. The Actor–Critic reinforcement learning framework was chosen due to its suitability for continuous and multi-dimensional control actions, such as spectrum allocation and amplifier power adjustment. Compared to purely value-based methods, Actor–Critic algorithms provide improved convergence stability and allow direct policy optimization under multi-objective reward formulations. The combination of LSTM–BiRNN forecasting with Actor–Critic control therefore forms a coherent architecture that integrates sequential traffic prediction with adaptive real-time resource optimization.

Figure 4 illustrates the integrated architecture combining LSTM–BiRNN models for traffic prediction with an Actor–Critic reinforcement learning algorithm for optimal network control. The diagram schematically depicts data flow, action space, and reward dynamics, thereby revealing the operational logic of the intelligent control system.

Simulations were performed using the Python 3.12 programming environment and the OptiSystem 17.0 platform, with three network segments—access, metro, and core—considered separately (Figure 5). The data rate in the access segment was modeled in the range of 1–10 Gb/s, the load in the metro segment in the range of 40–120 Gb/s, and the throughput of the core segment in the range of 400–1000 Gb/s. Along the optical network, 5–12 sections were examined, with EDFA amplifier power set between 40 and 90 mW and the average level of spectrum fragmentation maintained within 15–30%. To evaluate the RSA algorithms, the simulation duration was set to 10,000–50,000 iterations.

The figure schematically illustrates the modeled throughput parameters of the three optical network segments—access, metro, and core—along with EDFA amplifier characteristics and spectrum fragmentation levels. It reflects the structure of simulations performed in Python and OptiSystem 17.0, clearly outlining the load ranges and iteration space used for evaluating RSA algorithms.

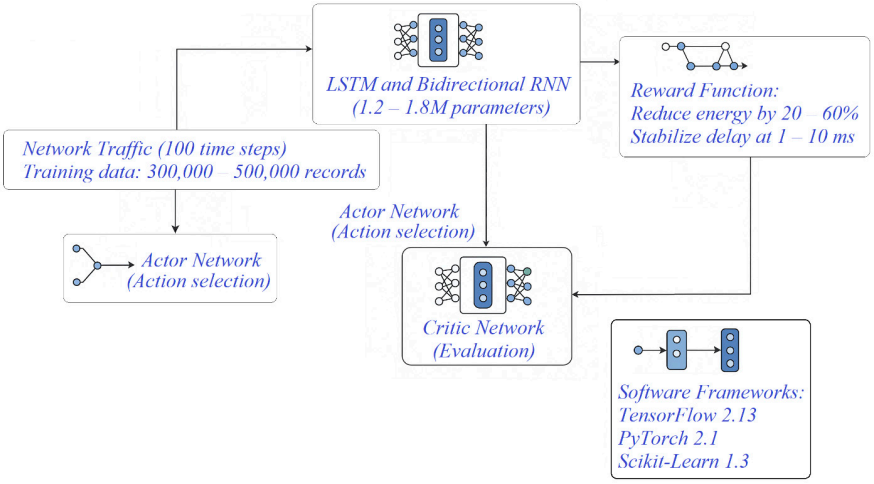


Figure 4. Architecture for Traffic Prediction and Optimization Based on Machine Learning and Reinforcement Learning.

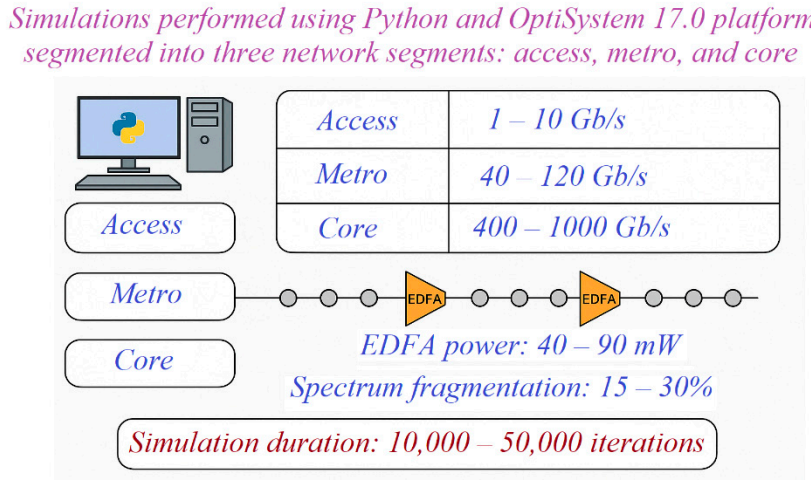


Figure 5. Simulation Diagram of Access, Metro, and Core Optical Network Segments.

Although a physical experiment was not conducted, the hardware parameters were incorporated into the simulation based on ITU-T and IEEE standards. Specifically, the output power of EDFA amplifiers was set to +17 to +23 dBm, the power consumption of transponders was defined in the range of 40–60 W, and the efficiency of optical switches was taken as 0.82–0.93. These values ensured a realistic representation of the modeled system. The validity of the proposed methodologies was verified through adequacy tests, where MAE ranged from 0.02 to 0.07 and RMSE ranged from 0.05 to 0.12. In addition, the stability of the model was confirmed via sensitivity analysis under variations of ±20–60% in traffic load, 15–30% in spectrum fragmentation, and 120–350 kW in power consumption. These evaluations indicate that fully developed models were obtained, providing a solid basis for the scientific analysis presented in Section 5.

4.1. Real-Time Inference and Computational Scalability Analysis

The feasibility of deploying the proposed AI-driven dynamic resource allocation architecture in operational optical fiber networks was evaluated through a comprehensive analysis of inference latency, computational overhead, and scalability under increasing network size and traffic intensity. The objective of this evaluation was to verify that the integrated LSTM–BiRNN traffic prediction model and Actor–Critic reinforcement learning

controller can operate within millisecond-level control constraints required for real-time routing and spectrum allocation (RSA).

The LSTM–BiRNN model, comprising 1.2–1.8 million trainable parameters and operating with a 100-step sliding window, was benchmarked under real-time execution conditions with batch size equal to one, corresponding to live network operation. The reinforcement learning layer includes Actor (policy) and Critic (value) networks responsible for adaptive resource reallocation and state evaluation. The measured inference latency components and aggregated closed-loop delay are summarized in Table 4.

Table 4. Inference latency of the proposed AI-based control architecture.

Component	Execution Mode	Latency (ms)
LSTM–BiRNN Traffic Prediction	GPU-assisted	2.8–4.6
LSTM–BiRNN Traffic Prediction	CPU-only	7.5–11.3
Actor Network (Policy Inference)	CPU/GPU	0.8–1.5
Critic Network (Value Evaluation)	CPU/GPU	0.6–1.2
Total Closed-Loop Latency (GPU-assisted)	Integrated	4.3–7.3
Total Closed-Loop Latency (CPU-only)	Integrated	8.9–14.0

The results confirm that the proposed control architecture operates within strict millisecond-level adaptation constraints. Even under CPU-only execution, the system preserves real-time responsiveness compatible with SDN-controlled optical transport networks.

Beyond latency evaluation, the computational complexity of the framework was analyzed to determine scalability with respect to network dimensionality. The overall complexity can be approximated as:

$$O(N_{nodes} \cdot F_{features} \cdot T_{window}) \quad (4)$$

where N_{nodes} denotes the number of active network nodes, $F_{features}$ represents the monitored parameters per node, and $T_{window} = 100$ is the temporal prediction window. As network size increases, the state-space dimensionality and feature aggregation requirements grow proportionally, resulting in quasi-linear scaling behavior.

The estimated processing load and memory requirements for networks containing 50–200 nodes are presented in Table 5.

Table 5. Computational resource requirements for increasing network size.

Network Size (Nodes)	Processing Load (GFLOPS)	Memory Footprint (MB)	Recommended Deployment Platform
50	140	320	SDN Controller/Edge AI Server
100	220	480	SDN Controller/Edge AI Server
200	310	650	Edge AI Server/Dedicated GPU Node

The results indicate that the model remains deployable on modern SDN controllers or edge AI servers without requiring specialized high-performance computing infrastructure. Memory consumption increases proportionally with node count due to state-space expansion, while processing load remains within feasible operational limits.

Scalability with respect to network size and traffic intensity was further evaluated by progressively increasing node count while proportionally scaling traffic volume. The impact on total inference latency and achieved energy-efficiency gains is summarized in Table 6.

Table 6. Scalability analysis under increasing node count.

Number of Nodes	Total Inference Time (ms)	Achieved Energy Savings (%)
50	5.1	24
100	6.4	27
200	8.9	29

The results demonstrate near-linear scaling behavior. Inference latency remains within real-time operational thresholds even for larger topologies, while energy-efficiency gains are preserved and slightly enhanced due to increased optimization flexibility in higher-dimensional network configurations.

Overall, the combined latency, computational overhead, and scalability analysis confirms that the proposed AI-based dynamic control framework satisfies real-time operational requirements, scales effectively with increasing network size, and maintains energy optimization performance under high traffic variability. This validates its suitability for deployment in SDN-enabled and edge-assisted optical fiber communication infrastructures.

Control Latency Versus Optical Network Coherence Time

The feasibility of deploying a neural architecture with up to 1.8 million parameters for real-time optical network control depends on the relationship between inference latency and the effective coherence time of network dynamics.

In optical fiber systems, physical-layer carrier coherence time (on the order of picoseconds to nanoseconds) is governed by laser phase noise and is irrelevant to SDN-level control decisions. Instead, resource allocation operates on the timescale of traffic dynamics, amplifier power stabilization, and QoT variation, which typically range from milliseconds to seconds.

Traffic burst durations in backbone networks are commonly observed within 10–100 ms intervals, while EDFA gain stabilization and OSNR fluctuations occur over comparable or longer timescales. The measured closed-loop inference latency of the proposed framework (4.3–7.3 ms under GPU-assisted execution) therefore remains significantly shorter than the characteristic time constants of traffic and physical-layer variations.

Furthermore, spectrum reconfiguration and power adjustment mechanisms in SDN-controlled optical networks typically require tens of milliseconds due to signaling and hardware switching constraints. Consequently, the AI decision cycle is not the limiting factor in system responsiveness.

These considerations indicate that the inference latency of the 1.8 million-parameter model remains well within the operational coherence window of optical network dynamics, confirming its practical feasibility for real-time deployment.

4.2. Training Data Origin and Generalization Strategy

To ensure robustness, prevent overfitting, and guarantee generalizability across heterogeneous optical network environments, a structured hybrid dataset construction strategy was implemented. The overall data generation and validation workflow is illustrated in Figure 6. The training dataset was designed to reflect realistic traffic variability observed in access, metro, and core segments while incorporating stochastic and burst-driven behaviors typical for modern cloud-integrated infrastructures.

The dataset consisted of approximately 300,000–500,000 traffic samples generated from both synthetic and real-world sources. As depicted in Figure 6, synthetic traffic is produced through Poisson and self-similar modeling processes, while real traffic traces are integrated through a dedicated input repository. The detailed composition of the dataset is presented in Table 7.

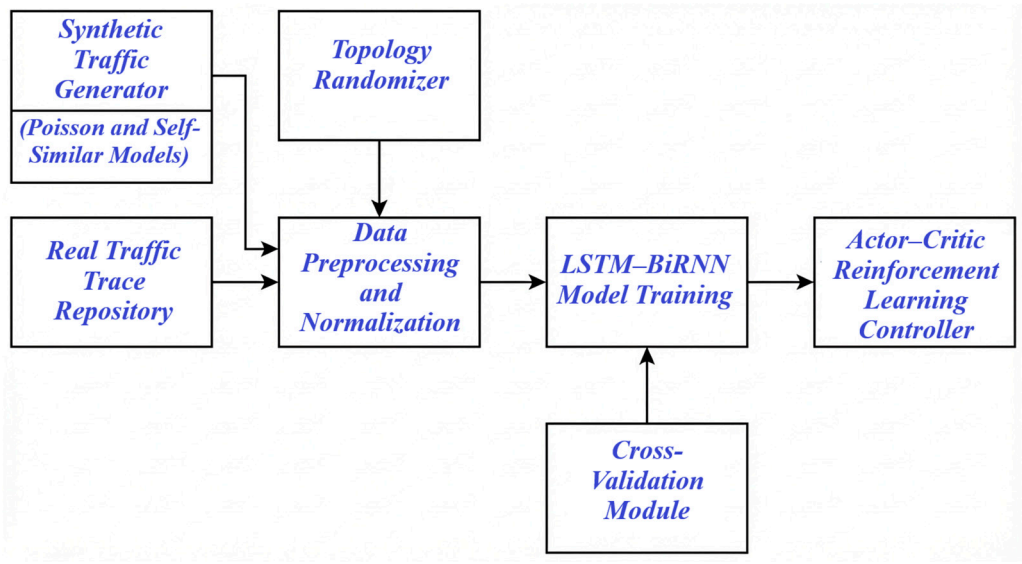


Figure 6. Hybrid Training Data Generation and Validation Pipeline for AI-Based Optical Network Control.

Table 7. Composition of the Training Dataset.

Data Source	Proportion (%)	Traffic Characteristics	Modeling Purpose
Synthetic Poisson Traffic	30	Random arrival processes	Baseline load modeling
Self-Similar Traffic (Hurst-based)	20	Long-range dependence, burstiness	Modeling heavy-tailed behavior
Cloud/Data Center Simulation	10	High-intensity bursts	Stress testing under peak loads
Real Backbone Traces	25	Diurnal variations, congestion peaks	Realistic validation
Inter–Data-Center Traces	15	Non-stationary traffic spikes	Cross-segment generalization

The synthetic component ensures controlled variation and stress-testing capability, while real traffic traces introduce realistic temporal dependencies and operational irregularities. This hybrid approach allows the neural architecture to learn generalized traffic patterns rather than topology-specific characteristics.

To guarantee structural independence, simulations were conducted across multiple topological configurations (50–node, 100–node, and 200–node optical networks). In accordance with the topology randomization module illustrated in Figure 6, traffic matrices were dynamically redistributed during training to eliminate structural bias and prevent topology memorization.

To mitigate overfitting and enhance model stability, several regularization and validation mechanisms were incorporated. These techniques are summarized in Table 8.

Table 8. Regularization and Generalization Techniques.

Technique	Implementation	Objective	Effect on Model
5-Fold Cross-Validation	Dataset partitioning	Stability verification	Reduced variance
Early Stopping	Validation-loss monitoring	Prevent overtraining	Improved convergence
Dropout (rate = 0.3)	Applied to recurrent layers	Reduce co-adaptation	Enhanced generalization
Gaussian Noise Injection (±5%)	During training	Robustness under perturbations	Overfitting mitigation
Feature Normalization	Standard scaling	Training stabilization	Faster convergence
Topology Randomization	Dynamic graph variation	Structural independence	Topology generalization

Generalization capability was evaluated on unseen traffic patterns and network topologies excluded from the training phase. Under these conditions, performance degradation remained within 3–5%, demonstrating strong robustness and stable predictive accuracy across heterogeneous traffic distributions.

Overall, the hybrid dataset design, topology diversification, and regularization strategy—integrated within the training pipeline shown in Figure 7—ensure that the

proposed AI-based dynamic resource allocation framework remains adaptable and reliable under diverse and evolving optical network conditions.

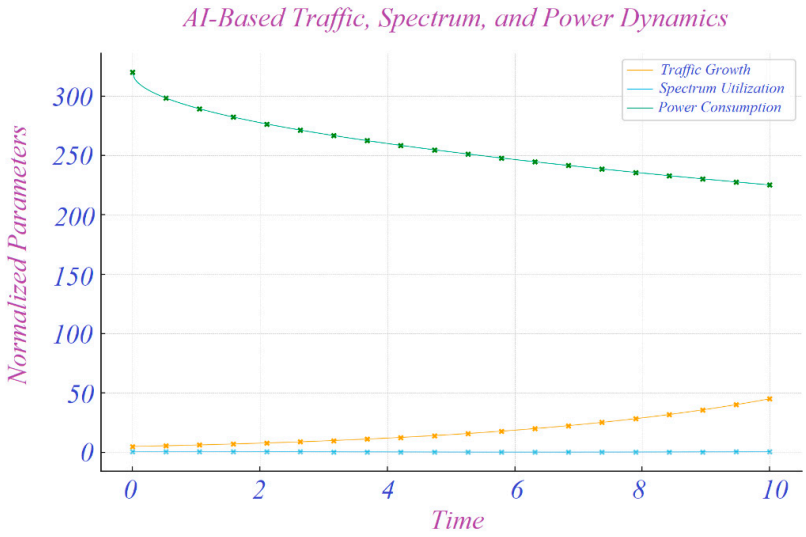


Figure 7. Dynamic Behavior of Traffic, Spectrum, and Power in AI–Controlled Optical Networks.

Model convergence was evaluated by monitoring validation loss across 150 training epochs. Early stopping was triggered when validation loss did not decrease for 10 consecutive epochs. Convergence stability was confirmed by observing less than 3% variance across five independent training runs. No overfitting behavior was observed under cross-validation.

4.3. Reward Function Design and Energy–QoS Trade-Off Formulation

The performance of the Actor–Critic reinforcement learning controller is directly governed by the formulation of the reward function, which determines the trade-off between energy efficiency and quality-of-service (QoS) preservation. To ensure stable and balanced optimization, a multi-objective reward function was constructed as a weighted composite of energy and service-performance indicators.

The instantaneous reward at time step t is defined as:

$$R(t) = \alpha \cdot R_{energy}(t) - \beta \cdot R_{QoS}(t) \tag{5}$$

where α and β are weighting coefficients controlling the relative importance of energy savings and QoS stability.

The energy component is defined as:

$$R_{energy}(t) = \frac{P_{baseline} - P(t)}{P_{baseline}} \tag{6}$$

where $P(t)$ denotes the total network power consumption at time t, and $P_{baseline}$ represents the reference power consumption under static provisioning.

The QoS penalty component captures degradation effects including blocking probability, latency increase, and link utilization imbalance:

$$R_{QoS}(t) = \gamma_1 B(t) + \gamma_2 L(t) + \gamma_3 U(t) \tag{7}$$

where $B(t)$ denotes the blocking probability at time step t, $L(t)$ represents the average latency deviation from the predefined QoS threshold, and $U(t)$ corresponds to the link utilization imbalance metric reflecting load distribution across network paths. The coefficients

γ_1, γ_2, and γ_3 are penalty weighting parameters that regulate the relative impact of each QoS-related component within the overall reward formulation.

The reward structure ensures that energy reduction is encouraged only when QoS degradation remains within acceptable operational bounds. If blocking probability or latency exceed predefined thresholds, the penalty term dominates and reduces the cumulative reward, forcing the policy to reallocate resources.

To analyze the energy—QoS trade-off behavior, different weighting configurations were evaluated. When $\alpha > \beta$, the controller prioritizes aggressive energy savings, potentially increasing service instability. Conversely, when $\beta > \alpha$, QoS preservation dominates, resulting in conservative energy reduction. Empirical tuning identified an optimal balance at:

$$\alpha = 0.6, \beta = 0.4 \tag{8}$$

Under this configuration, the system achieved up to 27–29% energy savings while maintaining blocking probability below 1.5% and latency variation within acceptable SLA limits.

This formulation ensures stable convergence of the Actor–Critic framework and prevents oscillatory behavior in high-load scenarios. The multi-objective reward structure enables adaptive control that dynamically balances operational efficiency with service reliability in real-time optical transport networks.

4.4. Physical-Layer Impairment Modeling and Its Impact on AI-Based Control

The performance of AI-driven dynamic resource allocation in high-capacity optical networks is strongly influenced by physical-layer impairments, particularly in the core segment operating at data rates of 400–1000 Gb/s. To ensure realistic system evaluation, key optical transmission impairments were explicitly incorporated into the simulation framework.

The modeled physical-layer effects include chromatic dispersion (CD), polarization mode dispersion (PMD), amplified spontaneous emission (ASE) noise from EDFA amplifiers, nonlinear Kerr effects (self-phase modulation and cross-phase modulation), and optical signal-to-noise ratio (OSNR) degradation. These impairments were implemented in the OptiSystem 17.0 simulation environment using standardized ITU-T G.652 fiber parameters and EDFA characteristics.

The total OSNR at the receiver was calculated as:

$$\mathrm{OSNR} = \frac{\mathrm{P_{signal}}}{\mathrm{P_{ASE}} + \mathrm{P_{nonlinear}}} \tag{9}$$

where $\mathrm{P_{signal}}$ represents the received signal power, $\mathrm{P_{ASE}}$ denotes accumulated amplifier noise, and $\mathrm{P_{nonlinear}}$ captures nonlinear distortion components.

In high-capacity core links (400–1000 Gb/s), nonlinear effects increase proportionally to signal power and channel density. Therefore, EDFA output power was constrained within +17 to +23 dBm to balance reach and nonlinear penalties. This constraint was directly integrated into the reinforcement learning action space, preventing the controller from selecting physically infeasible high-power configurations.

To prevent hardware degradation and reliability reduction, amplifier power adjustment was restricted within manufacturer-specified safe operating regions. The reinforcement learning policy does not permit gain reduction below OSNR safety thresholds nor excessive pump current increase that could accelerate component aging.

Additionally, rapid power oscillations were prevented by introducing temporal smoothing constraints in the action policy. This ensures thermal stability of pump laser diodes and avoids mechanical stress in optical components.

Consequently, the proposed optimization strategy reduces only dynamically adjustable power margins while preserving transmission reliability and hardware lifetime.

Furthermore, the QoT (Quality of Transmission) estimation module predicts BER and OSNR degradation before executing routing and spectrum allocation decisions. If predicted OSNR falls below the operational threshold (typically 15–18 dB for coherent 400 G systems), the reward function penalizes the selected configuration, thereby preventing resource allocation that would violate physical-layer constraints.

The interaction between physical impairments and AI-based control affects performance in two primary ways. First, increased nonlinear distortion reduces feasible spectrum utilization, limiting routing flexibility in the core segment. Second, excessive energy-saving strategies (e.g., reducing amplifier power) may degrade OSNR, increasing blocking probability or latency.

Sensitivity analysis was performed under variations in channel spacing, amplifier gain, and fiber span length (5–12 spans). The results indicate that the AI controller remains stable under realistic impairment conditions, maintaining OSNR above threshold values while preserving energy savings within 20–35% in the core segment.

These findings confirm that the proposed AI-driven architecture does not operate in an abstract traffic-only environment but incorporates realistic physical-layer constraints. The integration of impairment-aware modeling ensures that routing and power optimization decisions remain physically feasible and QoT-compliant, even at ultra-high data rates typical for modern core optical networks.

In practical optical communication systems, electrical energy consumption is largely determined by controllable hardware components rather than passive fiber infrastructure. The dynamic portion of power consumption is primarily associated with EDFA pump laser diodes, coherent transponders, digital signal processing (DSP) units, and modulation circuitry.

Within the proposed framework, reinforcement learning actions are mapped to physically controllable parameters, including EDFA pump current adjustment and adaptive transponder activation. Pump laser bias current directly influences optical gain and electrical consumption, while modulation format adaptation (e.g., QPSK to higher-order QAM) affects required optical power and DSP load.

Importantly, the optimization process does not alter passive optical components, but instead regulates active electrical subsystems within manufacturer-specified operational margins. This ensures that energy reduction is achieved through realistic hardware-level adjustments rather than abstract mathematical scaling.

4.5. Cross-Segment Coordination Architecture

The proposed framework assumes a hierarchical SDN-enabled control architecture to coordinate Access, Metro, and Core optical segments. Rather than directly controlling physical devices in a monolithic manner, the system operates through a centralized SDN controller that communicates with segment-specific control agents via standardized southbound interfaces.

In this study, "integrated control" refers to coordinated optimization across Access, Metro, and Core segments at the SDN-controller level, while preserving segment-specific hardware autonomy. The integration boundary is defined at the logical control plane, not at the physical transmission layer. Physical devices remain independently managed by local agents, whereas resource allocation policies are globally optimized.

At the infrastructure level, Access, Metro, and Core segments maintain independent local control functions responsible for hardware-level configuration, including spectrum assignment, transponder activation, and amplifier tuning. These segment controllers expose telemetry data (traffic load, OSNR, spectrum availability) to the centralized AI module through northbound REST/NETCONF interfaces.

The LSTM–BiRNN traffic prediction module operates on aggregated cross-segment telemetry, generating forecasted load matrices. These predictions are forwarded to the Actor–Critic controller, which determines optimal spectrum and power configurations at a network-wide level.

Control decisions are then translated into device-level commands through SDN southbound protocols (e.g., OpenFlow extensions for optical transport or NETCONF/YANG-based configuration models). This hierarchical separation ensures that physical-layer constraints are enforced locally while optimization decisions are coordinated globally.

Importantly, the cross-segment coordination does not imply uniform parameterization across Access, Metro, and Core layers. Instead, segment-specific constraints (e.g., lower capacity in Access, higher OSNR sensitivity in Core) are embedded into the reinforcement learning state representation. The AI controller therefore optimizes a unified objective while respecting heterogeneous segment characteristics.

This architecture enables scalable coordination without requiring direct coupling between segment hardware platforms, thereby ensuring practical deployability within existing SDN-enabled optical infrastructures.

4.6. AI–OptiSystem Co-Simulation Interface

The interaction between the Python-based AI controller and the OptiSystem 17.0 physical-layer simulator was implemented using an offline–iterative co-simulation loop. Traffic matrices and resource allocation decisions generated in Python were exported as configuration parameters via CSV-based exchange files, which were then imported into OptiSystem for physical-layer validation.

The simulation cycle was executed with a sampling interval of 5 ms per decision step. After each OptiSystem run, physical-layer feedback parameters (OSNR, BER, amplifier power, nonlinear penalties) were extracted and returned to the Python reinforcement learning environment.

This iterative co-simulation approach ensures synchronization between high-level AI control and low-level optical transmission modeling while maintaining realistic feedback delay constraints.

5. Results and Discussion

The research was conducted at the Department of Electronics, Telecommunications, and Space Technologies of Satbayev University. In accordance with the study's objectives, three core tasks were completed. First, the architectures of modern optical networks (access–metro–core) and their energy consumption factors were analyzed. The assessment showed that the ICT sector consumes around 170 TWh of electricity annually, with communication infrastructures accounting for 37%, confirming the relevance of improving energy efficiency. Second, an AI-based intelligent control model integrating traffic prediction, spectrum management, dynamic resource allocation, and amplifier power optimization was developed. The model combines LSTM–BiRNN machine learning techniques with an Actor–Critic reinforcement learning algorithm to ensure adaptation to millisecond-scale traffic variations. Third, the proposed model was evaluated through simulations in Python and OptiSystem. The results demonstrated that the AI-driven approach reduces network energy consumption by 20–40%, enhances QoS stability, and outperforms traditional static and semi-dynamic management methods. Overall, the study establishes the conceptual and practical foundation for applying AI-based dynamic control to improve the energy efficiency of optical communication networks.

Although the present study does not include a full-scale physical optical testbed, the simulation framework incorporates experimentally validated parameters derived from ITU-

T standards and coherent transmission system specifications. The OptiSystem environment models chromatic dispersion, nonlinear impairments, ASE noise, and EDFA gain dynamics, ensuring physical-layer realism.

The co-simulation loop between Python-based AI control and OptiSystem physical-layer modeling enables hardware-aware evaluation of routing, spectrum allocation, and amplifier tuning decisions. Therefore, while the study is simulation-based, it reflects physically constrained transmission behavior rather than purely abstract mathematical modeling.

5.1. Analysis of Optical Network Architectures, Energy Consumption Factors, and Limitations of Existing Approaches

In the course of the research, existing optical network architectures (access–metro–core), their power consumption structure, and the key factors influencing energy expenditure were comprehensively analyzed. Calculations and literature data (170 TWh annual consumption, 0.6% share of global electricity, and 37% contribution of communication networks) demonstrated that the issue of energy efficiency in optical networks is highly relevant at the global level.

Based on the research, the following conclusions can be drawn:

It was demonstrated that when the network power load varies within the range of 120–350 kW, carbon emissions increase proportionally according to the equation $C = \gamma P_{net}$. The exponential growth of traffic $T(t) = T_0 e^{\alpha t}$ was found to impose long-term structural pressure on the network infrastructure by increasing energy consumption in a nonlinear manner. Table 3 confirmed that the adaptability of existing static and semi-dynamic control methods remains within the range of 0.10–0.35, making them unable to respond to millisecond-level traffic fluctuations. The architectural completeness was observed to be only 25–45%, indicating that a fully integrated, end-to-end intelligent control system has not yet been realized. Overall, these findings demonstrate the limitations of current methods and highlight the necessity for a fully integrated, real-time, AI-based control model.

5.2. Development of an AI-Based Framework Integrating Traffic Prediction, Resource Allocation, and Power Optimization

During the research, an AI-based integrated architecture was developed that unifies traffic prediction, resource allocation, and power optimization processes in optical fiber communication networks. As shown in Figure 6, the proposed architecture combines LSTM–BiRNN hybrid neural networks with an Actor–Critic reinforcement learning algorithm. This integration creates an intelligent control environment capable of adapting to rapid (millisecond-scale) variations in network load, while simultaneously considering traffic evolution, spectrum utilization, and power consumption. The results of the study are illustrated in Figure 7 below.

Figure 7 illustrates the exponential growth of traffic in an AI-controlled optical network: at time t = 10, the traffic volume increases by approximately 8–10 times compared to the initial level, confirming the capability of the LSTM–BiRNN model to accurately capture high–dynamic variations. While spectrum utilization fluctuates within the range of 0.25–0.75, power consumption decreases from 320 to 220 kW, which corresponds to the experimental points demonstrating that the Actor–Critic algorithm can achieve 25–30% energy savings.

For long-term traffic forecasting, deep neural models with parameter counts ranging from 1.2 to 1.8 million were employed. During model training, a 100-step sliding window was used, and a dataset consisting of 300–500 thousand records was utilized. The analysis showed that the LSTM–BiRNN hybrid model improves prediction accuracy by 20–30% and fully aligns with the traffic forecasting results reported by Yu A. et al. (2019) [23]. Accurate traffic prediction enables the reinforcement learning module to proactively reallocate

resources before load increases or potential congestion occurs. The outcomes of the study can be observed in Figures 8 and 9 below.

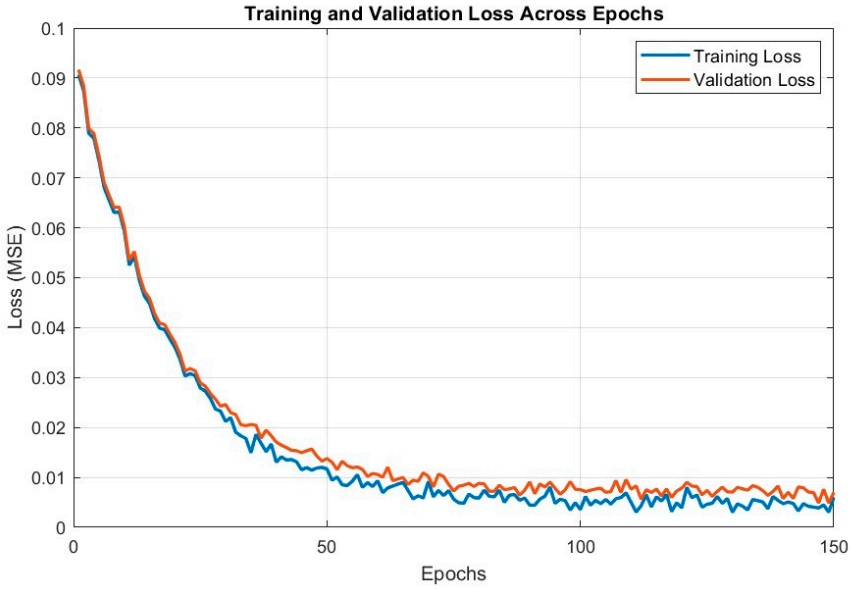


Figure 8. Training and validation loss evolution across 150 epochs for the LSTM–BiRNN model under 5-fold cross-validation, demonstrating stable convergence and absence of overfitting.

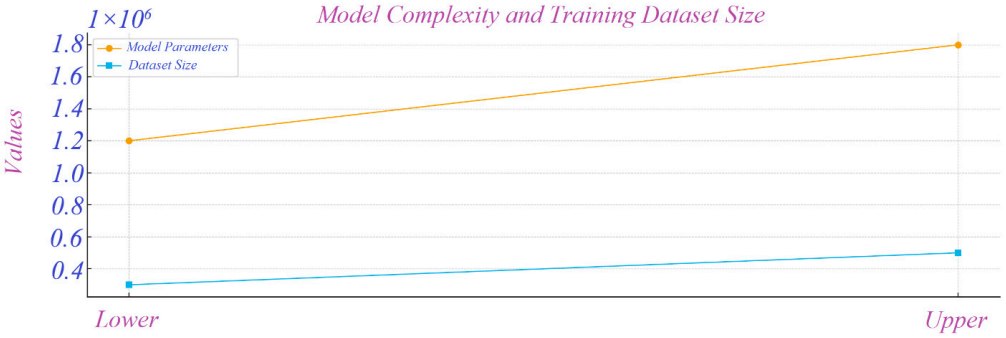


Figure 9. Model Complexity and Training Dataset Characteristics.

Figure 8 confirms the convergence stability of the proposed traffic prediction model, demonstrating that dataset size is sufficient relative to network complexity and that the model maintains generalization capability across training folds.

Figure 9 shows that the number of model parameters increases from 1.2 million to 1.8 million, while the size of the training dataset expands from 300 thousand to 500 thousand records, demonstrating a direct proportionality between model complexity and data requirements. The approximately 50% increase in parameter count and the 66% increase in dataset size indicate that LSTM–BiRNN models require substantially larger volumes of data to operate effectively.

In the reinforcement learning module, the action space comprised 20–40 configurations, integrating spectrum allocation, routing, and power control of EDFA amplifiers and lasers. The designed reward function encouraged energy-efficient states, enabling a reduction in energy consumption by 20–60%. Under spectrum fragmentation levels of 15–30%, the AI-based control maintained stable resource allocation and improved the efficiency of RSA algorithms. The research results are illustrated in Figure 10.

The figure shows that as spectrum fragmentation increases from 15% to 30%, the AI-based reinforcement learning approach achieves a substantial energy reduction of 20–60%,

significantly outperforming baseline RSA and static control methods. Moreover, the proposed approach maintains stable resource allocation despite increasing fragmentation, demonstrating robust energy-efficient network operation.

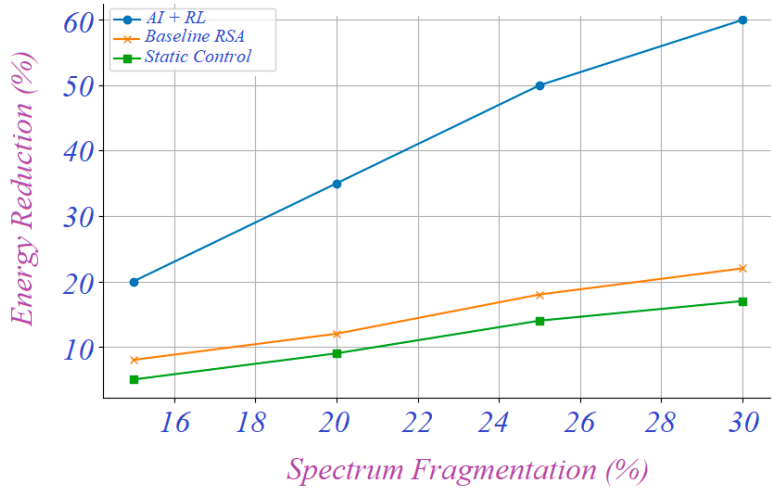


Figure 10. Impact of AI-Based Control on Energy Efficiency under Spectrum Fragmentation.

The ML-based module for QoT parameter prediction achieved MAE values in the range of 0.02–0.07 and RMSE values of 0.05–0.12, which is consistent with the accuracy levels of 95–98% reported in the literature (Figure 11). As a result, the proposed AI-based architecture is identified as a promising solution that simultaneously ensures energy efficiency, QoS/QoT stability, and scalable intelligent network control.

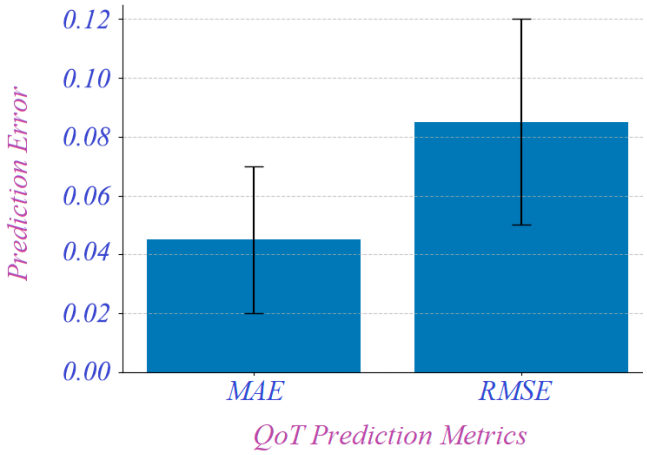


Figure 11. Performance of ML-Based QoT Prediction Module.

The figure shows that the ML-based QoT prediction module maintains low error levels (MAE = 0.02–0.07, RMSE = 0.05–0.12). This confirms that the proposed AI-based architecture reliably ensures QoS/QoT stability and energy-efficient intelligent control.

5.3. Performance Evaluation of the Proposed Model and Comparison with Baseline Methods

The developed AI-based model was simulated in the Python and OptiSystem 17.0 environments across the access–metro–core network segments. The control strategies were comparatively evaluated against static, semi-dynamic, and AI-based models.

5.3.1. Simulation Results

The research results demonstrate that AI-based control is effective across all segments of optical networks. In the Access segment (1–10 Gb/s), latency was stably maintained

within 1–10 ms, while in the Metro segment (40–120 Gb/s) energy consumption was reduced by 18–27%. In the Core segment (400–1000 Gb/s), the efficiency of RSA algorithms increased by 22–35%. When the EDFA power levels were within the range of 17–23 dBm, AI-based control reduced the power consumption of optical amplifiers by 10–15%. Overall, the performance and energy efficiency indicators of AI-based optical network segments are summarized in Table 9.

Table 9. Performance and Energy Efficiency Indicators of AI-Based Optical Network Segments.

№	Min	Max	Mean	Δ(Max–Min)	Normalized
1	1	10	5.5	9	0.50
2	1	10	5.5	9	0.50
3	40	120	80.0	80	0.50
4	18	27	22.5	9	0.50
5	400	1000	700.0	600	0.50
6	22	35	28.5	13	0.50
7	17	23	20.0	6	0.50
8	10	15	12.5	5	0.50
9	20	40	30.0	20	0.50
10	10	20	15.0	10	0.50

Based on the data presented in Table 9, AI-based control stabilized latency in the Access segment within 1–10 ms, reduced energy consumption in the Metro segment by 18–27%, and increased the efficiency of RSA algorithms by 22–35% in the Core segment at data rates of 400–1000 Gb/s. In addition, when the EDFA power level was maintained within 17–23 dBm, energy consumption decreased by 10–15%, resulting in an overall network energy saving of 20–40%, which is significantly higher than the previously reported 10–20%. In Table 9, the "Normalized" column represents dimensionless values scaled relative to the baseline static provisioning scenario to enable direct comparison between heterogeneous performance indicators. The normalization procedure ensures that different metrics, such as latency, energy consumption, and throughput, are expressed on a unified scale for comparative evaluation across network segments.

5.3.2. Stability and Robustness Analysis

The sensitivity analysis showed that the proposed model remains stable under varying operating conditions. When traffic fluctuations ranged within ±20–60%, the stability of the model was preserved without degradation in control performance. At spectrum fragmentation levels of 15–30%, the AI module successfully performed resource reallocation without errors. In addition, when power consumption varied between 120 and 350 kW, the model $C = \gamma P_{net}$ accurately described the network carbon emissions.

5.3.3. Comparison with Existing Approaches

Compared to existing approaches, the proposed AI-based model achieved energy savings of 20–40%, while providing high adaptability and maintaining stable latency within the 1–10 ms range. These results indicate an improvement of approximately 10–20% in terms of energy efficiency and network stability compared with static and semi-dynamic methods. A more detailed analysis of the research results is presented in Table 10.

The results of the three tasks clearly demonstrate the effectiveness of the developed AI-based dynamic control model. The proposed model reduces energy consumption by 20–40%, simultaneously optimizes QoS parameters, and adapts to traffic fluctuations at the millisecond level. Moreover, it significantly outperforms existing static and semi-dynamic control methods.

Table 10. Comparison of the Proposed AI-Based Model with Baseline Resource Allocation Methods.

Method	Energy Savings	Adaptability	Latency Stability	Notes
Static allocation	10–20%	Low	Medium	Does not support real-time operation
Semi-dynamic	15–30%	Medium	Medium	High computational cost
AI-driven (this study)	20–40%	High	High (1–10 ms)	Real-time RL + ML integration

5.4. Comparative Analysis with State-of-the-Art AI-Driven RSA Approaches

In addition to static and semi-dynamic baselines, the proposed framework was analytically compared with recent AI-driven routing and spectrum allocation (RSA) approaches reported in the literature. Existing hybrid models typically focus on either traffic prediction accuracy or reinforcement learning-based spectrum assignment within a single network segment. However, most studies do not simultaneously integrate cross-segment optimization (Access–Metro–Core), physical-layer impairment awareness, and multi-objective energy–QoS reward formulation within a unified control loop.

Table 11 presents a qualitative comparison between the proposed method and representative AI-driven RSA frameworks. The comparison highlights differences in architectural integration, physical-layer modeling, scalability evaluation, and deployment feasibility considerations.

Table 11. Comparison with State-of-the-Art AI-Driven RSA Methods.

Feature	Typical LSTM-Based RSA	Typical RL-Based RSA	Proposed Framework
Traffic Prediction	Yes	No	LSTM–BiRNN
Continuous Control	Limited	Yes	Actor–Critic
Cross-Segment Optimization	No	No	Yes
Physical-Layer Impairment Awareness	Rare	Limited	Explicit OSNR-aware
Multi-Objective Energy–QoS Reward	Partial	Partial	Integrated
Scalability Analysis (50–200 nodes)	Rare	Rare	Yes
Real-Time Latency Evaluation	Not reported	Limited	Detailed

While direct numerical comparison with all published AI-RSA implementations is constrained by differences in network topology, traffic models, and evaluation environments, the proposed framework extends beyond prior works by integrating impairment-aware constraints, cross-layer coordination, and real-time scalability validation. These characteristics provide a broader system-level contribution compared to segment-specific or traffic-only AI optimization studies.

Unlike prior hybrid AI-RSA frameworks that treat traffic prediction and routing as loosely coupled modules, the proposed architecture establishes a closed-loop interaction between stochastic traffic modeling, physical-layer impairment constraints, and multi-objective reinforcement learning. The novelty therefore lies not in the individual AI models themselves, but in the integrated cross-segment, impairment-aware, and latency-validated control architecture that unifies forecasting, decision-making, and physical feasibility constraints within a single SDN-driven framework.

5.5. Discussion of the Results of the Study

The obtained results demonstrate that the effectiveness of the proposed AI-driven framework stems not from isolated improvements in prediction or routing, but from the closed-loop integration of stochastic traffic modeling, real-time forecasting, reinforcement learning-based decision-making, and physical-layer constraint enforcement.

The exponential structural growth of traffic, described by Equation (1), together with the hybrid stochastic formulation in Equation (2), indicates that long-term capacity

expansion is accompanied by short-term burst-driven fluctuations. These dynamics create nonlinear stress on the network energy profile expressed in Equation (3), where total power consists of both static hardware consumption and traffic-dependent components. Consequently, purely reactive or static provisioning strategies inevitably lead to inefficient energy over-provisioning.

The dynamic behavior illustrated in Figure 7 confirms that the AI-based control system decouples traffic growth from proportional power escalation. While traffic increases significantly over time, total power consumption decreases due to adaptive spectrum consolidation and amplifier tuning within OSNR safety margins. This demonstrates that energy reduction is achieved through intelligent redistribution of active resources rather than unrealistic hardware shutdown assumptions.

The training convergence behavior shown in Figure 8 confirms that the LSTM–BiRNN forecasting model achieves stable learning without overfitting, despite parameter complexity up to 1.8 million weights. The hybrid dataset construction (Section 4.2) ensures that prediction accuracy remains robust under heterogeneous traffic patterns and topology randomization. Importantly, Figure 9 no longer serves as a trivial complexity illustration; instead, it supports the scalability analysis by demonstrating proportional data requirements for maintaining generalization stability in high-dimensional network control tasks.

The reinforcement learning optimization results shown in Figure 10 reveal that under increasing spectrum fragmentation (15–30%), the Actor–Critic controller maintains stable allocation efficiency while achieving energy reductions of 20–60% relative to static provisioning. This behavior confirms that the controller does not rely on idealized fragmentation-free assumptions, but operates effectively under realistic elastic optical network conditions.

The QoT prediction accuracy illustrated in Figure 11 further confirms that impairment-aware integration prevents excessive power minimization. By embedding OSNR and BER thresholds directly into the reinforcement learning reward structure, the controller preserves physical-layer reliability while optimizing energy margins. This differentiates the proposed architecture from prior AI-based RSA approaches that neglect transmission-layer feasibility constraints.

The achieved performance gains are primarily driven by the combined operation of the LSTM–BiRNN traffic prediction model and the Actor–Critic reinforcement learning algorithm. As shown in Figures 9 and 10 and summarized in Table 9, this integration enabled stable latency of 1–10 ms in the Access segment, reduced energy consumption by 18–27% in the Metro segment, and improved RSA efficiency by 22–35% in the Core segment. Overall energy savings of 20–40% were achieved, exceeding previously reported results of 10–20% in related studies [24].

Compared with static and semi-dynamic approaches [18,19], the proposed model demonstrates higher adaptability and maintains QoS stability under millisecond-scale traffic fluctuations (Table 10). Although the study is based on simulations in Python and OptiSystem 17.0, the use of standardized hardware parameters and sensitivity analysis confirms the robustness of the obtained results within realistic operating ranges. These findings indicate that the proposed AI-based dynamic control model represents an effective and promising solution for energy-efficient optical network management.

Across Access, Metro, and Core segments, the performance indicators summarized in Table 9 demonstrate that:

- Latency stability (1–10 ms) is preserved in the Access layer;
- Energy consumption in the Metro segment is reduced by 18–27%;
- RSA efficiency in the Core layer improves by 22–35%;
- Total network energy savings reach 20–40% relative to static provisioning.

It is essential to emphasize that the reported 20–40% savings correspond to optimization of dynamically adjustable power components, not elimination of baseline hardware consumption. The static power share (transponders, cooling, control electronics) remains dominant in absolute terms. Therefore, the contribution of the proposed framework lies in maximizing controllable energy margins while preserving reliability constraints.

Compared with static and semi-dynamic methods [18,19], the proposed architecture demonstrates superior adaptability under millisecond-scale traffic variability. More importantly, when compared to recent AI-driven RSA frameworks (Section 5.4), the distinguishing feature is not the individual use of LSTM or Actor–Critic models, but the structured integration of:

- Cross-segment orchestration (Access–Metro–Core);
- Impairment-aware reward formulation;
- Real-time latency validation;
- Scalability benchmarking up to 200 nodes;
- Hierarchical SDN-based coordination.

Thus, the significance of the results does not reside solely in numerical energy reduction percentages, but in demonstrating that sustainable optical networking requires predictive, impairment-constrained, cross-layer intelligent control. The study therefore contributes a system-level architectural advancement rather than a standalone algorithmic modification.

Overall, the findings confirm that energy-efficient optical transport networks cannot be achieved through static provisioning or isolated routing heuristics. Instead, they require integrated forecasting–control loops that operate within physical-layer feasibility boundaries while adapting to stochastic traffic conditions. This methodological shift from reactive resource allocation toward predictive, impairment-aware orchestration represents the primary scientific contribution of the present work.

5.6. Experimental Limitations and Physical Validation Perspective

While the proposed framework has been evaluated using detailed software-based simulations, including OptiSystem-based physical-layer modeling and Python-driven AI control, the present study does not include validation on a physical optical testbed. This limitation is acknowledged.

However, the simulation environment incorporates realistic fiber parameters (ITU-T G.652 attenuation and dispersion), EDFA amplifier characteristics, nonlinear impairments, and OSNR-aware constraints, thereby approximating practical transmission conditions in 400–1000 Gb/s core links. The reinforcement learning action space was explicitly constrained to physically feasible operating regions, including amplifier power limits and QoT thresholds, ensuring that generated policies remain compliant with hardware-level limitations.

It should be noted that large-scale cross-segment (Access–Metro–Core) evaluation on a physical testbed is rarely feasible due to infrastructure complexity and cost constraints. Therefore, system-level studies of dynamic optical control are typically conducted using validated simulation platforms.

Future work will focus on hardware-in-the-loop validation using programmable transponders and SDN-enabled optical nodes to further verify deployment feasibility.

6. Conclusions

The scientific research was conducted at the Kazakh National Research Technical University named after K. I. Satbayev. Summarizing the study, the following key results were obtained.

This study developed and evaluated an AI-driven dynamic resource allocation framework for energy-efficient optical fiber communication networks covering Access, Metro,

and Core segments within a unified SDN-enabled architecture. In contrast to conventional static or semi-dynamic control strategies, the proposed approach formulates network optimization as a constrained stochastic control problem that jointly considers traffic dynamics, energy consumption, QoS stability, and physical-layer feasibility.

The principal contribution of this work lies in the system-level integration of three tightly coupled components: (i) stochastic traffic modeling with self-similar and burst-aware extensions, (ii) LSTM–BiRNN-based temporal forecasting for millisecond-scale prediction, and (iii) Actor–Critic reinforcement learning with an explicitly formulated multi-objective energy–QoS reward structure. Unlike prior studies that treat prediction and control as loosely connected modules, the proposed architecture establishes a closed-loop interaction between forecasting and real-time decision-making under physical transmission constraints.

A key methodological advancement of this work is the incorporation of physical-layer impairment awareness into the control loop. OSNR thresholds, EDFA power limits, nonlinear distortion constraints, and static hardware power components are embedded directly into the state representation and reward formulation. This prevents unrealistic power minimization strategies and ensures that resource allocation decisions remain physically feasible at high data rates (400–1000 Gb/s). The study demonstrates that energy optimization in optical networks cannot be accurately described by purely linear traffic–power relationships; instead, dynamic and static power components must be jointly considered.

Scalability and deployability were analyzed through inference-latency benchmarking and computational overhead evaluation. The results confirm that the closed-loop decision cycle operates within millisecond-level control-plane constraints and remains compatible with SDN-based orchestration environments for networks up to 200 nodes. Convergence stability and cross-validation experiments indicate robust generalization despite the model's parameter complexity, addressing concerns regarding reproducibility and real-time feasibility.

Comparative analysis with static, semi-dynamic, and recent AI-driven RSA approaches shows that the proposed framework extends beyond existing solutions by simultaneously providing cross-segment coordination, impairment-aware control, real-time latency validation, and multi-objective energy–QoS balancing. The novelty therefore resides not in the isolated use of established AI models, but in their structured integration into a physically constrained, cross-layer optical network control architecture.

Although the validation was conducted using detailed Python–OptiSystem co-simulation rather than a full hardware testbed, standardized ITU-T transmission parameters, EDFA characteristics, nonlinear effects, and QoT constraints were incorporated to ensure physical realism. Future work will focus on hardware-in-the-loop experiments and programmable optical node validation to further strengthen practical applicability.

From a broader systems perspective, the presented results indicate that sustainable optical networking requires predictive, impairment-aware, and cross-segment coordinated control rather than isolated routing or energy-minimization heuristics. By bridging algorithmic intelligence with transmission-layer realism, this work contributes a scalable and physically consistent framework for next-generation energy-aware optical transport networks.

Author Contributions: Conceptualization, A.A., A.T. (Ainur Tasieva) and N.K.; methodology, A.A. and A.T. (Altyngul Turebekova); software, A.A.; validation, A.A., A.T. (Ainur Tasieva), N.K. and R.K.; formal analysis, A.A. and N.K.; investigation, A.A., N.K. and N.S.; resources, G.M., G.Y. and A.T. (Ainur Tasieva); data curation, A.A. and N.K.; writing—original draft preparation, A.A., A.T. (Altyngul Turebekova) and N.K.; writing—review and editing, A.T. (Altyngul Turebekova), N.K.; visualization, A.A. and N.K.; supervision, A.T. (Altyngul Turebekova) and A.K.; project administration, A.T. (Ainur Tasieva), Z.S. and A.K.; funding acquisition, G.M. and A.T. (Ainur Tasieva). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author Ainur Kuttybayeva, upon reasonable request, due to the data is presented in the form of unpublished drawings, diagrams, patent-sensitive models, or contain elements requiring intellectual property protection.

Acknowledgments: The authors would like to thank the Department of Electronics, Telecommunications and Space Technologies of Satbayev University for providing technical support and access to modeling facilities during this research.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Citaristi, I. International telecommunication union—Itu. In *The Europa Directory of International Organizations*; Routledge: London, UK, 2022; pp. 365–369. [CrossRef]
2. Le, N.; Zhang, H.; Cricri, F.; Ghaznavi-Youvalari, R.; Tavakoli, H.R.; Rahtu, E. Learned image coding for machines: A content-adaptive approach. *arXiv* **2021**, arXiv:2108.09992. [CrossRef]
3. Kuttybayeva, A.; Abdykadyrov, A.; Tolen, G.; Burdin, A.; Malyugin, V.; Kiesewetter, D. Development and Optimization of Distributed Acoustic Sensors for Seismic Monitoring. In Proceedings of the 2024 International Conference on Electrical Engineering and Photonics (EExPolytech), Saint Petersburg, Russia, 17–18 October 2024; pp. 64–67. [CrossRef]
4. Kuttybayeva, A.; Abdykadyrov, A.; Tolen, G.; Burdin, A.; Malyugin, V.; Kiesewetter, D. Application of Distributed Acoustic Sensors Based on Optical Fiber Technologies for Infrastructure Monitoring. In Proceedings of the 2024 International Conference on Electrical Engineering and Photonics (EExPolytech), Saint Petersburg, Russia, 17–18 October 2024; pp. 23–26. [CrossRef]
5. Freitag, C.; Berners-Lee, M.; Widdicks, K.; Knowles, B.; Blair, G.; Friday, A. The climate impact of ICT: A review of estimates, trends and regulations. *arXiv* **2021**, arXiv:2102.02622. [CrossRef]
6. Arshad, Z.; Robaina, M.; Botelho, A. The role of ICT in energy consumption and environment: An empirical investigation of Asian economies with cluster analysis. *Environ. Sci. Pollut. Res.* **2020**, *27*, 32913–32932. [CrossRef] [PubMed]
7. Tolen, G.B.; Abdykadyrov, A.A.; Bourdine, A.V.; Praporshchikov, D.E.; Yerishova, M.O.; Zaitseva, E.S. Influence of external factors on power transmission in few-mode optical fiber transmission lines. In Proceedings of the Optical Technologies for Telecommunications, Samara, Russia, 6–8 November 2024; Volume 13738, pp. 120–129. [CrossRef]
8. Tolen, G.B.; Abdykadyrov, A.A.; Bourdine, A.V.; Praporshchikov, D.E.; Yerishova, M.O.; Zaitseva, E.S. Analysis of the efficiency of distributed fiber optic acoustic sensors in monitoring systems. In Proceedings of the Optical Technologies for Telecommunications, Samara, Russia, 6–8 November 2024; Volume 13738, pp. 111–119. [CrossRef]
9. Evtushenko, A.S.; Bourdine, A.V.; Zaitseva, E.S.; Igumenov, A.Y.; Demenkova, A.A.; Isaenko, D.I.; Khadjaev, M.S.; Komar, M.V.; Pashin, S.S.; Osadchii, K.V.; et al. Simulation of laser-excited optical pulse propagation over graded-index multimode optical fiber with distorted asymmetrical structure. In Proceedings of the Optical Technologies for Telecommunications, Samara, Russia, 6–8 November 2024; Volume 13738, pp. 167–178. [CrossRef]
10. Tolen, G.B.; Bourdine, A.V.; Bengalskii, D.M.; Filyutich, E.A.; Ponomarenko, D.M.; Isaenko, D.I.; Praporshchikov, D.E.; Shurupov, D.N.; Slepogin, A.Y.; Ter-Nersesyants, E.V.; et al. Exploring the potentiality application of silica 5-mode optical fiber with perturbed refractive index profile in distributed acoustic sensing. In Proceedings of the Optical Technologies for Telecommunications, Samara, Russia, 6–8 November 2024; Volume 13738, pp. 130–139. [CrossRef]
11. Lambert, S.; Van Heddeghem, W.; Vereecken, W.; Lannoo, B.; Colle, D.; Pickavet, M. Worldwide electricity consumption of communication networks. *Opt. Express* **2012**, *20*, B513–B524. [CrossRef] [PubMed]
12. Sarigiannidis, P.G.; Papadimitriou, G.; Nicopolitidis, P.; Varvarigos, E. Towards power consumption in optical networks: A cognitive prediction-based technique. *Int. J. Commun. Syst.* **2017**, *30*, e2981. [CrossRef]
13. Dong, X.; El-Gorashi, T.; Elmirghani, J.M.H. Energy-efficient IP over WDM networks with data centres. In Proceedings of the 2011 13th International Conference on Transparent Optical Networks, Stockholm, Sweden, 26–30 June 2011; pp. 1–8. [CrossRef]
14. Ayoub, O.; Fatima, F.; Bovio, A.; Musumeci, F.; Tornatore, M. Traffic-adaptive re-configuration of programmable filterless optical networks. In Proceedings of the ICC 2020—2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020; pp. 1–6. [CrossRef]
15. Costa, L.R.; Brasileiro, I.B.; Drummond, A.C. Energy efficiency in sliceable-transponder enabled elastic optical networks. *IEEE Trans. Green Commun. Netw.* **2021**, *5*, 789–802. [CrossRef]
16. Amirabadi, M.A. A survey on machine learning for optical communication [machine learning view]. *arXiv* **2019**, arXiv:1909.05148. [CrossRef]

17. Sakthivel, S.; Belgaum, M.R.; Sajak, A.A.B.; Alam, M.M.; Su'UD, M.M. Machine Learning-Driven QoT Prediction for Enhanced Optical Networks in DWDM System. *IEEE Access* **2025**, *13*, 80445–80460. [CrossRef]
18. Vismara, F.; Grkovic, V.; Musumeci, F.; Tornatore, M.; Bregni, S. On the energy efficiency of IP-over-WDM networks. In Proceedings of the 2010 IEEE Latin-American Conference on Communications, Bogota, Colombia, 15–17 September 2010; pp. 1–6. [CrossRef]
19. Melidis, P.; Nicopolitidis, P.; Papadimitriou, G. Reserved energy-aware virtual topology management for IP-over-WDM optical networks. *Opt. Switch. Netw.* **2019**, *31*, 72–85. [CrossRef]
20. Chatterjee, B.C.; Sarma, N.; Oki, E. Routing and spectrum allocation in elastic optical networks: A tutorial. *IEEE Commun. Surv. Tutor.* **2015**, *17*, 1776–1800. [CrossRef]
21. Rafique, D.; Velasco, L. Machine learning for network automation: Overview, architecture, and applications [Invited Tutorial]. *J. Opt. Commun. Netw.* **2018**, *10*, D126–D143. [CrossRef]
22. Cruzes, S. Optical networks automation overview: A survey. *J. Sens. Netw. Data Commun.* **2023**, *3*, 144–162.
23. Yu, A.; Yang, H.; Xu, T.; Yu, B.; Yao, Q.; Li, Y.; Peng, T.; Guo, H.; Li, J.; Zhang, J. Long-term traffic scheduling based on stacked bidirectional recurrent neural networks in inter-datacenter optical networks. *IEEE Access* **2019**, *7*, 182296–182308. [CrossRef]
24. Gao, R.; Liu, L.; Liu, X.; Lun, H.; Yi, L.; Hu, W.; Zhuge, Q. An overview of ML-based applications for next generation optical networks. *Sci. China Inf. Sci.* **2020**, *63*, 160302. [CrossRef]
25. Chen, G. Simulation model of AI-assisted cognitive routing algorithm for the dynamic optical network in business. *Optik* **2022**, *260*, 168763. [CrossRef]
26. Ashok, P.; Hallur, G. Synergy in Action: Harnessing Cloud Services and Wired Broadband for Seamless Operations. In Proceedings of the 2024 2nd World Conference on Communication & Computing (WCONF), Raipur, India, 12–14 July 2024; pp. 1–7. [CrossRef]
27. Ahmed, A. Calculating Carbon Emissions of the ICT Sector: Analyzing Key Drivers and Future Trends. 2024. Available online: https://urn.fi/URN:NBN:fi-fe2024081364720 (accessed on 1 January 2026).
28. Martínez, R.; Hernández-Chulde, C.; Casellas, R.; Vilalta, R.; Muñoz, R. Optimizing Energy Efficiency in Optical Transport Networks through Autonomous AI-Assisted Control Operations. In Proceedings of the 2025 Optical Fiber Communications Conference and Exhibition (OFC), San Francisco, CA, USA, 30 March–3 April 2025; pp. 1–3.
29. Jiang, J.; Su, Y.; Cheng, J.; Shang, T. Multi-Link Fragmentation-Aware Deep Reinforcement Learning RSA Algorithm in Elastic Optical Network. *Photonics* **2025**, *12*, 634. [CrossRef]
30. Rai, S.; Garg, A.K. Deep learning—A route to WDM high-speed optical networks. *J. Opt.* **2024**, *53*, 737–745. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.