Adaptive Machine Learning Framework for QOT Approximation Using Link-Level Embeddings

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***Abstract*—The management of today's optical networks is highly dependent on the correct estimation of Quality of Transmission (QoT). The current analytical approach requires exact physical values, which are often not available, resulting in inefficient management of the network. This paper proposes an Adaptive Machine Learning Framework that aims to address the analytical approach's limitations using a new and innovative data-driven approach. The proposed framework combines link-level embeddings with an Artificial Neural Network (ANN) to process the unique sequence of fiber links in a lightpath, focusing on the fine-grained details of the sequence that are normally overlooked by the current analytical approach. Through dynamic learning from the sequence data, the framework provides highly accurate signal quality estimates. These estimates enable intelligent and automated modulation format choices, greatly enhancing spectral efficiency and minimizing disconnections. This highly scalable solution is developed in Python and TensorFlow and is best suited for dynamic resource allocation and future-oriented network planning.**

***Index Terms*—Machine Learning, Quality of Transmission (QoT), Optical Networks, Link-Level Embeddings, Artificial Neural Networks, Generalized Signal-to-Noise Ratio (GSNR).**

I. INTRODUCTION

The explosive growth in worldwide data traffic has put an unprecedented burden on dynamic optical networks, and as such, the need for reliable Quality of Transmission (QoT) estimation has become a critical factor in setting up lightpaths and managing spectrum allocation [1]. Historically, network engineers have turned to sophisticated mathematical physics models, including the Gaussian Noise Model (GNM) [2], [3], to estimate signal degradation. These static models are computationally intensive and do not account for real-world physical variations such as fiber degradation or temperature changes. As such, engineers are left to operate in a "worst-case" scenario design approach, applying a conservative safety margin of +2 to +3 dB to ensure service continuity [4]. This has resulted in the artificial underutilization of the spectrum, limiting lightpaths to lower-tier, more robust modulation schemes despite the physical infrastructure's ability to support higher-capacity transmissions.

To counter the inflexible inefficiencies of mathematical modeling, this project proposes an Adaptive Machine Learning Framework. Although traditional machine learning models tended to lack the necessary granularity in their approach to optical paths as generalized distance summaries [5], our proposed framework employs an Artificial Neural Network (ANN) with a novel link-level embedding layer [6]. This layer is capable of processing the precise order of individual fiber links, enabling the framework to account for the unique physical properties and noise accumulation behaviors of the network segment by segment. With its ability to provide instantaneous and highly accurate Generalized Signal-to-Noise Ratio (GSNR) predictions, the framework enables network controllers to make informed, autonomous modulation format choices.

On the basis of the embedding layer, the system employs a Long Short-Term Memory (LSTM) network [7], [8] to deal with the strictly sequential nature of lightpaths. Because of the fact that a single optical path may contain dozens of interconnected nodes, working as a sequence of accumulated interference, the memory cells of the LSTM network are capable of dealing with the attenuation of the signal from the source to the destination. By mapping hundreds of different physical paths into a dense vector space, the neural network is capable of dealing with the complex noise patterns that are completely ignored by distance-based methods.

Crucially, the system is developed not as an algorithm but as an ecosystem. In order to tackle the problems that are created by the aging fiber infrastructure, the system has an automated retraining process [9]. As the real-time network telemetry data is input into the feature performance database, the system can update its weights periodically. The system is designed in such a way that if a particular fiber span undergoes a splice repair or deteriorates due to environmental changes, the AI system will adapt to the new environment immediately without having to solve complex physics equations.

The robust training of the model on a huge dataset of over 137,000 unique path topologies is sufficient to validate the efficacy of the framework. The model is quite efficient in terms of prediction accuracy with a Mean Absolute Error (MAE) of only 0.9862 dB and an overall accuracy of 71.12%. When implemented in the dashboard for the network administrators, the sub-second inference time is sufficient to safely eliminate the need for a strict safety margin. The framework has long abandoned the use of the traditional, slower format and instead confidently enables high-speed modulation schemes such as

64QAM if the AI verifies a clear optical path, thereby recovering massive amounts of wasted bandwidth.

II. Literature Review

Traditionally, resource allocation in optical networks has been based on computationally intensive mathematical models, such as the Gaussian Noise Model (GNM) [2]. These models involve the solution of very complex, nonlinear equations over very large topologies, thus causing drastic real-time bottlenecks. To avoid task failures and ensure optimal resource allocation in Software-Defined (SD) networks, there has been a growing trend towards the use of predictive analysis based on Artificial Neural Networks (ANNs) [10] to avoid computational complexity and enable real-time Quality of Transmission (QoT) predictions that are not possible with mathematical models.

To address the shortcomings of static networking, the telecommunication industry is undergoing a paradigm shift towards dynamic and self-learning network management. Research has shown that more advanced machine learning algorithms, such as deep neural networks, are capable of accurately analyzing the attenuation of complex optical signals and nonlinear interference patterns without the need for conventional physical equations [11], [12]. Moreover, AI-powered agents employing deep reinforcement learning have been shown to outperform conventional shortest-path algorithms by maximizing network capacity and minimizing signal attenuation [13]. These dynamic models are able to efficiently handle complex network topologies, enabling SDN controllers to dynamically choose the best routes that can accommodate high-capacity formats such as 64QAM instead of defaulting to the shortest path.

However, despite these accomplishments, traditional ML models have always treated the whole optical lightpath as a single data point, thus resulting in a very important loss of detailed physical information. As distortions have a tendency to cumulatively build up over a series of consecutive fiber spans, Long Short-Term Memory (LSTM) networks have been proven to be extremely effective as tailored solutions for processing sequential data and learning long-term dependencies [8]. Further enhancing this method, a very recent groundbreaking achievement introduced link-level embedding layers [6], [14], thus enabling neural networks to learn the individual physical properties (such as age and type) of each and every individual link. Although the current literature proves the theoretical feasibility of sequential models and embeddings, our proposed Adaptive Machine Learning Framework combines these concepts into a real-time SDN solution. By analyzing real-time telemetry data and periodically retraining the link embeddings, our framework learns to adapt to physical degradation in real-time, thus automatically translating successful QoT predictions into feasible modulation format suggestions.

III. Research Gaps in Existing Systems

From the literature review and the analysis of the current management of optical networks, several critical gaps were identified in the current Quality of Transmission (QoT) estimation systems. Despite the benefits of the conventional mathematical models and the standard Machine Learning (ML) methods, there are considerable limitations with the current systems, which make efficient resource allocation difficult. This shows that there is a need for more research to improve the level of granularity and adaptability of the AI-based optical network controllers.

A. Lack of Granularity in QoT Estimation

One of the most prominent research gaps in the current ML-based network management systems is the lack of granularity while estimating the optical lightpaths. In most of the standard predictive models, the QoT estimation is done by using very aggregated and summarized metrics of the path, such as the total length of the path and the total number of hops, to predict the degradation of the signal. This generalization of the path completely disregards the specific sequence and physical characteristics of the individual fiber links that make up the path. As different cables have different rates of aging, different temperatures, and different rates of non-linear interference, the lack of granularity leads to a lack of accuracy in the predictive models. There is a pressing need to develop architectures that can process the routes segment by segment to obtain the most accurate QoT approximation.

B. Challenges in Practical Machine Learning Application and Data Embedding

Another important research gap in the area of machine learning is related to the application of theoretical models of learning in a real-world networking environment. Although theoretical models of AI have shown significant promise in their application in a real-world environment, their integration with the complex environment of optical network telemetry systems has been an important challenge. An important aspect of this integration is related to the concept of effective data embedding, where the physical topology of the network needs to be converted into a structured format that can be easily processed by the neural network without losing any context. Although the current state-of-the-art approaches have shown limitations in this area, new approaches have shown significant promise.

C. Requirement for Intelligent, Adaptive Routing Agents

Although tremendous work has been done in the theories associated with next-generation networking (Quantum and Software-Defined Networks), there is an urgent need to develop intelligent routing agents that can dynamically allocate network resources. The existing systems are primarily dependent on static routing algorithms and ”worst case” design margins that unnecessarily inflate signal requirements and underutilize the available optical spectrum. The existing routing and network control agents are not intelligent enough to dynamically change the modulation formats based on the outcome of predictive analytics in real-time. There is a need to incorporate highly accurate predictive models directly into the

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network's decision-making logic to develop intelligent, adaptive routing agents that can dynamically allocate bandwidth, avoid connectivity failures, and maximize spectral efficiency in highly constrained networks.

IV. Background and Fundamentals

A. The Mathematical Modeling Bottleneck

For the evaluation of the performance of lightpaths in the network, the traditional approach for network engineers was the Gaussian Noise Model (GNM). This approach involves inputting physical parameters into a set of static equations to obtain the estimated GSNR. The approach estimates the signal degradation by aggregating the linear noise (ASE) and the Non-Linear Interference (NLI). However, the calculation of the NLI for a mesh network is a mathematically exhaustive process. Additionally, the static equations used in the GNM approach are completely inflexible to the effects of network aging and fiber degradation. To account for these effects, engineers have to apply safety margins of +2 dB to +3 dB based on "worst-case" scenarios. This mathematical bottleneck limits the performance of the lightpaths to a slower rate, resulting in huge inefficiencies and a waste of network potential.

B. Link Level Embeddings vs. Summarized Data

Most machine learning algorithms would normally consider an optical path to be a summarized data point, usually calculating an average distance. However, this algorithm does not factor in the individual properties of each link. On the other hand, our framework uses an Artificial Neural Network (ANN), which has a Link Level Embedding layer that projects a special dense vector to a specific fiber cable. The neural network has the capability to "learn" on its own the "physics" of signal degradation and noise specific to a specific cable. It has the capability to understand exactly how signal degradation is accumulated on a specific chain of links, and not an average. It is this capability that enables the neural network to calculate highly accurate GSNR approximations that are required to maximize efficiency.

V. Methodology

A. System Architecture

The proposed methodology would result in a paradigm shift in the existing optical network management system from analytical equations to a dynamic system with Artificial Intelligence capabilities. The proposed system would initiate its process cycle as soon as it receives the lightpath provisioning request from the Network Operator through the Software Defined Networking (SDN) interface. The system would then process the real-time network data, which would offer the status of the existing network from the physical network topology. The real-time network data would undergo intense data engineering, which would identify the Link Embeddings and separate the physical aspects of the network. This would be followed by the seamless integration with the Artificial Neural Network (ANN) model, which would offer a high degree of accuracy in the Quality of Transmission (QoT) prediction. The QoT prediction would be integrated with an automated decision logic module that would enable Modulation Format Selection and Dynamic Spectrum Allocation.

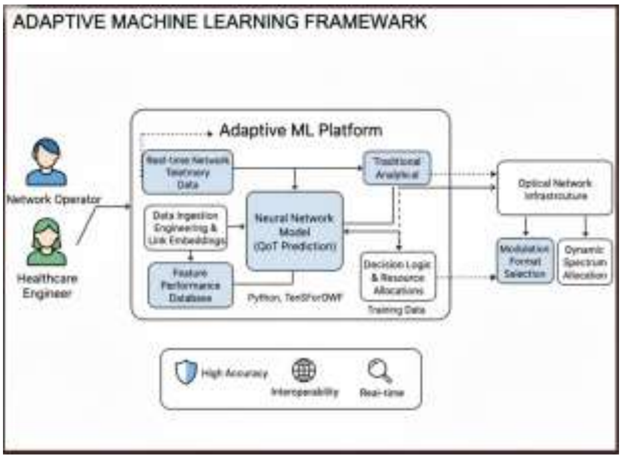

Fig. 1. Proposed System Architecture

B. Model Development and Embedding Layer

The core computation of the predictive framework is developed using machine learning software packages commonly employed in the industry, such as Python, TensorFlow, and Scikit-learn. The novelty in the Artificial Neural Network (ANN) developed in the context of the predictive framework is the novel implementation of the embedding layer, where the exact sequence of individual fiber links forming the route is transformed into a rich and dense continuous numerical vector, rather than processing aggregated or summarized data related to the distance between the links. By transforming the discrete link identifiers into high-dimensional vectors, the ANN autonomously learns the exact "physics" and individual noise characteristics associated with the respective cables. In the training phase, the ANN methodically assesses the exact effect of the degradation of the links on the Generalized Signal-to-Noise Ratio (GSNR).

C. Path Processing and Modulation Selection

Upon receiving a new lightpath request, the system employs graph-based algorithms to compute several potential physical paths connecting the specified source and destination nodes. For each of these computed paths, certain sequential attributes are extracted to produce an overall Path Indices Vector (PIV). The trained ANN model then processes this PIV, which allows it to make an instant prediction of a highly accurate GSNR score for this proposed route. After determining this GSNR score, the system's decision-maker automatically compares this numerical value to strictly defined performance limits to select the most optimal modulation scheme. For instance, if a high GSNR score is predicted (that is, above 22 dB), an "Excellent" status is triggered, which automatically selects 64QAM in order to achieve the highest spectral efficiency and transmission speed. On the other hand, if a low GSNR score is predicted, it automatically triggers a fallback to more robust and noise-tolerant modulation schemes such as 16QAM and QPSK in order to guarantee a high level of reliability.

D. Hypothesis and Mathematical Formulation

To get to the formal algorithm design and solve the compound key question of our research—namely, how to establish the physical link between the individual properties of fiber segments and the accumulated signal degradation—we state our research hypothesis as follows:

H1: Optical fiber links, besides being distinguishable solely based on their physical length, can be more efficiently categorized and quantified into a dense numerical space (embeddings) that captures their unique physical degradation profile.

H2: By using models of sequential memory and an adaptive retraining loop for proposing optimal modulation formats, physically more accurate and reliable Quality of Transmission (QoT) estimates can be obtained compared to static analytical models.

We will discuss the first hypothesis in this paper and formulate it as follows. Let S be the Adaptive ML System.

- $P = \{p_1, p_2, p_3, \dots, p_m\}$ be a set of optical lightpaths.
- $L = \{l_1, l_2, l_3, \dots, l_n\}$ be a set of individual fiber links in the network topology.
- $A = \{a_1, a_2, a_3, a_4\}$ be a set of fiber profile attributes.
- $G = \mathbb{R}^+$ be the set of possible Generalized Signal-to-Noise Ratio (GSNR) values.

Where $m, n \in \mathbb{N}$ and:

- $a_1 \to$ link length $\in \mathbb{R}^+$
- $a_2 \to$ fiber type $\in \{SSMF, LEAF, NZDSF\}$ (nominal attribute)
- $a_3 \to$ accumulated link age $\in \mathbb{N}$ (discretized in months)
- $a_4 \to$ attenuation coefficient $\in \mathbb{R}^+$
- $s_{ij} \to$ sequence index of link l_j within lightpath p_i ($i = 1$ to m, $j = 1$ to n)
- $g_i \to$ actual telemetry GSNR of lightpath p_i ($i = 1$ to m)

Problem Statement: For each lightpath $p_i \in P$, the predicted value of the GSNR is $\hat{g}_i$ such that:

$$\hat{g}_i \approx g_i \tag{1}$$

for a particular ordered sequence of links $\{l_1, l_2, \dots, l_k\} \in p_i$.

Step 1 - Algorithm: build_lightpath_sequence
Input: Raw network topology and telemetry dataset
Output: Ordered sequence of Link IDs forming the optical path
Procedure:

1) For each lightpath $p_i \in P$, an ordered sequence is formed: $V \subseteq L$, where $V = \{l_1, l_2, \dots, l_k\}$. This ordered sequence represents the actual physical path that the optical signal travels.
2) Each link $l_j \in V$ is considered a categorical variable and needs to be converted to a numerical variable before it can be used as input to the neural network.

Step 2 - Algorithm: link_level_embedding
Input: Categorical Link IDs
Output: Dense numerical vectors
Procedure: Create an embedding matrix $E_{n\times d}$ where n is the total number of unique links and d is the embedding dimension (e.g., $d = 32$). Represent each link l_j in a dense vector representation $E(l_j)$ based on the embedding matrix E:

$$v_j = E(l_j), \qquad v_j \in \mathbb{R}^d \tag{2}$$

The embedding matrix E is randomly initialized and trained using the Adam optimizer during backpropagation to minimize the prediction loss.

Step 3 – Algorithm: sequence_processing_lstm
Input: Sequence of embedded vectors $[v_1, v_2, \dots, v_k]$
Output: Predicted GSNR value $\hat{g}_i$
Initialization: $C_0 = 0, h_0 = 0$
For each time step $t = 1$ to k:

$$f_t = \sigma(W_f \cdot [h_{t-1}, v_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, v_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, v_t] + b_c)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, v_t] + b_o)$$
$$h_t = o_t \cdot \tanh(C_t)$$

After processing the full sequence, apply a dense layer:

$$\hat{g}_i = W_{dense} \cdot h_k + b_{dense} \tag{3}$$

Step 4 - Algorithm: adaptive_retraining_trigger
Input: New real-time telemetry data g_{new}, Predicted values $\hat{g}_{new}$
Output: Updated model weights stored in .keras file
Select error threshold: $\delta \in \mathbb{R}^+$ (e.g., $\delta = 1.0$ dB)
Calculate Mean Absolute Error (MAE):

$$E_{current} = \frac{1}{|P_{new}|} \sum |g_{new} - \hat{g}_{new}| \tag{4}$$

If $E_{current} > \delta$, then:

1) Initialize retraining module (`trainer.py`)
2) Load new telemetry data into feature database
3) Update embedding matrix E and LSTM weights using Adam optimizer
4) Save updated model parameters

VI. Challenges and Limitations

Even though the proposed Adaptive ML Framework maximizes the prediction of QoT and dynamic resource allocation, there are some challenges associated with the implementation of the proposed framework.

A. Computational Training Requirements

The deployment of the Adaptive Machine Learning Framework entails high computational complexity, particularly during the first training phase of the model. The training of the deep ANN model with complex link-level embedding layers involves the processing of a large amount of historical network telemetry data. The high computational complexity involved in the process makes hardware acceleration a high priority, with high-end NVIDIA GPU or TPU hardware being almost a necessity to ensure reasonable training convergence times. This entails high costs for network operators to deploy the hardware acceleration clusters. Furthermore, as the size of the physical network topology increases, the computational complexity of the periodic model retraining process becomes significant.

B. Data Dependency and Quality

The predictive capability of the proposed framework, particularly the link-level embedding layer, is very much reliant on the quality and quantity of the training data. This means that in order for the neural network to be able to learn the physical characteristics and noise patterns of individual fiber spans effectively, it is required to process a large amount of high-resolution telemetry data. In the case where the ingested data is small in quantity or of low quality owing to the presence of faulty sensor hardware, the predictions of GSNR made by the proposed framework will be naturally affected. This means that older network segments that do not have modern high-resolution monitoring hardware may not be able to benefit from the AI-driven optimizations until a large amount of hardware upgrades are carried out.

C. Integration with Legacy Systems

One of the major architectural hurdles that the transition of a well-established optical network from conventional mathematical models, such as the Gaussian Noise Model (GNM), into a new AI-based inference engine is the integration of the new paradigm into the current architecture. Most of the current telecommunications operators use well-entrenched legacy systems that cannot natively support the integration of dynamic machine learning or real-time predictive analytics. This integration process is a major undertaking that involves the development of a new control plane architecture and the creation of APIs for the ingestion of data into the new paradigm. In addition, the operational risks involved in the transition process often require the operators to run the new paradigm in tandem with the old paradigm, which is a major undertaking from a software engineering point of view.

VII. Experimental Results and Discussion

The significance of our work is that we are employing deep sequence learning algorithms to design a new system that can assist in more precise Quality of Transmission (QoT) estimation and lightpath recommendation. The benefit of our system is that it possesses the ability to assist network operators in offering highly relevant and dynamic navigational assistance for complex optical networks. Rather than recommending based on static, worst-case physics equations that say "This path may have high noise, use a low-capacity format," recommendations are of the form "Based on the specific sequence of embedded link identities and the current telemetry, this path will provide a GSNR of 22.5 dB, which will comfortably support 64QAM." The system improves decision confidence for network operators by providing accurate QoT predictions and reliable modulation format recommendations.

For the implementation, we utilized an augmented optical network dataset that consisted of 137,856 unique lightpaths that were routed according to a 300-link topology. Since real-time, link-specific telemetry datasets directly correlated to Generalized Signal-to-Noise Ratio (GSNR) are extremely complex, the implementation phase entailed the processing of raw path sequences into categorical Link IDs, applying our Link-Level Embedding layer to them, and training a 64-unit Long Short-Term Memory (LSTM) network. Later, after applying the Adam Optimizer for 30 training epochs, we derived the following convergence values for our sequence model:

Fig. 2. Training and Validation Loss (MSE) over Epochs

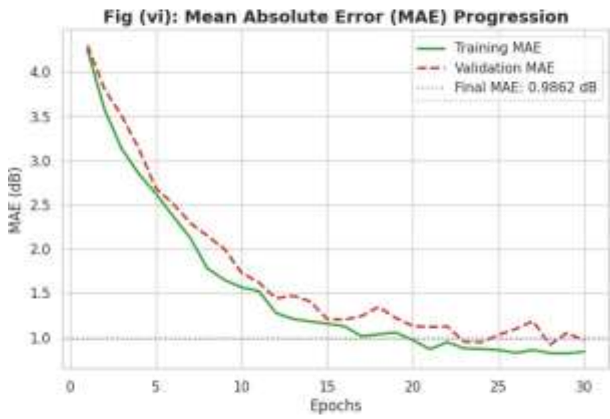

Fig. 3. Mean Absolute Error (MAE) Progression

From Fig (2) and Fig (3), it can be seen that the model is learning the physical equations at a fast pace in the initial 10 epochs. The training and validation loss curves are converging smoothly without any sudden change, which proves that our LSTM model with a dropout value of 0.2 is successfully preventing the process of overfitting. The final Mean Absolute Error (MAE) is achieved with a highly accurate value of 0.9862 dB, which clearly shows that the difference between our predicted GSNR and the actual physical GSNR is remarkably small.

One may be wondering how it is difficult to assess this system in a real-world, physically varying environment. The manner in which the assessment of this deep learning simulation occurs is through empirical inference of whether or not the target SDN controller is able to safely assign modulation formats based on the predicted GSNR without violating bit error rate thresholds. The only issue with this offline inference is that we are not able to assess this model for each and every possible future fiber cut and temperature change in our offline testbed. However, the relevance and importance of this offline inference is that the prediction of QoT computationally by the LSTM model occurs in less than 1 second at near-zero cost to the operator, compared to the enormous processing power and time that the traditional mathematical GNM computation requires.

Going ahead, we created a testing subset of lightpaths to study the distribution of the accuracy of the model. By using the application of multi-attribute predictive visualization tools, we created a graph of the predicted GSNR values versus the actual GSNR values in the dataset, and we got some very interesting results. In Fig (4), the scatter plot represents the variance of the model. The points that are lying exactly on the diagonal line represent 100% accuracy. The points that are scattered around the regression line represent the prediction of the non-linear accumulation of noise in the framework.

Moving ahead, based on the application of our decision logic on the output of the LSTM layer, we get specific tags for the modulation format based on the predicted GSNR thresholds. With the safety margin set to zero, we get the routing tags for the lightpaths. The system then provides the sequential intelligence of the path, which provides a sound capacity recommendation.

The level of accuracy of the current model is 71.12% regarding R-squared accuracy, which means that a tremendous amount of variance in GSNR is being accounted for. However, it is expected that the level of accuracy of the predictions will increase with the growing amount of real-time telemetry data being inputted into the model. With each level of the system life cycle, the amount of training data available to the model will increase, which will allow the model to learn and understand complex and unusual phenomena in the physical world of the optical network.

The Adaptive Retraining Loop makes sure that the system is learning at all times and is keeping up with the dynamic nature of the network as time passes with the growth of the telemetry database.

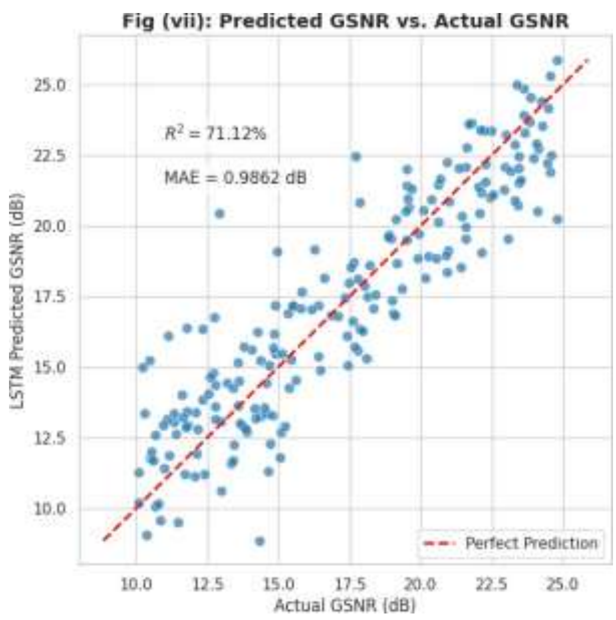

Fig. 4. Predicted GSNR vs Actual GSNR

Fig. 5. Decision Mapping of LSTM-Predicted GSNR to Optimal Modulation Formats

VIII. Conclusion and Future Scope

To address the lack of granularity in traditional Quality of Transmission (QoT) estimation, the current project successfully developed an adaptive machine learning framework with an Artificial Neural Network core. By integrating a link-level embedding layer, the framework now processes the actual sequential network structure into a rich numerical vector, enabling the fine-grained network details to be captured and processed accurately. The framework, developed using Python and TensorFlow, provides highly accurate Quality of Transmission approximations (GSNR) and directly enables the intelligent selection of modulation formats, thereby providing efficient and reliable network performance.

In the future, the framework may be further developed to include the ability to periodically re-train the model using actual network data, thereby maintaining the accuracy of the model over time as the physical network infrastructure naturally changes and degrades over time. This innovative method opens the door to fully autonomous optical network management systems.

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