

Multi-factor Fused Lightpath QoT Prediction for Optical Networks: A Multiple Reservoir Analysis Strategy

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Abstract

For responsive and instant transparent optical network management, investigating the channel quality of transmission (QoT) in-depth is crucial. However, current lightpath QoT predictions devote to univariate modeling. Due to the QoT metrics complicated time-varying process and the existing effects of inter-channel factors, despite the use of advanced and efficient echo state network (ESN), it is difficult to obtain ideal results in univariate prediction mode. Thus, in this paper, we considered multi-factor fused mode for lightpath performance prediction based in multiple ESN (MSEN). In fact, despite the optical backbone network's ultra-high data rates, long-distance transmission networks are frequently subject to erratic and dynamic external factors that have a negative impact on service quality. As a result, network managers are forced to increase operating costs and add more design margins. Therefore, it is crucial to track the physical layer performance of optical networks to promptly and accurately detect and address optical link problems and provide transparent, real-time network intelligent management. Experimental results on real-world optical-layer characteristics from the Microsoft optical backbone network demonstrate that the proposed MESN performs much better in prediction than the classic ESN approaches.

Keywords: Quality of Transmission; Optical backbone network; Multiple echo state network; multi-factor prediction

INTRODUCTION

The continuous growth of smart modern applications in 5G and 5G beyond networks, such as Industrial Internet, smart agriculture, and unmanned technology, leads to a capacity higher demand for the transport network segments [1]. In this context, the flexible optical backbone network with high-performance and low latency is an alternative to accommodate this scenario, which complies with the massive access signals reliable carry [2].

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As for ultra-high data rates of the optical backbone network, the long-distance transmission network is often vulnerable to some random and dynamic external factors, which severely influences the quality of service, forcing network managers to deploy more design margins and increasing the operating costs [3]. Thus, to identify and handle optical link failures in a timely and accurate manner, achieving transparent and real-time network intelligent management, it is essential to monitor physical layer performance of optical networks.

The performance monitoring process is a series of measurements performed on the physical layer

intermediate network nodes for optical signals [4]. For the monitored data, it is feedback needed for guaranteeing optical network quality of transmission (QoT). Specially, due to the dynamic link provision in intelligent optical networks operating in low-margin states, the management strategy of precise and fast QoT estimation is extremely vital [5].

Recently, many studies have focused on univariate QoT prediction, mainly using optical signal quality metrics as modeling inputs [6–9]. Li et al. [10] considered echo state network (ESN) and its variants to prediction the Q-factor of a certain channel in wide-area optical backbone network, the results significantly outperform the state-of-the-art models with an effective training time. Whereas, traditional ESNs are consisted of a shallow reservoir, which may be challenging to support large amounts of data analysis. Using a stacked reservoir structure as a modeling strategy is an effective alternative to ensure computational efficiency while improving prediction accuracy. In addition, with the reconfiguration of optical networks and changes in modulation methods, the optical channel QoT is usually affected by the cumulative influence of optical channel state parameters (OCSP) of neighboring channels in wavelength division multiplexing (WDM) systems, including chromatic dispersion (CD), and polarization mode dispersion (PMD) deployed in different channels [11–12]. Therefore, modeling and analyzing the quality metrics merely is insufficient. Once considering the effect of inter-channel OCSPs, the accurate QoT prediction performance is ensured.

Therefore, in this article, we investigate a novel optical lightpath QoT analysis method based on multiple reservoir architecture. This is the first attempt to evaluate the lightpath performance from a view of multi-factor fused, considering multiple ESN (MESN). As the prediction step increases, the prediction accuracy achieved by our proposal is better than that of classic ESN, i.e., shallow ESN (SESN). The rest of this paper is structured as follows: Section 2 discusses the proposal contributions, introducing the MESN structure. In Section 3, we discuss the stimulation results which confirm the validity of our proposal, while the conclusion and future work are given in Section 4.

PROPOSED APPROACH

In this section, we mainly give a detailed description for the multiple reservoir structure. Concretely, we introduce the whole framework, and then the MESN architecture is depicted, followed by the reservoir update strategy and the acquisition of optimal output weights. Ultimately, the MESN is recommended for our multi-factor lightpath QoT prediction task.

Overview

In Figure 1, the 5G wireless communication network motivates the smart city constructions with multiple wireless access base stations. These base stations receive a large amount of access traffic signals, which are routed and converted to different wavelengths $\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_n$ via optical cross connector (OXC) and transmitters. Then, the carrier signals are coupled into the same lightpath by multiplexers (MUX) for efficient transmission.

Moreover, the raw traffic signals are decoupled by demultiplexers (DEMUX) and obtained via receivers. Further, the OXCs repeat the signal processing process described above to transmit the traffic data to other cities for network interconnection [13].

To accommodate high bandwidth scenarios resulting from exponential traffic growth, it is imperative to design intelligent management optical transport network. Thus, optical performance monitoring (OPM) serves as a potential control mechanism for dynamic optical network performance diagnosis and management, aiding accurate decision-making at the physical layer and improving network transparent visibility.

Based on this, we obtain original optical performance monitoring data (Q-factor, TP, CD and PMD, etc.) and use machine learning methods for modeling and analysis. To further boost the analysis

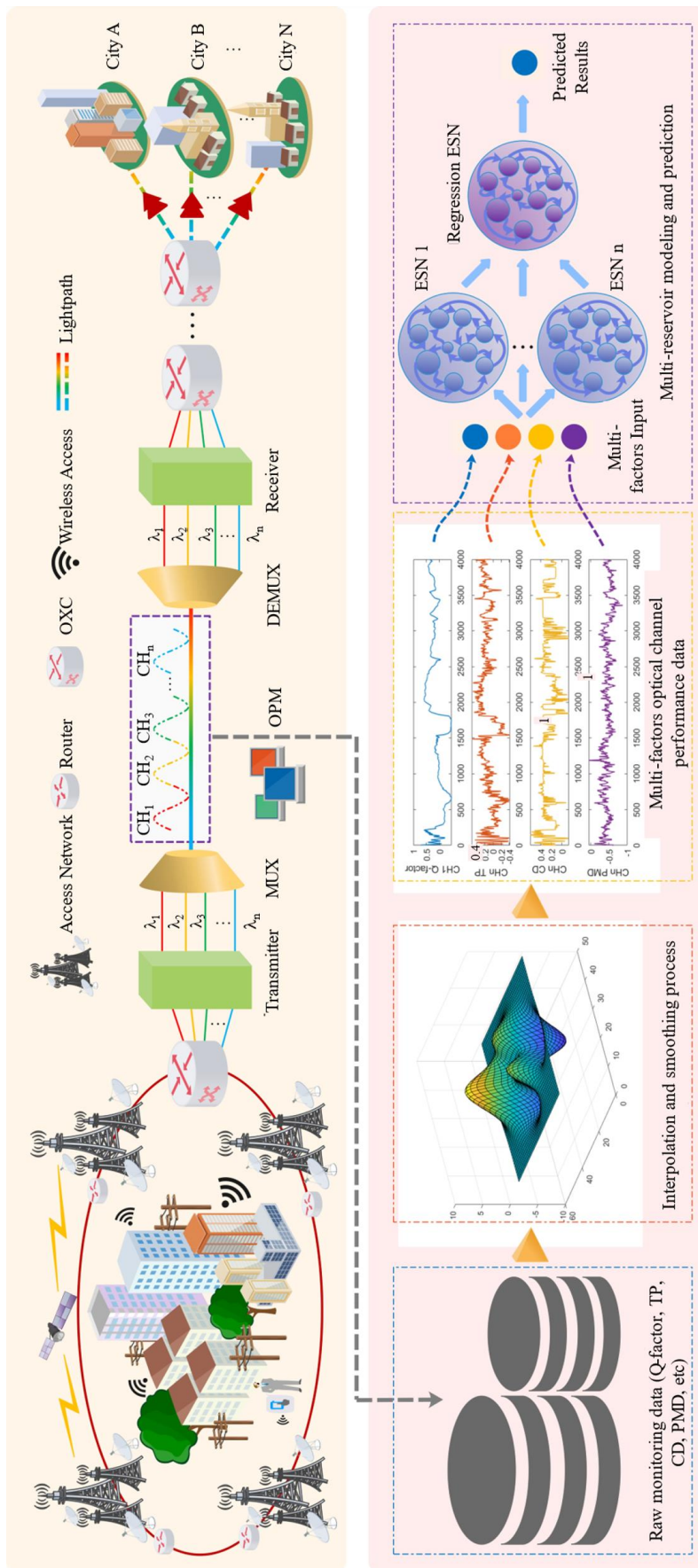


Figure 1. An illustration of multi-factor fusion lightpath QoT prediction task.

performance of the learner, these data are we pre-processed through normalization, interpolation, and smoothing. On the basis of considering the influence of the neighboring channel impairment factors, we use the multi-reservoir computing method for multi-factor fusion prediction of optical channel QoT. In addition, we also consider a multi-step forward prediction strategy, on one hand, this analysis mode can provide optical network fault warning within a certain period of time, thus assisting network managers with auxiliary decisions for uninterrupted normal operation of optical networks. On the other hand, the learning capability of multiple reservoir modeling approach is further validated, while the following gives the detailed structure descriptions.

Prediction Model Structure

Here, the considered optical lightpath prediction model is investigated from the dominance in MESN, which is shown in Figure 2. Taken as a whole, the several vertically tiled reservoirs sufficiently map each variable of a complex time series to the characteristic space, while the network depth and short-term memory capacity of the reservoir are enriched via the regression ESN. The above advantages significantly improve nonlinear approximation performance of the model so that ensuring the superior performance in the multi-factor lightpath prediction tasks. The MESN update modes are depicted as follows

$$x_K(t+1) = (1-\alpha)x_K(t) + \xi \cdot \alpha [W_{in}^{(K)}r(t+1) + Wx_K(t)] \quad (1)$$

$$x^{REG}(t+1) = (1-\alpha)x^{REG}(t) + \xi \cdot \alpha \{W_{in}^{REG}[x_1(t+1); \dots; x_K(t+1)] + Wx^{REG}(t)\} \quad (2)$$

$$c(t+1) = \xi \cdot [W_{out}x^{REG}(t+1)] \quad (3)$$

where $r(t)$ represents the model input, analyzed by each of the tiled reservoirs, $x(t)$ and $c(t)$ represent the reservoir state and the readout. W_{in} denotes the weight matrices between input and vertically tiled reservoir layers, while each tiled ESN internal weight matrix is defined by W , W_{out} denotes the weight matrices between regression reservoir and output. $\zeta(\cdot)$ is the activation function, i.e., \tanh . K and α depict every tiled reservoir serial number and leaky rate respectively, $[\cdot]$ represents matrix merging operation. Specially, to guarantee each reservoir echo state property, the W need to be measured as of which $|\mu_{max}|$ denotes the maximum spectral radius of each reservoir, and the range of δ is limited to $(0,1)$.

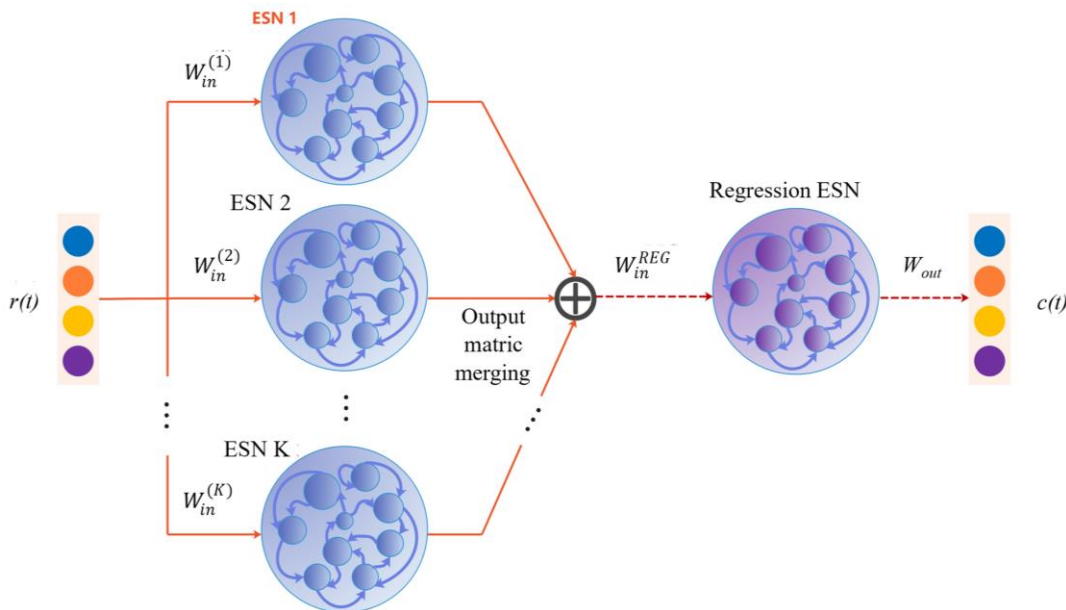


Figure 2. The structure of MESN.

$$W \leftarrow \frac{\delta}{|\mu_{\max}|} W \quad (4)$$

Actually, obtaining the optimal W_{out} is the final goal of the modeling process, where the calculated reservoir states are collected as matrix X , their corresponding outputs are assembled into matrix Y . Hence, the W_{out} is computed as

$$W_{\text{out}} = Y^T X (X X^T)^{-1} \quad (5)$$

Finally, once the optimal output weight is obtained, it indicates that the multi-reservoir model has the ability to solve multivariate prediction issues, such as multi-impairments fusion lightpath QoT prediction task.

EXPERIMENTS

In this section, to verify the proposed MESN modeling capacity for the multi-factor lightpath prediction tasks, we perform a comprehensive experimental simulation. Concretely, the investigated dataset is introduced firstly, followed by the description of measure criterions. Then, we compare the predicted values stemmed from all the models with the real outputs in multi-step analysis configurations, while also considering the computational efficiency. Moreover, we further validated the superior performance of MESN from a statistical analysis perspective. All the simulations are performed based on the matlab 2021b platform.

Dataset and Measure Criterions

The dataset contains Q-factor and impairment parameters, i.e., TP (dBm), CD (ps/nm), and PMD, which is originated from Microsoft optical backbone in North America with O(50) optical cross-connects, O(100) WAN segments, and O(1000) optical channels. It is specified over 14 months from February 2015 to April 2016, and each performance factors are sampled per 15 minutes [14]. In our implementation, the Q-factor in a particular channel is regarded as a performance measurement, while the impairment parameters in local and neighboring channels are the influence factors. Concretely, we select channel 1, channel 2 and channel 4 in segment 1 as analysis object, considering Q-factor in channel 1 and impairment parameters in all evaluated channels. To eliminate the outliers in original data and avoid unreasonable analysis decisions, guaranteeing the prediction accuracy, we first reduce the polling frequency to 5 minutes via cubic interpolation, and then the interpolated data is processed by Kalman smoothing. Finally, we select $L_{\text{train}} = 72000$ and $L_{\text{test}} = 18000$.

In addition, in order to better measure the different modeling methods performance, we consider Normalization Root Mean Square Error (NRMSE) and Goodness of Fit (R²) as testing criterions, which are depicted in Eq. 6 and Eq. 7.

$$\text{NRMSE}(\hat{Y}, Y) = \sqrt{\frac{\sum_{k=1}^L (Y^{(k)} - \hat{Y}^{(k)})^2}{D(Y) \cdot L}} \quad (6)$$

$$R^2(\hat{Y}, Y) = \frac{\sum_{k=1}^L (\hat{Y}^{(k)} - \overline{Y^{(k)}})^2}{\sum_{k=1}^L (Y^{(k)} - \overline{Y^{(k)}})^2} \quad (7)$$

where \hat{Y} and Y represent the desired and predicted output Q-factor respectively, L denotes the Q-

factor series length. Specially, in Eq. 6, $D(Y)$ indicates the Y variance.

Prediction Performance Evaluation

In our experiment, for comparing the evaluated model's performance against baseline, we investigate several prediction steps, i.e., $S_1 = 6$, $S_2 = 12$, and $S_3 = 24$, corresponding to the horizons of 0.5h, 1h, and 2h for network managers decision and deployment in advance. Table 1 reports the models' multi-step ahead prediction performance for the lightpath performance data. From a macroscopic view, our proposal particularly outperforms to the competitor in different prediction step configurations, i.e., SESN. It is owed to the decision of multiple reservoirs, which better adapts the multi-factor and disorder series analysis scenarios. Taking the example of R2, its prediction performance is increased by about 23% over the SESN at the horizon of 2h.

In order to visualize the fit degree more intuitively, the prediction error fitting results are plotted between desired outputs and system outputs obtained by evaluated models over a selected region from the time step 1001-1500, which is shown in Figure 3. Obviously, the SESN has a higher error amplitude than MESN at different horizon analysis scales, which implies relatively worse prediction performance. For further verify the superior of MESN, we consider statistical analysis method, i.e., Cumulative Distribution Function (CDF) plots.

Table 1. Performance analysis in the case of multi-factor fusion prediction task.

Criterion	S_1		S_2		S_3	
	<i>NRMSE</i>	<i>R2</i>	<i>NRMSE</i>	<i>R2</i>	<i>NRMSE</i>	<i>R2</i>
SESN	0.0777	0.9947	0.1950	0.9655	0.5188	0.7746
MESN	0.0379	0.9986	0.0937	0.9912	0.2188	0.9527

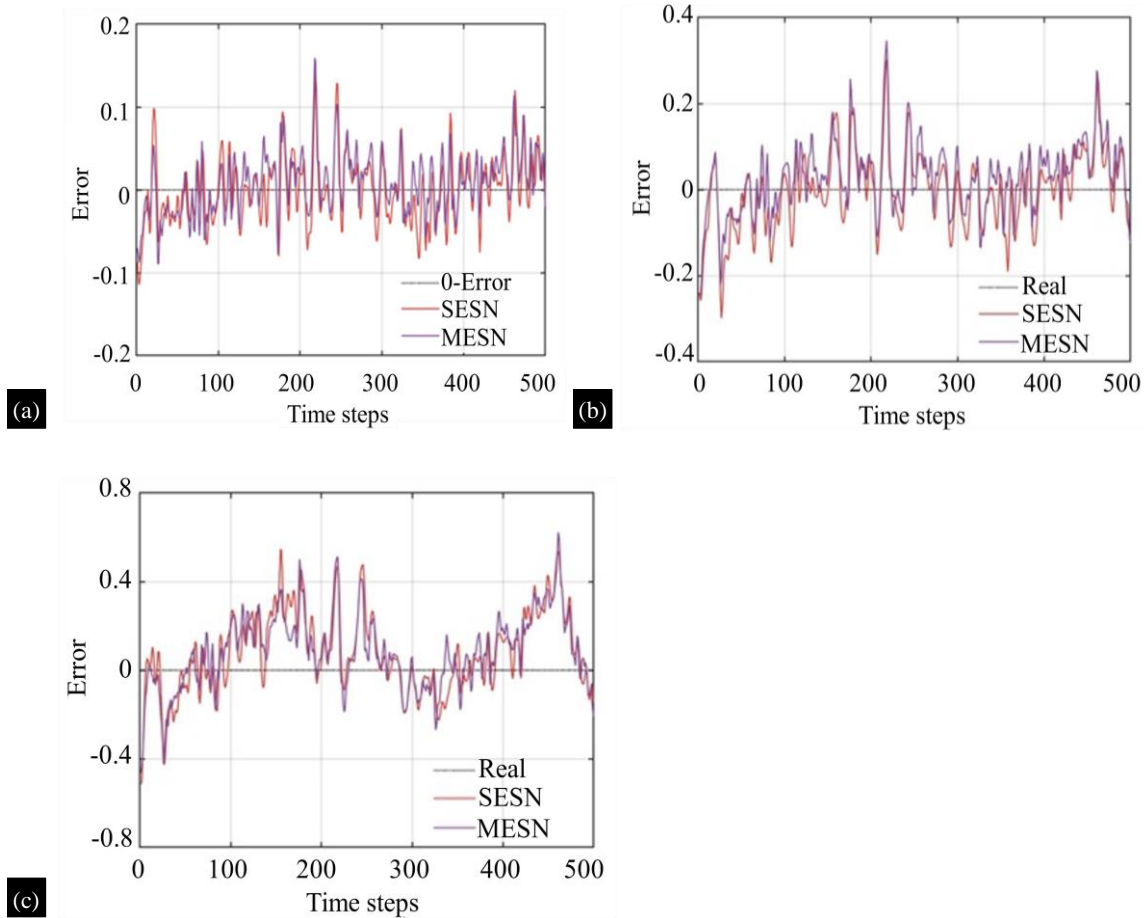


Figure 3. Test errors of evaluated models. (a) Step=6; (b) Step=12; (c) Step=24.

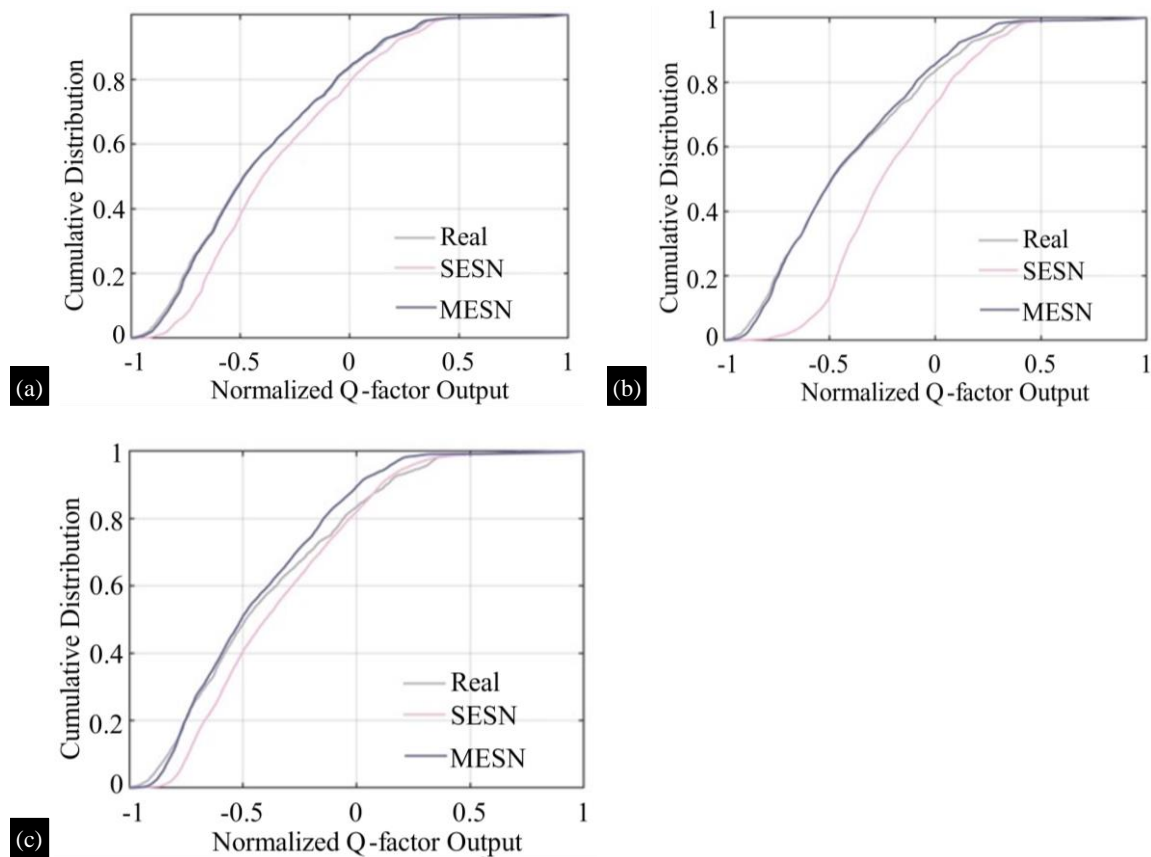


Figure 4. CDF estimation of multiple steps. (a) Step=6; (b) Step=12; (c) Step=24.

Figure 4 shows the comparative CDF plots on the evaluated models' outputs in a bid to validate the utility of our proposal. Mathematically the CDF plot illustrates whether the a certain predicted QoT value is equal to or less than a specific value. Obviously, it can be seen from Figure 4 (a-b) that the distribution of outputs generated by MESN basically curves the expected values. While our proposal in Figure 4 (c) have some deviations compared to the true values, but SESN has relatively more deviations. The analysis phenomenon is consistent with the results in Figure 3.

CONCLUSIONS

In this article, a novel multi-factor fusion lightpath performance analysis is developed on the basis of the MESN structure. Experimental results on real-world QoT data demonstrate that MESN can achieve superior prediction performance, significantly outperforming SESN. Under multiple prediction time steps, our proposal can obtain an average NRMSE and R2 of 11.68% and 98.08% on the Q-factor dataset. In future work, we will examine how horizontal stacking reservoirs affect prediction accuracy and attempt to incorporate attention mechanisms into MESN.

Supplementary Materials: None.

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