First Demonstration of Machine-Learning-based Self-Optimizing Optical Networks (SOON) Running on Commercial Equipment

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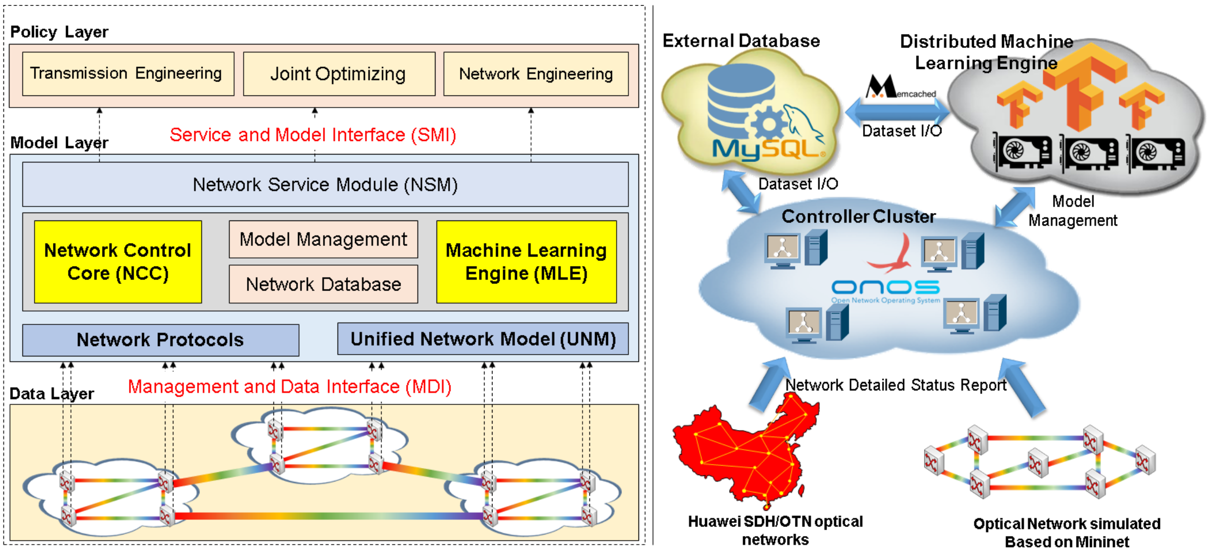
Abstract This paper first demonstrates machine-learning-based self-optimizing optical networks (SOON), which can enhance network automation and reduce operation expense. Three typical use-cases including alarm prediction, failure localization, and traffic-prediction-based service adjustment are developed to show the advantages of SOON.

Overview

The operation expense (OPEX) of optical networks today is significant for vendors [1], and growing rapidly with the fast deployment of optical fiber communications infrastructure all over the world. Although software defined networking (SDN) enables applications to control networks to facilitate management for telecom operators, it still cannot avoid the involvement of human operators and corresponding OPEX in some scenarios that rely heavily on the human experience. In general, there are potential regularities in the cases that depend on artificial expertise, and machine learning (ML) is the representative technique that is concerned with the automatic discovery of regularities in data [2]. Until now, some researchers have studied the application of ML in optical networks. A ML-based method is introduced for solving fiber linear/nonlinear damage and estimating key signal parameters in optical networks [3]. In order to reduce the occurrence of failures in the optical networks, the deep learning algorithm is used to predict failures, and reach 95% accuracy rate [4]. In Ethernet passive optical networks, in order to optimize video transmission, a nonlinear auto-regressive neural network model is proposed to predict the H.265 video bandwidth requirements, which can reach accuracy rate more than 90% [5]. Two ML-based control plane intrusion detection schemes were proposed in SDON, and results showed that the accuracy of intrusion detection scheme could reach 83% [6]. In this paper, we first propose and demonstrate ML-based self-optimizing optical networks (SOON) to integrate SDN and ML deeply, which aims to reduce OPEX and enhance network automation.

Architecture of SOON

In optical network, SOON is designed by following the universal procedure of application for ML algorithm that could be divided into data collection, model training, and policy for model application.



(a) (b)

Fig. 1: (a) SOON architecture (b) SOON testbed

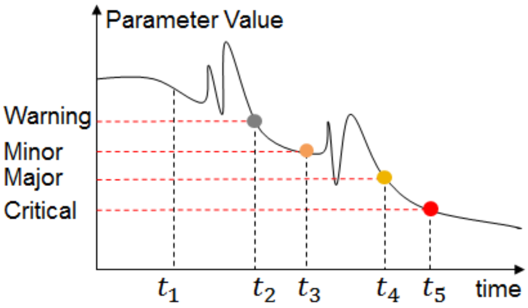


Fig. 2: alarm prediction demonstration

As Fig. 1(a) shows, SOON has three layers and two interfaces. ***Data layer*** provides the statistical data of optical networks, reports detailed network status and physical equipment parameters to model layer. Data layer could be implemented by physical optical networks, SDN controller, or network simulator.

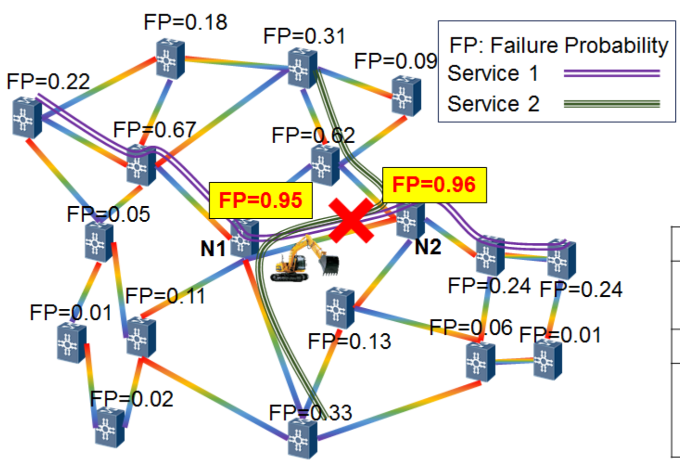
Model layer is built with two kernel modules, which are network control core (NCC) and machine learning engine (MLE). NCC is a suite of basic network control functions. MLE maintains efficient ML algorithm library, and also provide management interfaces to control the ML model's life cycles. Network database holds historical and current network status. Model management is a wrapper for MLE to enable model-level operations. Besides, in model layer, there are network protocols and unified network model (UNM) in the south, and network service module (NSM) in the north. Model layer connects to data layer by using protocols for obtaining network status and controlling it. UNM is responsible for building consolidated network view through filtering, standardizing, and reformatting original data. Usually, the physical parameters are variant among different optical equipment and different boards. The original data collected from data layer is quite dirty (e.g., data missing, data exception, data format chaos, etc.), and needs to be pre-processed before used for model training. NSM aggregates basic network functions into abstracted network services, e.g., building a path from source to destination. And NSM also provide unified method for calling ML model.

Policy layer has three types of ML-based policies based on powerful awareness of optical networks and intelligent analysis using ML. Transmission engineering and network engineering focus on the quality of transmission (QoT) and quality of service (QoS). The joint optimizing policy considers both QoT and QoS.

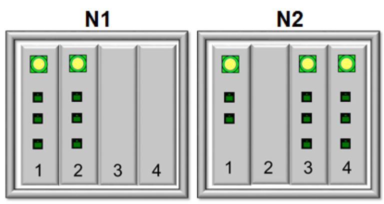
Besides, management and data interface (MDI) provides data report and network control channel between data layer and model layer. And service and model interface (SMI) provides channel to apply policy and invoking ML model between model layer and policy layer.

Demonstration of SOON Prototype

We developed a SOON prototype according to the proposed architecture. Fig. 1(b) shows our SOON testbed. Our believable network original data comes from physical large-scale SDH/OTN network running on State Grid, whose equipment are from Huawei Corp.. Then we develop policy layer, protocols, UNM, NCC, and NSM of model layer based on ONOS controller cluster, and build MLE on ML platform named TensorFlow that is developed by Google. Model layer is located on the T630 server with two E5-2620v4 CPUs and two TITAN XP GPUs. In order to improve data I/O speed, MySQL is used to store massive data, and Memcached system is used to provide fast data access. Based on the waring and performance data from commercial networks, we trained three ML models (i.e., alarm prediction, failure localization, and service adjustment) and



(a)



(b)

Board of N1	Failure Prob.
Board 1	0.88
Board 2	0.95
Board of N2	**Failure Prob.**
Board 1	0.76
Board 3	0.96
Board 4	0.68

(c)

Fig. 3: (a) Node-level failure localization; (b) boards of nodes with highest FP; (c) board-level failure localization

demonstrated them on the SOON prototype. In these three use cases, we focus on QoS guarantee of service. Alarm prediction is helpful for normal running of optical equipment, failure localization is useful to repair fault in time, and service adjustment is beneficial for performance improvement.

Use Case 1: alarm prediction

As Fig. 2 shows, there are four types of alarms in Huawei SDH/OTN equipment, and they are warning alarm, minor alarm, major alarm, and critical alarm according to severity level. Warning alarm and minor alarm usually indicate that there are some events in equipment, but less influence on it. Major alarm and critical alarm usually indicate that the event has affected the carried network service. In SOON, we got 9831657 performance data items, and 14857 alarm data items from commercial network in a month. Based on these data, Fig. 2 shows some parameter variation of optical equipment as time goes. In SOON, operator can predict alarms using ML model before warning/minor/ major/critical alarm occurs, according to the correlation between parameters and alarms from time dimension. Based on the prediction, operators can check, maintain, or replace the devices that may cause the alarms in advance.

Use Case 2: failure localization

Generally, the exception in one device would cause a series of alarms on many related equipment. There are two services (connectivity) in Fig. 3(a), Routing of Service 1 crosses network from east to west, and routing of Service 2 crosses network from north to south. If the fiber between N1 and N2 is cut off suddenly, major/critical alarms will be reported by N1, N2, and other nodes along the paths of service 1 and 2. In SOON, we marked 3769 failure data items extracted from all alarm data, and build dataset. By means of ML algorithm, the controller is able to evaluate fault probability (FP) of all nodes, and choose the one with the highest FP as the fault source. In Fig. 3(a), both N1 and N2 are selected, and the detailed boards in them are showed in Fig. 3(b). Then, specific ML model would execute more accurate localization in board level as Fig. 3(c) shows, and find the fault source.

Use Case 3: service adjustment

Fig. 4(a) shows a simple optical network with one business area (BA) and two residential areas (RA). Three charts of Fig. 4(b) indicate the traffic load variation in RA or BA within two days. Fig. 4(c) compares the traffic trend of RA and BA. Controller could get the predicted traffic distribution in future via ML model, and make service adjustment scheme to improve service capability in advance.

Conclusions

In this paper, we proposed a ML-based self-optimizing optical networks (SOON) architecture to enhance network automation and reduce operation cost. The proposed SOON architecture with three use cases are demonstrated on commercial optical transport equipment.

Acknowledgements

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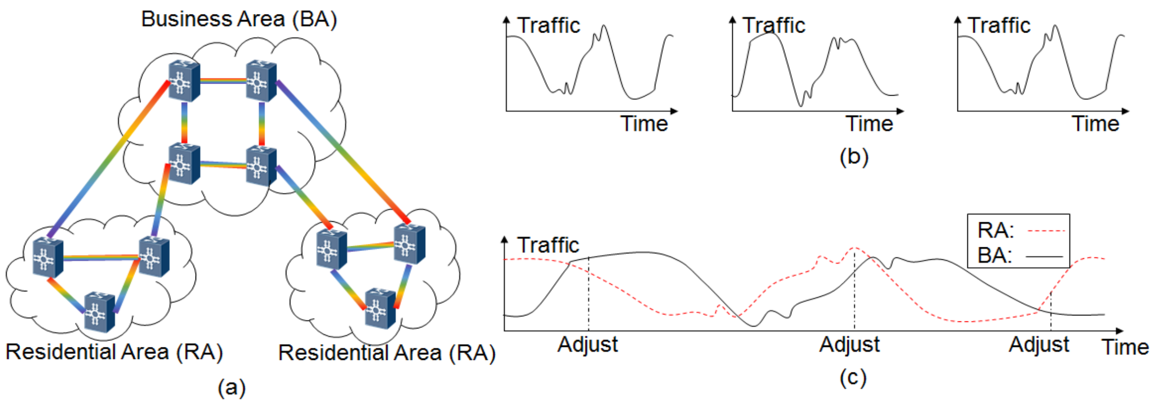

Fig. 4: (a) Scenario of traffic variation; (b) traffic pattern matching; (c) service adjustment