A Novel Reliability Evaluation Model for an End-to-End Optical Transmission Channel

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***Abstract*—A novel reliability evaluation model for end-to-end optical transmission channels is proposed, consisting of QoT and steady-state operation probability. We verify the accuracy of evaluating the reliability by using machine learning and the Markov process.**

***Index Terms*—reliability, machine learning, end-to-end optical transmission channel, Markov process**

I. Introduction

Optical networks are essential to modern communication networks, which carry many data and communication services. Over the last few decades, numerous advancements have been made in developing optical networks. For instance, researchers have proposed various techniques such as time-space-frequency multiplexing technology and multiple transport protocols, including path computation element (PCE) and software-defined optical networks (SDON). Further, several protection structures, such as p-cycles and shared backup path protection (SBPP), have been proposed to ensure reliable network performance and minimize latency while achieving large bandwidth and high transmission rates [1]. However, the reliability of the end-to-end optical transmission channel is difficult to guarantee due to various reasons, such as the environment, natural disasters, human damage, load imbalance, and the aging of optical fibers or optical devices [2]. To allocate resources as reasonably as possible and guarantee reliable data transmission, we need to evaluate the reliability of the end-to-end optical transmission channel. By quantitatively evaluating the reliability of end-to-end optical transmission channels, we can identify highly reliable end-to-end optical transmission channels and channels with potential risks. This will help researchers to determine the appropriate protection measures when deploying services on optical networks. In addition, quantitative assessment can help operators better understand transmission performance, enable planning of optical network upgrades and maintenance, and predict possible future problems to provide more accurate decision-making services.

In [3], the authors proposed a model for segment protection and evaluated the availability of segment protection. In [4], the authors evaluated the reliability of the line based on matrix-based connection unavailability. In [5], the authors evaluated the accurate real-time availability of end-to-end optical transmission channel transmission parameters to improve the efficiency of control and management operations significantly. The existing studies on end-to-end optical transmission channel reliability only analyze from the perspective of failure rate but do not consider the quality of transmission (QoT) and steady-state probability of the end-to-end optical transmission channel, which to some extent, limits the comprehensive evaluation of the end-to-end optical transmission channel reliability.

This paper proposes a novel reliability evaluation model for end-to-end optical transmission channels. The model consists of two factors, one is the QoT, and the other is the steady-state operation probability. By training the transmission data obtained from the simulation by machine learning, we can accurately predict the QoT. The steady-state operation probability of the system can be calculated by modeling the end-to-end optical transmission channel through the Markov process. Compared with existing studies, the innovation of this paper is to combine QoT with reliability probability to give the probability of maintaining the current reliability and to evaluate the reliability of the end-to-end optical transmission channel quantitatively.

II. Reliability evaluation Model

This paper proposes a novel reliability evaluation model for end-to-end optical transmission channels. We classify the factors affecting the reliability of end-to-end optical transmission channels into two categories: slow change and drastic change factors. Slow change factors include device aging, unsuitable

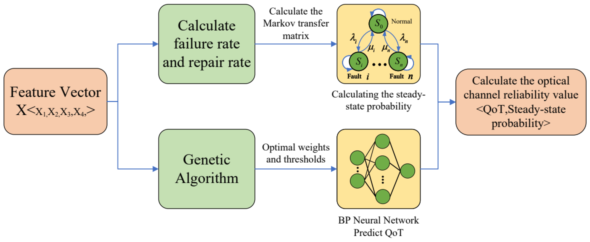

Fig. 1. Reliability evaluation model

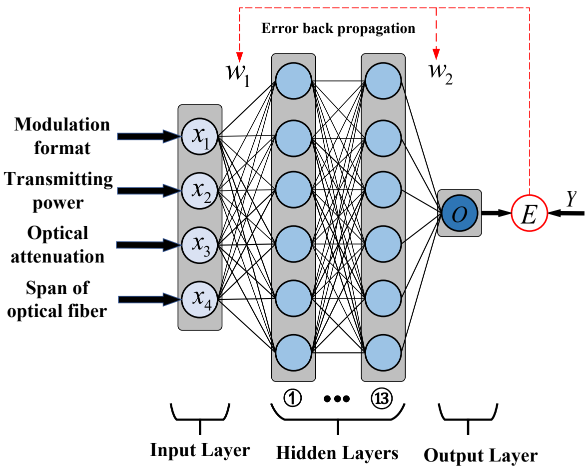

Fig. 2. BP neural network-based QoT prediction method for the end-to-end optical transmission channel

temperature, fiber stress, etc. These factors degrade QoT. The drastic change factor is the interruption of data transmission caused by device failure. Both slow change and drastic change factors directly degrade the reliability of the end-to-end optical transmission channel. Therefore, we consider the impact of both slowly and drastically changing factors on the end-to-end optical transmission channel. Finally, we define the reliability metric as a two-dimensional vector$< QoT, A >$.

QoT is a critical metric that can be expressed regarding optical signal strength, optical signal-to-noise ratio (OSNR), and bit error rate (BER). If the QoT is poor, the signal will be severely distorted during transmission, resulting in reception errors at the receiving end and reducing communication reliability. A represents the steady-state availability probability of the system. Availability refers to the ability of the end-to-end optical transmission channel to operate normally at a given time. Supposing network components or optical fiber links fail. In this case, the availability of the end-to-end optical transmission channel becomes poor, leading to transmission interruptions or data loss and reducing the reliability of the network. In practical applications, we can easily obtain data on the QoT of end-to-end optical transmission channels, the failure rate, and the repair rate of optical fibers and components. Therefore, the evaluation model proposed in this study is highly feasible in existing networks.

As shown in Fig.1, we demonstrate the reliability evaluation model for the end-to-end optical transmission channel. To predict QoT, we build a genetic algorithm-based BP neural network (GA-BP) and obtain a large amount of data for GA-BP training through simulation. In addition, we calculated the probability of maintaining the reliability of the end-to-end optical transmission channel in steady-state operation using the Markov process. Based on these two metrics, we can obtain the end-to-end optical transmission channel reliability values.

III. QoT PREDICTION BASED ON GA-BP

This section details the prediction of QoT for end-to-end optical transmission channels based on a GA-BP neural network framework and describes the specific process of optimization using a genetic algorithm (GA).

A. *Construction of GA-BP model*

BP neural network is a commonly used artificial neural network that trains the model by the backpropagation algorithm, minimizes the loss function using the gradient descent method, and updates the weight and bias value of each neuron layer by layer according to the error. The BP neural network constructed in this study is shown in Fig.2. The BP neural network consists of one input layer, thirteen hidden layers, and one output layer. The number of neurons in the input layer equals the input feature value, while the output layer represents the value of the BER at the receiver side. We use the trial-and-error method during the training process to determine the number of hidden layers and the learning rate. However, BP neural networks have the disadvantage of easily falling into local minima. To address the shortcomings of traditional BP neural networks, we use a GA to optimize the initial weights and thresholds of the optimal BP neural network. The GA is a global optimization algorithm that simulates natural selection and genetic laws. The goal is to optimize the neural network's parameters for high data prediction accuracy. As shown in Fig.3, we show the overall computational flow of the algorithm. We encode the genes and generate a population size of a specific size. The initial fitness of the population is calculated. Specifically, this study chooses the means square error function (MSE) as the fitness function. The chromosome length equals the number of weights and thresholds in the BP neural network, and each gene represents a weight or threshold. Then we select individuals by roulette algorithm and use a uniform crossover operator and uniform variation operator for crossover operation and variation operation. The fitness of the population is calculated again after generating a new population, and the individuals with the best fitness are saved for each generation. Until the number of iterations is reached, the optimal initial weights and thresholds of neurons can be obtained.

IV. STEADY-STATE AVAILABILITY CALCULATION BASED ON MARKOV PROCESS

This section describes the Markov modeling process and presents the use of the Markov process to calculate the

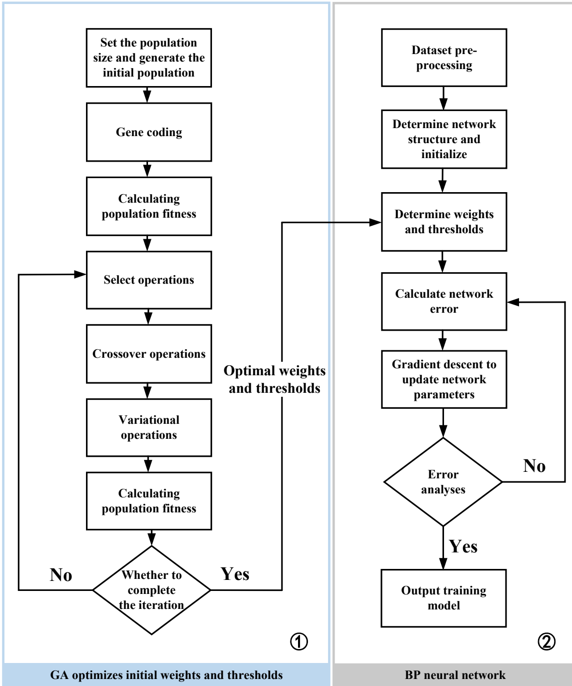

Fig. 3. Implementation mechanism of QoT prediction based on GA-BP algorithm

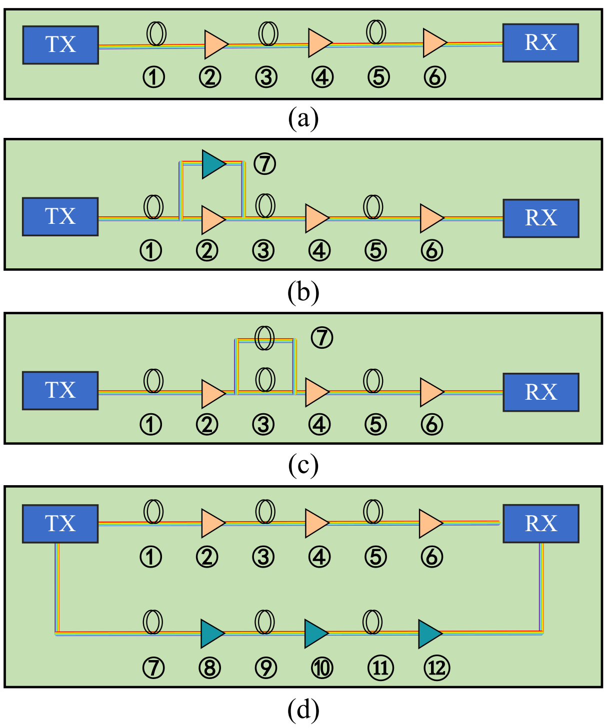

Fig. 4. Four types of end-to-end optical transmission channels (a)Unprotected end-to-end optical transmission channel (b)End-to-end optical transmission channel protected only for EDFA (c)End-to-end optical transmission channel protected only for fiber (d)1+1 protection for end-to-end optical transmission channels

availability of a single unprotected channel, protection for a single optical component, and 1+1 protection for the end-to-end optical transmission channel, respectively.

A. Availability of unprotected end-to-end optical transmission channels

The mean time to failure (MTTF) or system mean failure rate is commonly used to calculate the reliability of the end-to-end optical transmission channel. However, these calculation methods are inadequate as the reliability of the system is affected by numerous factors. The Markov process is widely utilized to evaluate complex systems' reliability accurately. Markov process is based on a transfer probability matrix to describe the probability of the system from one state to another so that it can consider various complex interactions and dependencies in the system. The probability and steady-state availability of transmission channels in each state can be determined by applying the Markov process to the end-to-end optical transmission channel. Thus reliability can be assessed more accurately. There are several assumptions for the application of Markov theory [6].

- Components have only two states, fault and working.
- All components fail independently and do not affect each other (not considering the case of multiple failures).
- Components have a constant failure rate and repair rate.
- The next state of the components is only related to the current state and not to the past state.

As shown in Fig.4(a), the system consists of three EDFAs and three fiber segments, numbering each of the six components. The Markov transfer probability diagram is displayed in Fig.5. Where $\lambda_1, \lambda_2, \cdots \lambda_6$ and $\mu_1, \mu_2 \cdots \mu_6$ represent the failure rate and repair rate of components $1-6$, respectively. $S_0, S_1, S_2, \cdots S_6$ represents the state space of the system. S_0 represents the states where the system works normally, and $S_1 - S_6$ represents the states where components $1-6$ fail, respectively. The Markov process is applied to describe the system's transfer probability. The Markov transfer equation is shown in (1) [7].

$$\frac{dP_i(t)}{dt} = -\sum_{i \neq j}^{N} a_{ij} P_i(t) + \sum_{k \neq i}^{N} a_{ki} P_i(t) \tag{1}$$

Where a_{ij} denotes the rate of leaving the state i and a_{ki} denotes the rate of entering state i. Calculating the state equations for all states and representing them in a matrix, we can obtain (2).

$$\begin{bmatrix} \frac{dP_0(t)}{dt} \\ \frac{dP_1(t)}{dt} \\ \vdots \\ \frac{dP_N(t)}{dt} \end{bmatrix} = \begin{bmatrix} -\sum_{i=1}^{N} \lambda_i & \mu_1 & \cdots & \mu_N \\ \lambda_1 & -\mu_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_N & 0 & \cdots & -\mu_N \end{bmatrix} \begin{bmatrix} P_0(t) \\ P_1(t) \\ \vdots \\ P_N(t) \end{bmatrix} \tag{2}$$

$$\sum_{i=0}^{N} P_i(t) = 1 \tag{3}$$

Based on the (2) and (3), and considering the initial state of the system, the probability of occurrence of each state can be

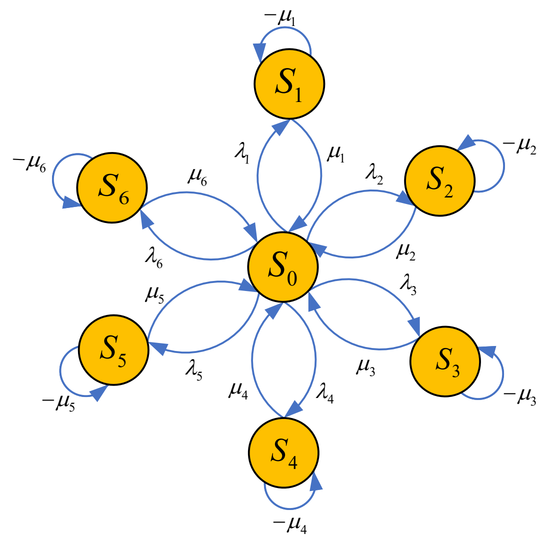

Fig. 5. Markov transfer probability diagram for unprotected end-to-end optical transmission channel

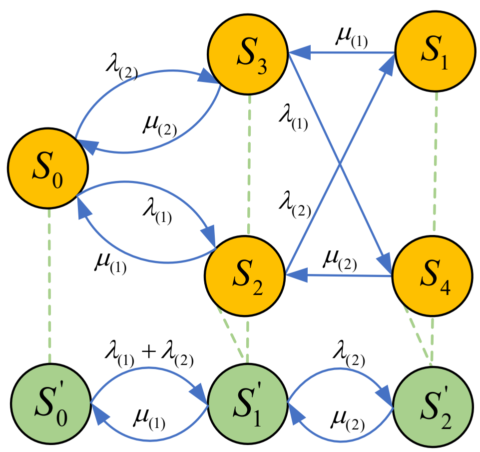

Fig. 6. Markov transfer probability diagram for a single component in the protected end-to-end optical transmission channel

calculated. In practical applications, steady-state availability is usually used to measure the availability of the system. When the system reaches the steady state, (4) can be obtained.

$$\lim_{t\to\infty}\frac{dP_i(t)}{dt}=0(i=0,1,\cdots N) \tag{4}$$

The system steady-state transfer matrix is shown in (5) and can be calculated by combining (2) and (4).

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} -\sum_{i=1}^{N}\lambda_i & \mu_1 & \cdots & \mu_N \\ \lambda_1 & -\mu_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_N & 0 & \cdots & -\mu_N \end{bmatrix} \begin{bmatrix} P_0(t) \\ P_1(t) \\ \vdots \\ P_N(t) \end{bmatrix} \tag{5}$$

The probability of each state when the system reaches a steady state can be found in (3) and (5). The sum of the availability state probabilities is the steady-state availability of the system. For this system, the steady-state availability is represented as $P_0(t)$.

B. Availability based on multiple protective end-to-end optical transmission channels

We analyze the protection availability of individual components and transmission channels based on the Markov process. As shown in Fig.4(b), (c), and (d), the protection systems are based on EDFA, fiber segment, and transmission channel, respectively. For Fig.4(b) and (c), both systems are series-parallel systems, and the modeling process is similar. In contrast, the modeling process of Fig.4(d) is part of Fig.4(b). Therefore, taking Fig.4(b) as an example, we calculate the availability by dividing the system into three parts. In this case, the two parallel EDFAs constitute system 1 and system 2, and the other components in the series part constitute system 3. The analytical approach is first to perform Markov modeling of the parallel system to calculate the probability of the parallel system in each state and the failure and repair rates. Then consider the parallel system and the other components in system 3 as a whole and perform series Markov modeling. Finally, calculate the overall system's steady-state availability. Five states exist for a parallel system consisting of system 1 and system 2.

- S_0-System 1 and system 2 are working properly.
- S_1-System 1 is working, and system 2 is being repaired.
- S_2-System 1 is being repaired, and system 2 is working.
- S_3-System 1 is being repaired, and system 2 is waiting for the repair.
- S_4-System 1 is waiting for the repair, and system 2 is being repaired.

The state transfer diagram is shown in Fig.6. $\lambda_{(1)}$ and $\lambda_{(2)}$ represent the failure rate of system 1 and system 2, respectively. $\mu_{(1)}$ and $\mu_{(2)}$ represent the repair rate of system 1 and system 2, respectively. In this example, the same two EDFAs are connected in parallel so that $\lambda_{(1)}$=$\lambda_{(2)}$, $\mu_{(1)}$=$\mu_{(2)}$. The transmission system normally works when the parallel system consisting of systems 1 and 2 is in states S_0, S_1, and S_2. On the contrary, the system fails when the system is in states S_3 and S_4. In particular, we simplify the five states into three for easy calculation. S_0' represents the case where both two series systems are working correctly, S_1' represents the case where there is a fault, and S_2' represents the case where the parallel system is not working. According to (1), the Markov process of the parallel system is expressed as in (6).

$$\begin{bmatrix} \frac{dP_0(t)}{dt} \\ \frac{dP_1(t)}{dt} \\ \frac{dP_2(t)}{dt} \end{bmatrix} = \begin{bmatrix} -(\lambda_{(1)}+\lambda_{(2)}) & \mu_{(2)} & 0 \\ \lambda_{(1)}+\lambda_{(2)} & -(\lambda_{(2)}+\mu_{(2)}) & \mu_{(2)} \\ 0 & \lambda_{(2)} & -\mu_{(2)} \end{bmatrix} \begin{bmatrix} P_0(t) \\ P_1(t) \\ P_2(t) \end{bmatrix} \tag{6}$$

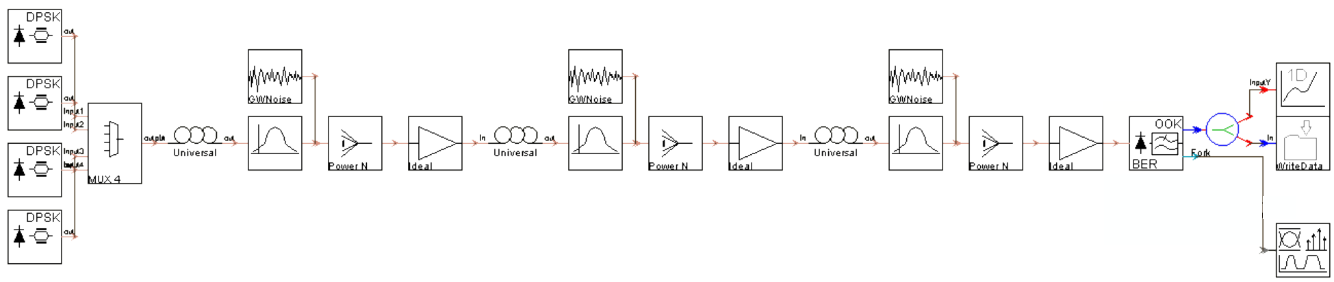

Fig. 7. The simulation diagram of VPI Transmission Maker

According to the equations (3), (4) and (6), the values of $P_0(t)$, $P_1(t)$ and $P_2(t)$ of the parallel system at steady state can be found. From this, the steady-state availability of the parallel system can be calculated as $A = P_0(t) + P_1(t)$. Then, the total failure rate and repair rate of the parallel system consisting of system 1 and system 2 can be calculated by the definition of failure rate and repair rate. Finally, by converting the parallel system and system 3 into a series system model and performing Markov modeling again, the availability of the system in a steady state can be derived.

V. Simulation and Results Analysis

In this section, we simulate the end-to-end optical transmission channel in the VPI Transmission Maker environment and analyze the results to prove the effectiveness and accuracy of the evaluation method.

A. Simulation of the end-to-end optical transmission channel

In this paper, we study a simple WDM network. As shown in Fig.7, the network consists of a transmitter, a receiver, three EDFAs, and three single-mode fiber spans and is simulated in the VPI Transmission Maker environment. Each sample consists of vectors $<X,Y>$, where X denotes the feature vector of the end-to-end optical transmission channel and Y is the label vector. During transmission, the amplifier will introduce ASE noise, and the bandwidth and transmit power will introduce crosstalk. An amplifier is deployed on each fiber link to compensate for attenuation during optical signal transmission. We assume that the number of amplifiers and the gain do not increase or decrease dynamically in the simulation. We choose the input feature values for the neural network, transmit power, modulation format, fiber span, and attenuation factor. We discuss the process of training the neural network. Each sample in the training dataset is randomly generated, the transmission rate is set to 10Gbps, and the modulation format is randomly selected from OOK, DPSK, QDPSK. The power of each transmitter is set from -20dBm to 10dBm. The fiber length is selected from 40km to 80km, and the attenuation factor is determined from 0.2dB/km to 0.4dB/km.

B. Analysis of results

This study uses the BP and GA-BP neural networks to predict the QoT of end-to-end optical transmission channels. We first obtain the data by simulation and compare the MSE of the two algorithms in Fig.8(a). The experimental results show that the optimization algorithm proposed in this paper converges better. Then, the results of different ratios of training and test sets on the prediction accuracy are tested in Fig.8(b). A training model with a ratio of 8/2 between the training and test sets is finally selected. For MSE, the BP neural network optimized by the GA is 1.28, which is 1.4 lower than the traditional BP neural network. Therefore, the optimized BP neural network performs better regarding convergence speed and prediction accuracy, which can provide higher accuracy and stability for QoT prediction of end-to-end optical transmission channels.

To further verify the prediction accuracy of this model, we will predict the QoT of the end-to-end optical transmission channel at different temperatures. After simulating the test data based on the fiber attenuation factor versus temperature in [8], we use the GA-BP model used in this study to make predictions. As shown in Fig.8(c), the prediction results show that the error of the algorithm proposed in this paper is controlled within 0.002, and the prediction is excellent.

Finally, based on the Markov process, we quantified the availability of the four scenarios in Fig.4. The failure rate and repair rate of EDFA is 0.4×10^{-4} and 0.5, respectively, and the failure rate and repair rate of fiber is 0.38×10^{-6} and 0.083, respectively [9]. Based on Markov process calculations, the values of the four end-to-end optical transmission channels available in Fig.4 are shown in Table I. With a suitable temperature and unprotected end-to-end optical transmission channel, the reliability of the end-to-end optical transmission channel is $<$0.21538, 0.999746$>$, according to the evaluation model proposed in this study, which does not reach 99.999% reliability [10]. However, by protecting the end-to-end optical transmission channel with 1+1, the reliability can reach 99.9999%.

TABLE I
RESULTS OF MARKOV-BASED AVAILABILITY EVALUATION

	Figure 4(a)	Figure 4(b)	Figure 4(c)	Figure 4(d)
Availability	0.999746	0.999826	0.999751	0.999999

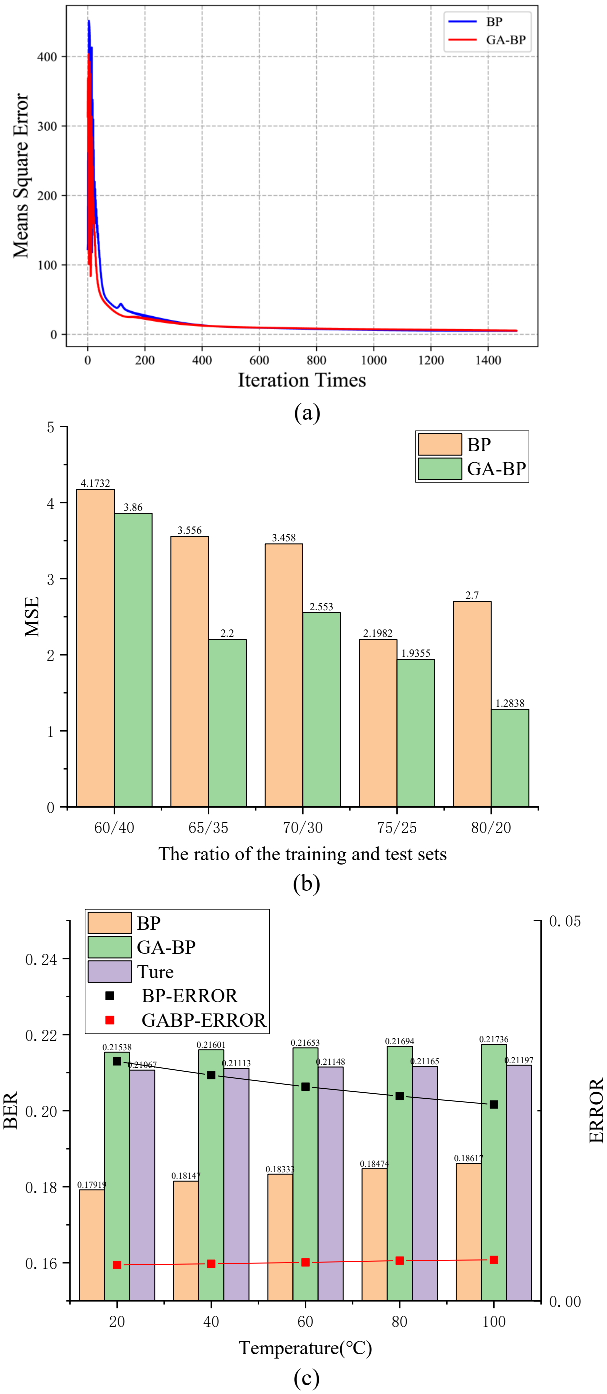

Fig. 8. Algorithm results graph (a)Error drop curve of the training set (b)Effect of training set and test set ratio on prediction accuracy (c)Comparison of predicted values with true values at different temperatures

VI. Conclusion

This paper proposed a novel reliability evaluation model for end-to-end optical transmission channels to provide a comprehensive and accurate solution for the reliability evaluation of end-to-end optical transmission channels in terms of both QoT and system availability. This study provided quantitative evaluation results for the reliability of end-to-end optical transmission channels and calculated the probability of maintaining transmission reliability. The simulation results showed that our model had high accuracy and practicality, which could provide valuable guidance for managers and maintenance personnel.

Acknowledgment

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