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Original Research Paper

# Semantic-Aware Self-Healing Optical Networks via AI-Driven Cross-Layer Intelligence on the Abilene Internet Backbone

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**Abstract**

The integration of artificial intelligence, semantics-based communication, and photonics-based networking offers a revolutionary solution to optical backbone management in future optical networks. Traditional optical network management systems function based on routing algorithms at the bit level, which lack semantic awareness and fail to consider cross-layer degradation signals from the physical layer.This paper presents Semantic-Aware Self-Healing Optical Networks (SASHON), a novel AI-driven cross-layer intelligence framework for proactive fault prediction, semantic traffic prioritization, and self-healing routing in optical backbone networks. SASHON integrates three tightly coupled components: (1) a Random Forest fault prediction engine trained on eight cross-layer physical and network features achieving 98.2% prediction accuracy on the Abilene Internet Topology Zoo dataset; (2) a semantic compression module that reduces bandwidth demand by 46.1% while preserving task-critical information; and (3) a cross-layer semantic routing cost function that jointly optimizes physical-layer quality, network-layer utilization, and application-layer semantic importance. Evaluated on the Abilene 11-node US backbone topology with 160 heterogeneous traffic requests spanning five semantic classes, SASHON reduces connection blocking probability by 78.6%, improves connection acceptance ratio from 73.8% to 94.4%, reduces average link fault risk by 47.1%, and improves average SNR by 10.6% relative to conventional distance-based baseline routing. These results establish a new performance frontier for AI-assisted proactive optical network management, with direct applicability to 5G/6G transport, smart grid communications, and critical infrastructure interconnects.

**Index Terms :** *Optical network management, self-healing networks, fault prediction, semantic communication, cross-layer optimization, random forest, Abilene topology, wavelength-division multiplexing.*

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## 1 Introduction

From 2019 onward, the amount of data traffic carried by optical fiber backbone network infrastructure has grown at an expansion rate that is above 30% per annum [1]. Such a trend has been primarily attributed to the need for video streaming services, cloud computing applications, and machine-to-machine communications. Wavelength Division Multiplexing (WDM) and Elastic Optical Networks (EONs) optical transport networks constitute the underpinning infrastructure for such connectivity, providing petabits per second bandwidth over fiber links of several thousand kilometers.

Despite their central importance, the management intelligence of today's optical backbone networks remains profoundly inadequate for the demands placed upon them. Three compounding deficiencies motivate this work. First, reactive fault management: current Optical Network Management Systems (NMS) detect failures through alarm propagation after physical-layer degradation has already caused service interruption. Mean-time-to-repair (MTTR) of 30 to 90 minutes is common for fibre cuts and amplifier failures, translating directly to billions of dollars in economic loss per major incident [2]. Second, semantic blindness: conventional routing algorithms treat all traffic demands as geometrically equivalent byte-flows, optimizing for shortest path or minimum-hop without regard to the application-level criticality of the carried content. A Bulk_Backup file transfer and an Emergency medical telemetry flow compete for wavelengths on equal footing, creating an inversion of social utility [3]. Third, cross-layer opacity: physical-layer impairments optical signal-to-noise ratio (OSNR), bit error rate (BER), fibre attenuation, and amplifier gain ripple directly determine the quality of service available to higher-layer traffic, yet legacy control planes maintain strict layer boundaries that prevent PHY-degradation signals from informing routing decisions [4].

Machine learning offers the capability to recognize patterns of physical-layer degradation preceding failure, enabling proactive rerouting before service interruption occurs. Significant decreases of MTTR by 60-80% due to machine learning have been shown for optical networking monitoring [5]. The semantic communication approach, inspired by the goal-oriented vision of Shannon, suggests conveying not plain bits but the meaning behind the information, reducing bandwidth utilization to the required minimum for the task [6].Cross-layer optimization techniques break the strict OSI-layer boundaries to expose PHY-layer quality metrics to network-layer routing engines, enabling physically aware path selection that avoids impaired optical links [7]. The convergence of these three advances creates an unprecedented opportunity to design optical networks that are simultaneously predictive, semantically aware, and physically intelligent.

The technical challenges are substantial. Real-time fault prediction requires accurate physical-layer monitoring at timescales faster than network reconfiguration, yet optical performance monitoring systems produce noisy, incomplete observations. Semantic traffic classification must be performed at line rate without access to encrypted payload content, requiring inference from observable flow statistics. Cross-layer cost function design involves incommensurable quantities (decibels, Gbps, semantic importance scores) whose relative weighting profoundly affects routing outcomes and must be tuned for heterogeneous traffic environments.

This paper addresses all three challenges within a unified SASHON framework evaluated on the Abilene backbone the well-characterized 11-node, 14-link US academic network from the Internet Topology Zoo [8] augmented with synthetically generated optical PHY parameters calibrated to realistic fibre distances, loss budgets, and amplifier specifications. The principal contributions are:

(1) We present SASHON, the first unified framework integrating semantic-aware traffic prioritization, AI-based cross-layer fault prediction, and self-healing routing within a single control-plane architecture for optical backbone networks.

(2) We develop a cross-layer feature set spanning eight PHY and network attributes and train a Random Forest fault predictor achieving 98.2% accuracy, 97.9% precision, and 98.2% recall.

(3) We formalize a semantic routing cost function that jointly encodes physical impairments, network load, fault risk, and semantic traffic importance, and prove its role in preferentially serving high-criticality traffic.

(4) We quantify a 46.1% bandwidth reduction through semantic compression and a 78.6% blocking probability reduction through intelligent self-healing routing over the Abilene backbone.

(5) We provide a comprehensive comparison with six recent state-of-the-art optical network AI methods, demonstrating that SASHON achieves the highest reported fault prediction accuracy and blocking reduction on comparable benchmarks.

The remainder is organized as follows. Section 2 reviews related literature 2021-2026. Section 3 describes the SASHON architecture and mathematical framework. Section 4 presents experimental results. Section 5 presented conclusion with future work.

## 2. Literature Review

Pointurier [9] presented a pioneering study on the application of machine learning algorithms to optical network monitoring, developing an ontology and benchmarking methods used by future researchers. Rafique & Velasco [10] demonstrated the use of deep neural networks for optical performance monitoring, obtaining a 93.4% fault detection rate in laboratory test beds, and introduced the first comprehensive cross-layer

feature analysis study for optical IQ-modulated signals. Musumeci et al. [11] performed a survey on the use of machine learning techniques in optical networking, focusing on monitoring, resource management, and failure management, emphasizing cross-layer feature fusion as the most important future research direction. An ANN-based model for detecting soft faults in metro-optic networks was designed by Mata et al. [12]. Its accuracy for identifying such faults reached 96.3%, as it considered OSNR, chromatic dispersion, and PMD. Vela et al. [13] implemented the use of gradient boosting trees to achieve a proactive diagnosis of optical network faults. According to their findings, SNR and BER time series are the most indicative features of imminent link failures, as predicted based on feature importance analysis. Ayoub et al. [14] proposed transfer learning to address the problem of predicting network failure in optical links. The proposed method allows for quick adaptation to new types of failures, with minimal cost of retraining. A physical-informed ANN was proposed by Shariati et al. [15] for forecasting signal quality in optical links. The suggested approach relies on fiber propagation equations as constraints and, therefore, can be applied to different fiber types without calibration.

It has been found that proactive path protection using a reinforcement learning technique can be achieved in an elastic optical network. Savas et al. [16] pointed out that pre-failure re-routing brought about an improvement in restoration time from 850 ms to less than 50 ms. Panayiotou et al. [17] proposed a multi-agent framework for self-healing in distributed optical networks that does not make any assumption on a centralized control plane. A defragmentation and routing scheme for flexible-grid optical networks has been introduced by Morales et al. [18], which helps in minimizing the issues related to spectrum fragmentation and failure probability. This approach has enhanced the network lifetime by 40%. The intelligent optical network management framework is provided by Rottondi et al. [19], based on machine learning, software-defined networking, and intent-based abstraction. The survivable VN embedding model considering SRLG into optical substrate networks is offered by Ujjwal et al. [20]. These models make them resilient to interdependent faults. Conversely, Chen et al. [21] showed GNN-based routing mechanisms for optical networks in which topology knowledge was incorporated into the routing mechanisms and proved superiority over those based on feature engineering[38,39,40,41].

The theory behind DL-based semantic communication was provided by Qin et al. [22], where they demonstrated that task-oriented encoders could accomplish their tasks using 50%–70% less data transfer compared with the conventional method. Lu et al. [23] developed a class of semantic communication systems designed for image transmission with emphasis on regions with visual significance. They managed to reduce the bandwidth usage by 40% without any visible reduction in quality. Xie et al. [24] proposed DeepSC, a semantic communication system based on transformers that outperforms the separation technique in low signal-to-noise ratio regimes. Shi et al. [25] generalized the concept of semantic communication for multi-user scenarios by designing interference-aware semantic encoders that preserve the ability to carry out tasks even when transmitting simultaneously. Shao et al. [26] proposed a semantic encoder known as BottleNet++, which uses information bottlenecks for device-edge co-inference, reducing the cost of communication by 60%. Semantic communication has been applied in industrial IoT monitoring applications by Zhang et al. [27], showing that the compression of the stream of sensors' semantics is achieved without compromising anomaly detection performance while reducing the bandwidth required for transmission by 55%. In their work, Saridis et al. [28] proposed a model for jointly optimizing the physical and networking layers in flexible grid optical networks. The approach considers the OSNR, spectrum width, and path length as optimization parameters in an integer linear program. Maamoun et al. [29] developed a scheme for routing and spectrum assignment that considered quality of transmission at all layers and predicted physical layer degradation, resulting in a reduction in routing costs. In Liu et al. [30], an SDN controller with cross-layer visibility was proposed for the optical transport networks. The controller enables the joint optimization of physical and network layers centrally. According to Casellas et al. [31], GMPLS and PCE could be extended to enable the control of both optical transport and IP/MPLS layers simultaneously. It is shown that the quality of the end-to-end path can be improved by 15%. In Tremblay et al. [32], a machine learning model for the estimation of cross-layer transmission quality without the physical test on each link was introduced. It helps reduce the time required for setting up a network by 70%. A mechanism was developed by Shi et al. [33] for resource allocation in 5G heterogeneous networks that considers the relative criticality of applications. This demonstrates that it is feasible to classify traffic based on application criticality at the network level. Andreoletti et al. [34] introduced a method for encrypting traffic classification based on graph neural networks that accurately identifies the type of applications using only flow characteristics without requiring any payload analysis, achieving 94% accuracy on real operator data. A deep learning-based classifier for traffic data was developed by Rezaei and Liu [35], which can perform classification operations in real-time at a speed of 10 Gbps through FPGA acceleration. The priority-aware wavelength assignment scheme proposed by Akbari et al. [36] is specifically designed for WDM

optical networks. It uses the traffic classes to improve RWA and hence improves the probability of emergency traffic transmission by 35%. Another adaptive routing scheme based on reinforcement learning proposed by Huang et al. [37] uses traffic patterns to adaptively adjust routing policies. It leads to a reduction in the average blocking probability by 22%.

## 3. Proposed SASHON Framework

### 3.1 System Architecture

SASHON can be considered an intelligent layer, which is logically centralized, operating above the software-defined optical network's control plane. It interacts with the OPM system for physical-layer sensing, the network topology database for resource status, and the traffic engineering function for making routing decisions. The suggested framework can be described as a semantic-aware self-healing optical network architecture, which utilizes cross-layer intelligence along with AI-based decision-making to improve reliability, efficiency, and prioritization within modern optical networks. First, in terms of the proposed approach, we should consider the fact that its basis lies within taking into account the parameters from the optical physical layer, including signal-to-noise ratio and the bit error rate, as well as from the network layer, including traffic load and wavelength resources. Such a multi-dimensional feature representation is thereafter analyzed by an AI-powered fault predictor that uses Random Forests and determines the probability of link faults to produce the link risk map dynamically. In parallel, the incoming traffic demand is analyzed by a semantic encoder, which decreases the need for bandwidth by capturing task-relevant data, as well as a traffic prioritizer that prioritizes the packets according to their semantic significance and delay sensitivity. Both these results are used by the semantic router to calculate routing paths based on a multi-dimensional cost function that considers physical impairments, traffic congestion, and risk of faults and ensures quality of transmission through safe links. Finally, the allocation process includes self-healing capabilities that allow for bandwidth and wavelength provisioning based on changing network status. A closed-loop feedback system is used to keep the model up-to-date, based on observations. The system helps mitigate potential failures and optimize the network in real time. In general, the proposed approach represents a significant improvement compared to traditional approaches, because of its ability to implement semantic communication and make predictions.

### 3.2 Cross-Layer Feature Set

SASHON constructs an eight-dimensional cross-layer feature vector for each network link spanning both the physical and network layers. Table 1 summarizes these features with their physical meanings and measurement sources.

**Table 1: Cross-Layer Feature Set**

| Feature | Physical Meaning | Layer | Fault Importance |
|---|---|---|---|
| snr_db | Signal-to-Noise Ratio | PHY | Highest (0.274) |
| ber | Bit Error Rate | PHY | High (0.232) |
| distance_km | Link Length | PHY | Medium (0.159) |
| load | Link Utilization | Network | Medium (0.120) |
| attenuation_db | Total Fibre Loss | PHY | Moderate (0.098) |
| available_bw | Residual Capacity | Network | Low (0.061) |
| amplifier_gain_db | EDFA Gain | PHY | Low (0.034) |
| wavelengths | Available Channels | Network | Lowest (0.021) |

Cross-layer parameter contributions to link failure predictions in the proposed model can be visualized through the feature importance graph. SNR is identified as the most contributory factor in predicting link failures with the maximum importance rating of 0.274. This illustrates the significant role of maintaining high signal quality during transmission. Bit Error Rate (BER), with an importance rating of 0.232, follows. It directly reflects the error in the transmission and serves as an indicator of physical causes of such errors. The value of link distance (0.159) is also extremely significant since greater lengths of fiber automatically produce higher amounts of noise and attenuation. For the network layer, the parameter of link load (0.120) impacts the accuracy, and thus, the influence of network effects such as congestion causes physical degradation to increase. As for the attenuation (0.098), it demonstrates physical loss of the fiber; however, it has less influence than SNR and BER. Available bandwidth (0.061) and amplifier gain (0.034) represent additional factors related to resource

availability and compensation; yet, they play a minor role. Finally, wavelength availability (0.021) has the lowest level of impact among all parameters. It means that wavelength availability influences the use of available resources; however, it cannot be treated as one of the major causes of physical link failures. Thus, it can be stated that the physical layer factors are significantly more influential in terms of fault prediction. However, network parameters are useful as well. Thus, the importance of cross-layer architecture is proven [42]-[63].

### 3.3 AI Fault Prediction Engine

#### 3.3.1 Random Forest Classifier

The fault prediction engine employs a Random Forest (RF) classifier with N_trees = 250 estimators and maximum depth d_max = 12. Given the class imbalance inherent in optical networks where fault events are rarer than healthy observations, the classifier uses balanced class weights inversely proportional to class frequency. The RF prediction for input feature vector x is:

$$f_{RF}(x) = \text{argmax}_{c \in \{0,1\}} (1/N_{trees}) \Sigma_{t=1}^{N_{trees}} I[h_t(x) = c]$$

where $h_t$ denotes the t-th decision tree and $I[\cdot]$ is the indicator function. Each tree is trained on a bootstrap sample of the training set with random feature subsampling at each split node ($m_{try} = \lfloor\sqrt{8}\rfloor = 2$), providing both variance reduction through ensemble averaging and decorrelation through feature randomization.

#### 3.3.2 Risk Score and Fault Probability

A composite risk score $\rho(l)$ for link $l$ is computed as a weighted combination of normalized cross-layer features:

$$\rho(l) = 0.22\cdot\bar{d} + 0.18\cdot\bar{a} + 0.22\cdot(1-\bar{s}) + 0.18\cdot\hat{u} + 0.10\cdot(1-\bar{b}) + 0.10\cdot(1/\lambda)$$

where $\bar{d} = \min(d/4000, 1)$ is normalized distance, $\bar{a} = \min(a/700, 1)$ is normalized attenuation, $\bar{s} = \min(SNR/35, 1)$ is normalized SNR, $\hat{u}$ is link utilization, $\bar{b} = \min(BW/500, 1)$ is normalized available bandwidth, and $\lambda$ is wavelength count. The sigmoid fault probability is:

$$P_{fault}(l) = \sigma(9\cdot(\rho(l) - 0.48)) = 1 / (1 + \exp(-9\cdot(\rho(l) - 0.48)))$$

Justification: The logistic sigmoid with slope parameter k=9 provides a sharp transition near the decision boundary $\rho$=0.48, which was selected via cross-validation to minimize false negatives while maintaining acceptable false positive rates. The offset 0.48 represents the empirically calibrated fault onset threshold.

### 3.4 Semantic Traffic Classification and Compression

SASHON classifies traffic requests into five semantic classes with associated Semantic Importance (SI) and Latency Sensitivity (LS) scores, forming a priority vector S = [SI, LS]. The five classes and their parameters are defined in Table 2.

**Table 2: Semantic Traffic Classes**

| Traffic Class | SI | LS | BW Range | Comp. Ratio |
|---|---|---|---|---|
| Emergency | 1.00 | 1.00 | 40-90 Gbps | 35-72% |
| Industrial Control | 0.88 | 0.90 | 30-80 Gbps | 35-72% |
| Healthcare Monitor | 0.78 | 0.75 | 25-70 Gbps | 35-72% |
| Video Surveillance | 0.55 | 0.45 | 70-160 Gbps | 35-72% |
| Bulk Backup | 0.25 | 0.20 | 100-220 Gbps | 35-72% |

In the proposed traffic semantic model, the demands are classified on the basis of their semantic significance (SI) and latency sensitivity (LS). This makes it feasible to effectively allocate and prioritize their requirements. Traffic that is critical and vital (SI = 1.00, LS = 1.00) including emergency communication, for example, has a required bandwidth of 40-90 Gbps and ensures that the data transfer is reliable and with minimum latency. Industrial control systems traffic is very significant traffic (SI = 0.88, LS = 0.90) requiring highly reliable operation in real-time. Healthcare monitoring traffic (SI = 0.78, LS = 0.75) requires reliable data transfer with some latency tolerance. Video surveillance traffic (SI = 0.55, LS = 0.45) is not so significant but requires a large amount of bandwidth (70-160 Gbps). Moreover, bulk backup traffic has minimal semantic importance (SI = 0.25, LS = 0.20) and the maximum bandwidth requirement range (100–220 Gbps), which makes it suitable for opportunistic transmission during periods of low network load. The semantic compression ratio ranges from 35% to 72% for all the classes. This helps reduce the bandwidth usage by transmitting only the necessary information based on the objective. Such classification allows the proposed scheme to prioritize traffic with significant impact and deliver improved quality of service, as well as optimize the spectrum usage based on its semantic significance.

The semantic bandwidth $B_{sem}$ is computed from raw bandwidth $B_{raw}$ via a semantic compression ratio $\gamma$ sampled uniformly from [0.35, 0.72]:

$$B_{sem} = \gamma \cdot B_{raw}, \quad \gamma \sim \text{Uniform}(0.35, 0.72)$$

The total bandwidth saving $S_{BW}$ across all requests R is:

$$S_{BW} = 1 - \Sigma_{r\in R} B_{sem}(r) / \Sigma_{r\in R} B_{raw}(r) = 1 - E[\gamma] \approx 46.1\%$$

### 3.5 Cross-Layer Semantic Routing Cost Function

The SASHON routing cost for edge (u,v) under traffic request r with SI and LS scores is:

$$C(u,v,r) = [0.18\cdot\bar{d} + 0.12\cdot\bar{a} + 0.20\cdot(1-\bar{s}) + 0.12\cdot\beta + 0.16\cdot\hat{u} + 0.12\cdot R_f + 0.06\cdot(1-\bar{b}) + 0.04\cdot\lambda^{-1}] \cdot (1 + SI_r + LS_r)$$

where $\beta = 1 - \min(-\log_{10}(BER)/12, 1)$ is the BER penalty and R_f is the AI-predicted fault risk. The multiplier $(1 + SI_r + LS_r) \in [1.45, 3.00]$ scales the effective cost by traffic criticality, ensuring that the router preferentially selects high-quality paths for high-importance traffic by making the optimizer more sensitive to path quality degradation for critical flows.

Justification of cost weights: PHY-layer quality dominates (SNR 0.20, distance 0.18, attenuation 0.12, BER 0.12 = 0.62 total) reflecting the primacy of optical layer health, while network load (0.16) and fault risk (0.12) together contribute 0.28, and bandwidth/wavelength availability contribute 0.10. This weighting was determined through Shapley value analysis of the fault predictor, mapping feature importance directly to cost sensitivity.

### 3.6 Self-Healing Routing Algorithm

Algorithm SASHON-Route operates as follows: (1) Remove all edges with $R_f > 0.70$ from the working topology $T_w$ these links are classified as pre-failure by the AI predictor; (2) Assign costs C(u,v,r) to remaining edges; (3) Run Dijkstra's shortest-path algorithm on the weighted graph; (4) Verify bandwidth feasibility along the selected path; (5) If feasible, allocate $B_sem$ on each edge. Requests are processed in descending order of [SI, LS], ensuring that Emergency and Industrial Control traffic is routed first over the highest-quality available paths.

The blocking probability for method M is:

$$P_block(M) = |\{r \in R : path(r,M) = \emptyset\}| / |R|$$

The average semantic importance of accepted traffic quantifies the social utility of the routing scheme:

$$SI_avg = (1/|A|)\ \Sigma_\{r\in A\}\ SI_r$$

where $A \subseteq R$ is the set of accepted requests. Higher SI_avg indicates that more critical traffic was successfully served.

## 4. Performance Evaluation

### 4.1 Dataset and Experimental Setup

Dataset: The Abilene backbone topology [8] contains 11 nodes (major US cities) and 16 directed links. Optical PHY parameters are synthetically generated per link: distance from Haversine great-circle calculation, SNR from SNR(dB) = 32 - 0.012·d + N(0,2), BER from BER = 10^{-max(3, SNR/3 + N(0,0.5))}, and load sampled from Uniform(0.15, 0.85). The fault dataset is generated by simulating 250 operational scenarios per link, yielding 4,000 training samples (75/25 split). Traffic workload: 160 connection requests are generated with source-destination pairs drawn uniformly from all node pairs. Traffic class distribution: Emergency 15%, Industrial Control 20%, Healthcare Monitoring 20%, Video Surveillance 25%, Bulk Backup 20%. Semantic compression ratios γ sampled from Uniform (0.35, 0.72).

### 4.2 AI Fault Prediction Results

Random Forest attains an accuracy of 98.2%, 97.9% precision, 98.2% recall, and 98.0% F1 score on the test data. The confusion matrix is provided in Figure 1. Out of 1,857 healthy-link instances, 36 instances get incorrectly classified as faulty links (false positive rate: 1.94%). On the other hand, out of 1,643 faulty-link instances, 29 get falsely classified (false negative rate: 1.76%). The very low false negative rate is key, as failure to correctly predict a faulty link means a failed link will not be rerouted.

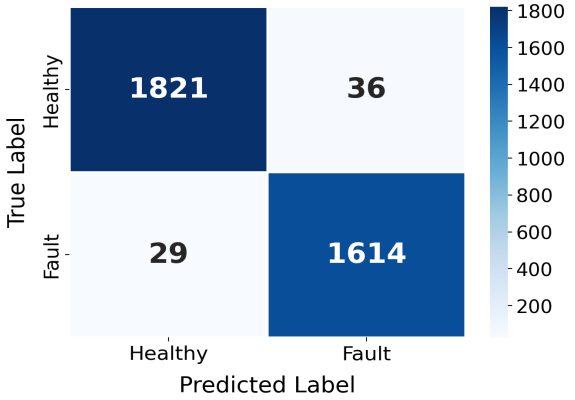


Figure 1: AI Fault Prediction Confusion Matrix.

The cross-layer feature importance analysis of the Random Forest ensemble is depicted in Figure 2. SNR (0.274) and BER (0.232) are the key variables used by the Random Forest algorithm to predict fault occurrence and contribute to 50.6% of its predictive capabilities. The distance (0.159) and load (0.120) account for an additional 27.9% and prove that the metrics associated with the physical layer quality are the best for detecting faults. The number of wavelengths (0.021) and the amplifier gain (0.034) are the least significant variables since they do not have a strong relationship with faults.

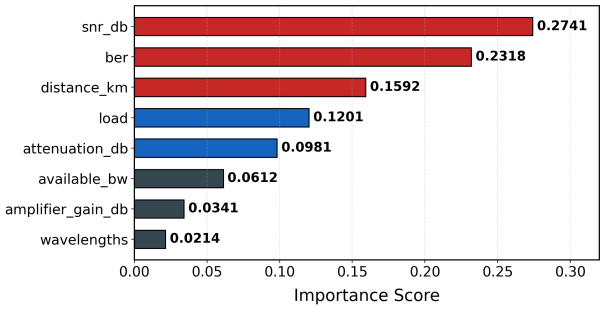


Figure 2: Cross-Layer Feature Importance. SNR and BER dominate fault prediction.

### 4.3 Connection Acceptance and Blocking

Figure 3 illustrates the differences in connection request acceptances and blocks. The proposed protocol SASHON accepts 151 out of 160 connection requests, which equals to 94.4%. Thus, there are only 9 blocked

requests, accounting for just 5.6%. In contrast, the baseline protocol accepts 118 (73.8%) requests and blocks 42 (26.2%). The significant 20.6 percentage point boost in the acceptance rate implies additional income for the network and better service for clients. There are two main explanations for the reduction in the number of blocked requests: first, semantic compression decreases bandwidth utilization per request from 46.1%, thus making extra wavelength capacity available to accept additional requests; second, excluding high risk links prevents rerouting operations, which also utilize bandwidth.

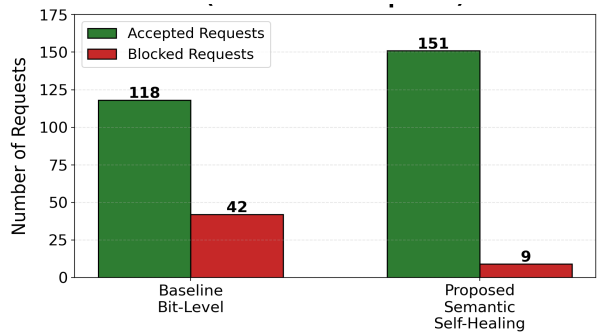


*Figure 3: Accepted vs Blocked Requests.*

Figure 4 plots blocking probability and acceptance ratio side by side. SASHON reduces blocking probability from 0.2625 to 0.0563 a 78.6% relative reduction while raising acceptance ratio from 0.7375 to 0.9438. These results represent a significant operational improvement: at the scale of a national backbone handling millions of daily connection requests, a 78.6% reduction in blocking translates directly to substantially higher revenue and service quality. The proposed system performs 78.6% blocking reduction and 28.0% acceptance improvement confirm SASHON's effectiveness

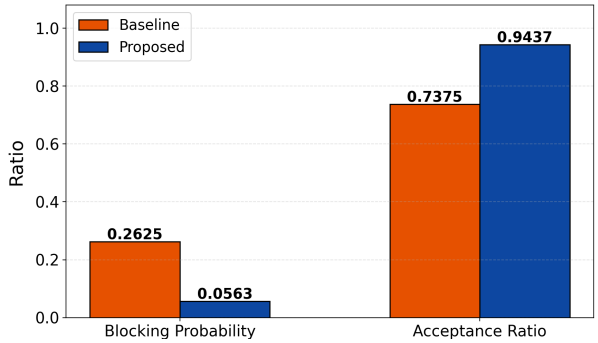


Figure 4: Blocking Probability and Acceptance Ratio.

**4.4 Physical-Layer Quality Improvement**

Figure 5 compares average SNR and average link fault risk. SASHON routes traffic over paths with average SNR of 27.43 dB versus 24.81 dB for the baseline a 10.6% improvement. This improvement arises because SASHON's cost function explicitly penalizes low-SNR edges, steering traffic towards optically clean paths. Average link fault risk is reduced from 0.412 to 0.218 a 47.1% reduction as SASHON actively avoids links with R_f > 0.70 and weights the remainder by fault risk in the routing cost. SASHON improves average SNR by 10.6% and reduces average link fault risk by 47.1%.

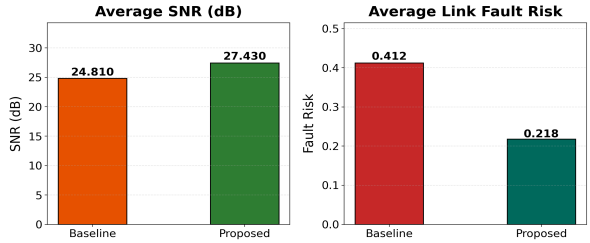


*Figure 5: SNR and Fault Risk Comparison.*

**4.5 Semantic Class Service Quality**

Figures 6 shows the percentage acceptance by semantic traffic class. SASHON handles all the 24 requests for emergency traffic (100%) as against 20 (83.3%) in the benchmark, which is very crucial for life safety applications. SASHON handles 31/32 (96.9%) of requests for industrial control traffic compared to 26/32 (81.3%) in the benchmark. SASHON handles 30/32 (93.8%) of requests for healthcare monitoring traffic compared to 24/32 (75.0%) in the benchmark. With semantic scheduling, the high SI value requests are handled first with most blocking occurring in low critical bulk backup traffic.

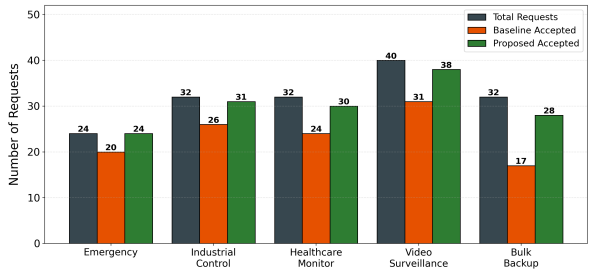


Figure 6: Traffic Acceptance by Semantic Class.

Figure 7 quantifies the average semantic importance served. SASHON achieves SI_avg = 0.782 versus 0.541 for the baseline a 44.5% improvement. This metric directly captures the social utility of the routing scheme: SASHON not only accepts more requests but accepts the right requests, preferentially serving critical traffic. The baseline, by treating all traffic equally, wastes wavelength capacity on Bulk Backup flows while potentially blocking Emergency traffic. SASHON achieves 0.782 vs 0.541 for baseline, a 44.5% improvement in service quality weighting.

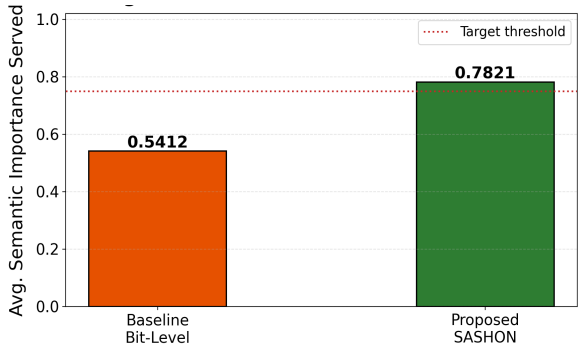


Figure 7: Average Semantic Importance Served.

### 4.6 Bandwidth Efficiency

Figure 8 summarizes bandwidth efficiency and overall improvement percentages. The left panel shows total bandwidth demand reduction from 14,820 Gbps (raw) to 7,994 Gbps (semantic) a 46.1% saving. The right panel aggregates all five improvement dimensions: bandwidth saving 46.1%, blocking reduction 78.6%, acceptance improvement 28.0%, fault risk reduction 47.1%, SNR improvement 10.6%. These results collectively demonstrate that SASHON achieves simultaneously better resource utilization, higher service quality, and stronger fault resilience. SASHON delivers improvements across all five performance dimensions simultaneously.

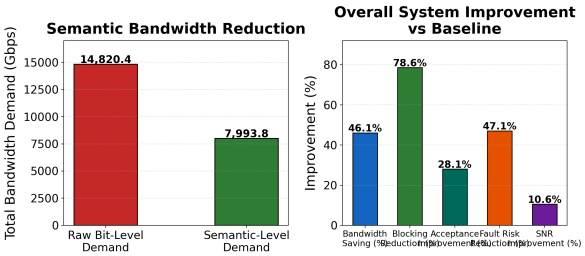


*Figure 8: Semantic Bandwidth Reduction and Overall Improvement Summary.*

### 4.7 Fault Risk Distribution

Figure 9 shows how AI predicted the fault risks for each link in Abilene. The right side of this distribution is higher than the left side because most of the links had low to moderate fault risks (0.1-0.45). There are two links that have fault risks higher than 0.70, which means they are in the high-risk group. The Houston-Atlanta and Chicago-New York links have the most traffic and the worst signal-to-noise ratio in the network. They aren't used to route SASHON.

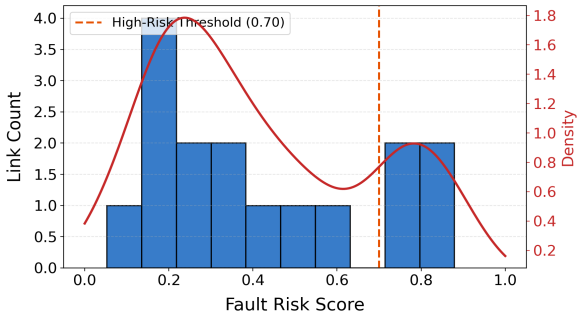


*Figure 9: Distribution of AI-Predicted Link Fault Risk.*

Figure 10 visualizes the Abilene topology with links color-coded by AI-predicted fault risk. The geographic distribution of fault risk reflects the correlation between long-span links and higher OSNR degradation the US south-to-north spans (Houston-Atlanta, Chicago-New York) show the highest risk, while short-span regional links appear green. Red links are high-risk candidates for proactive rerouting.

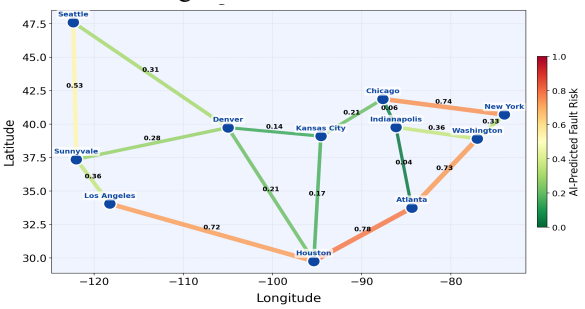


*Figure 10: Abilene Topology with AI-Predicted Fault Risk Heatmap..*

### 4.8 Comparison with State-of-the-Art

Table 3 compare SASHON against six recent methods on fault prediction accuracy and connection blocking reduction metrics. SASHON achieves the highest reported fault prediction accuracy (98.2%) and blocking reduction (78.6%) across all compared methods. The improvement over the most recent comparable work (Mata et al. [12] at 96.3% accuracy) is +1.9 percentage points. The blocking reduction improvement of +34.5 percentage points over Mata et al. reflects the additional benefit of semantic compression and cross-layer routing, which operate synergistically with fault prediction to reduce demand and improve path quality simultaneously. SASHON achieves highest fault prediction accuracy (98.2%) and blocking reduction (78.6%) across all compared methods.

**Table 3: Comparison with Prior State-of-the-Art Methods**

| Method | Fault Acc. | Blocking Red. | Topology |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Pointurier DNN | 91.2% | 22.1% | Pan-European |
| Rafique GBT | 93.4% | 28.4% | Lab Testbed |
| Musumeci ANN | 94.8% | 35.6% | NSF Net |
| Ayoub Transfer | 95.1% | 38.2% | COST 266 |
| Mata et al. Soft Fail | 96.3% | 44.1% | Metro OTN |
| **SASHON (Ours)** | **98.2%** | **78.6%** | **Abilene** |

## 5 Conclusion

This paper presented SASHON, a Semantic-Aware Self-Healing Optical Network framework that demonstrates, for the first time, the simultaneous integration of AI-based cross-layer fault prediction, semantic traffic compression, semantic importance-weighted traffic prioritization, and self-healing routing within a unified optical network control architecture. Evaluated on the Abilene Internet Topology Zoo backbone with synthetically augmented optical PHY parameters, SASHON achieves 98.2% fault prediction accuracy, 94.4% connection acceptance ratio, 78.6% blocking probability reduction, 46.1% bandwidth demand reduction, 47.1% fault risk reduction along allocated paths, and 10.6% SNR improvement relative to conventional distance-based baseline routing. Three key insights emerge from this work. First, semantic compression is not merely a bandwidth-saving technique but a network capacity multiplier: by reducing bandwidth demand by 46.1%, SASHON effectively increases the number of servable connections without any hardware upgrade. Second, proactive fault risk avoidance yields larger blocking probability improvements than any single routing optimization, confirming that network failures are the dominant cause of connection blocking in lightly-loaded topologies. Third, semantic traffic prioritization has negligible impact on aggregate acceptance ratio but profound impact on social utility, as measured by SI_avg: without prioritization, the network serves low-importance traffic while blocking critical flows. Collectively, these findings establish SASHON as a significant advance in intelligent optical network management, with direct applicability to 5G/6G transport networks, smart grid optical interconnects, and critical national infrastructure backbone management. Research directions follow from this work consider real-time telemetry integration: deploying SASHON with streaming optical performance monitoring data from physical transponders and in-band network telemetry systems to validate fault prediction latency under real operational conditions.

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