Reliable and Low-complexity Multiple Performance Parameters Prediction for Optical Network Equipment

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Abstract: A multi-objective and multi-step performance parameters prediction scheme based on SCINet for optical network equipment is proposed. It not only saves 83.96% of training time on average, but also has high reliability.

1. Introduction

Performance parameter prediction plays a significant role in optical networks, such as traffic and Q-factor. Traffic prediction assists operators in network planning by predicting network traffic trend information [1]. Q-factor prediction is used to predict the lightpath QoT to help operators maintain in advance [2]. The operation state of the monitoring object in the optical network can be prejudged by the threshold system based on performance parameters [3]. However, there are few studies on the performance parameters prediction for optical network equipment, while common prediction schemes for single target or single step are difficult to be applied to scenarios where multiple performance parameters need to be predicted simultaneously. For the single-objective prediction scheme, the correlation of different performance parameters is ignored. For the single-step scheme, the trend of performance parameters in the time dimension is also ignored. Moreover, with the increase in the number of monitoring equipment performance parameters or prediction time, the number of networks those schemes need to be trained greatly increases, which means an increase in computational cost. Therefore, for the prediction task of massive performance parameters of optical network equipment in the future, the benefits brought by a reliable and low-complexity multi-objective and multi-step prediction scheme will be huge.

Temporal convolutional network (TCN) has the same ability to predict sequence data as recurrent neural network, which has the advantages of parallel data processing, stable gradients, and low memory requirement for training, and it has been used in time series prediction tasks in many fields [4]. Sample convolution and interaction network (SCINet) is a new network model developed based on TCN. Its interactive learning scheme and continuously stacked convolutional layers allow the network to learn more effective local-to-global temporal relationships for multivariate time series [5].

In this paper, the multi-objective and multi-step scheme (MM) based on SCINet is proposed, which makes multiple time steps prediction for multiple performance parameters simultaneously use a single network model. Single-objective and single-step scheme (SS), single-objective and multi-step scheme (SM) and multi-objective and single-step scheme (MS) were used for comparative analysis. The experimental results show that, compared with the other three schemes, MM can save much training time and achieves higher prediction accuracy. In addition, MM has a stronger capability to maintain the correlation between different performance parameters and the trend of performance parameters in the time dimension, that is, the prediction results of MM are more reliable.

2. Operating Principle of SCINet

The multi-objective and multi-step performance parameters prediction scheme based on SCINet for optical network equipment is shown in Fig.1(a-c). It mainly includes data collection and data cleaning, selection of prediction networks and prediction schemes, and subsequent steps to take proactive measures based on the prediction results. Our research focuses on the part of proposing a reliable and low-complexity prediction scheme using SCINet. In this section, we will briefly introduce the prediction principle of SCINet.

Figure.1(d) is the structure of SCINet, which is flexible and can adapt to the scale of training data and the complexity of the input sequence by changing the hyperparameter *level*. Module B in the network is SCI-Block as shown in Fig.1(e). After the observation sequence is input into SCINet and passes through the first layer of the block, it will be divided into two sub-sequences containing rich information. Then these two subsequences will continue to enter their respective blocks and continue to complete the operation of sample convolution and interactive learning. Finally, the network realigns and connects the output by the last layer of the block into a new sequence, adding the original time series to connect to the final fully connected neural network and outputs the prediction results.

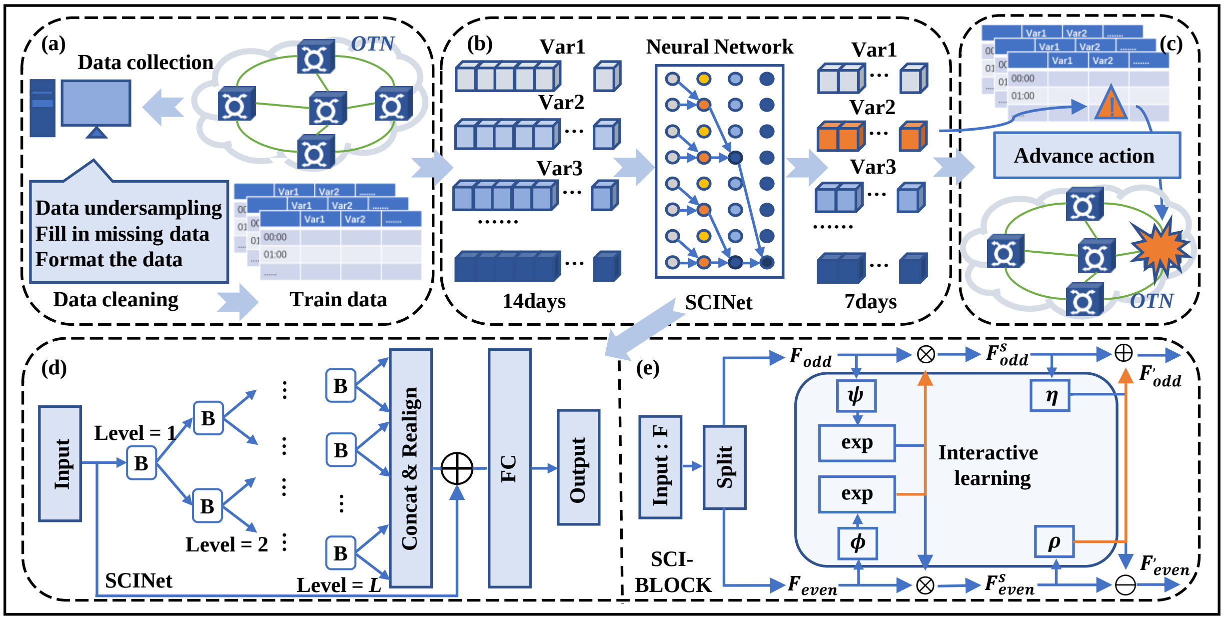

Fig. 1. Multi-objective and multi-step performance parameters prediction scheme based on SCINet for optical network equipment

SCI-Block is the core of SCINet's ability to predict future sequences, which splits the input F into odd-numbered items F_{odd} and even-numbered items F_{even}. The SCI-Block uses two different convolution kernels to extract features from these two subsequences, and since the kernels are separated, the features extracted from them will have homogeneous and heterogeneous information that enhances the representation capabilities. Meanwhile, the subsequent interactive learning strategy compensates for the potential information loss of down-sampling [5]. As shown in Fig.1(e), taking F_{even} as an example, it goes through a 1D convolution kernel (Φ) and converts it into exp form, and multiplies it element-wise with F_{odd} to get F^s_{odd}. Similarly, F^s_{even} can be obtained. Then F^s_{even} and F^s_{odd} go through a layer of 1D convolution kernel (η or ρ) respectively, and exchange information with each other. The brief calculation process of $F'even$ is shown in Eq (1) [5].

$$F^s_{even} = F_{even} \odot \exp(\psi(F_{odd})), \quad F'_{even} = F^s_{even} \pm \eta(F^s_{odd}) \tag{1}$$

3. Experimental Results and Analysis

The experimental data comes from OTN equipment managed by operators. It contains 323 types of boards, 44 days of performance parameters, and the sampling interval is 15 minutes. To verify the effectiveness of the proposed scheme, a certain type of OTN board after the screening was selected as the research object. The performance parameters recorded include output optical power, input optical power, board environment temperature, and module internal temperature, and the average value of these performance parameters was used as the prediction object (P1, P2, P3, and P4). During data cleaning, the missing data were filled, and the sampling interval was set to 6 hours. Finally, the number of the data set we got is 1006, and the test set is 106. Each piece of data consists of 14 days of observation data and 7 days of prediction data. In this paper, we assume that one day is one step, where multi-step means that 7 days of data are predicted at the same time and single-step means that only one day of data is predicted.

For the evaluation criteria, in addition to the traditional prediction accuracy metric Mean Square Error (MSE), the model training time and model parameters that can represent the computational complexity of the scheme were also used. It should be noted that in the single-objective schemes, the input of the model was the 14-day data of a single parameter, while in the multi-objective schemes, all the parameters were input. In SS, we used twenty-eight separate models to predict the four parameters in the next seven days, and finally combined the best result of each model to calculate the mean value. Similarly, in SM and MS, four separate models and seven separate models were used respectively, and finally, the averages of all models' best results under each scheme were recorded. As shown in Fig.2(a), compared with other schemes, MM saves 67.38% training time (compared to SM), saves 87.59% (compared to MS), and saves 96.91% (compared to SS) while achieving the best MSE. Meanwhile, except SM, the number of model parameters of MM is also the lowest. So, we can conclude that MM has the best prediction accuracy with the least training time and less model parameters in the four schemes. The reason is that, on the one hand, MM only uses a single model to make its calculation cost less than other multiple model schemes; on the other hand, MM can learn more about the correlation between parameters and parameters' time trend information, so that

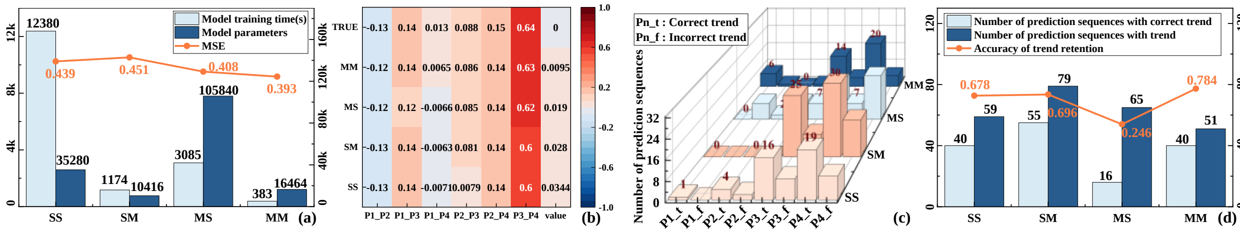

Fig. 2. (a). Evaluation metrics of four schemes (b). Pearson correlation coefficient between parameters of prediction results. (c). Time trend detection of each parameter of prediction results uses Mann-Kendall (d). Schemes' ability to retain the time trend of parameters.

its prediction accuracy is higher. Considering that the model in the prediction scheme needs to be retrained and updated when operators collect new data in the future, the shorter the training time of models in the scheme, the lower the cost and the higher the operation and maintenance efficiency.

To quantify the reliability of the prediction results of the above four schemes, we calculated the correlation between performance parameters and tested the trend in the time dimension of each performance parameter separately. Pearson correlation coefficient was used to measure the correlation between different performance parameters, as shown in Fig.2(b). It can be seen from Fig.2(b) that P3 (board environment temperature) shows a high correlation with P4 (module internal temperature), which is synchronized with expert cognition. Moreover, we defined the value (Eq (2)) which measures the difference between the prediction results of each scheme and the real data. The smaller the scheme's value, the better it preserves the correlation. Moreover, it is worth noting that a higher prediction accuracy does not mean a smaller value. The MSE of SS is lower than that of SM, but the value of SM is smaller. We can conclude that the value of two multi-objective schemes is smaller than that of two single-objective schemes from Fig.2(b). The reason is that multi-objective schemes consider the correlation characteristics of performance parameters to be predicted in the training set. Moreover, MM has a lower value than MS, indicating that considering the time trend information of the prediction objects can help the network strengthen the ability to maintain the correlation between prediction objects.

$$value = \sum_{i=1}^{6} \left| pred_{[i]} - true_{[i]} \right| \times \left| true_{[i]} \right| \tag{2}$$

Time series data trend detection algorithm Mann-Kendall (MK) can judge whether there is an upward or downward trend of sequence in the time dimension. As shown in Fig.2(c), we conducted MK test on each parameter of the prediction results of each scheme, and the number of sequences that have the same trend as the true performance parameter value was labeled. It can be found that two multi-step schemes can better retain the time trend of three parameters: P1, P3, and P4. Meanwhile, there are many sequences with the different trend from the true performance parameter value. Therefore, the proportion of the number of sequences with correct trend in the prediction results should be taken as one of the evaluation criteria, as shown in Fig.2(d). Meanwhile, we can conclude that higher MSE does not imply a better ability of trend retention from Fig.2(d). MS has a higher MSE relative to SS and SM but has the lowest accuracy of trend retention. In general, the accuracy of the two multi-step schemes is higher than that of the two single-step schemes. Because multi-step schemes take into account time trend characteristics of the performance parameters to be predicted in the training set. In addition, MM's accuracy of trend retention is higher than SM, indicating that considering the characteristics of the correlation of prediction objects is beneficial to enhance the ability of the network to maintain the time trend of prediction objects.

4. Conclusion

We proposed a multi-objective and multi-step performance parameters prediction scheme based on SCINet for optical network equipment, which saved much training time and achieved more reliability than the other three schemes. The reliability is not only reflected in that the proposed scheme gets better MSE but also in its ability to retain the correlation between different parameters and the trend of the parameters in the time dimension is stronger.

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5. Reference

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