Intent Defined Optical Network: Toward Artificial Intelligence-Based Optical Network Automation

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Abstract: Toward AI-based optical network automated operation, we propose an intent defined optical network (IDON) architecture with self-adapted generation and optimization (SAGO) policy. The feasibility and efficiency are verified on the enhanced SDN testbed.
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1. Introduction

Along with the rapid evolution of internet of things and high-bitrate applications in beyond 5G (B5G), the operators are thinking to reconfigure their optical network architecture for intelligence operation and maintenance [1]. As one of the transport technologies in B5G, elastic optical network [2] can dynamically allocate the customized optical spectrum with a fine granularity for user's demands, and provide the connection with large bandwidth and low latency. In B5G scenario, more and more new services have appeared which require the interworking with human behavior and environment [3]. For instance, automatic pilot can drive the vehicle and perform collision avoidance in accordance with the changing surroundings. Different from traditional request giving the network metrics, e.g., bandwidth and latency, the current service just provides the desired impact and effectiveness to operator without specific network performances. It is hardly to address the smart network control and configuration in such black-box environment without anything specific metrics [4]. Due to the complexity of services, intelligence network control faces the huge challenges to adapt diversified services and new ecosystem especially for optical transport network. Moreover, software defined optical network (SDON) just focuses on the how to control the optical network using the customized interface after receiving the configuration parameter. To the best of our knowledge, how to convert user's objective into network transmission has been not addressed especially for optical network.

On the basis of our previous work introducing fault detection [5], this paper extends to propose a novel intent defined optical network (IDON) architecture toward artificial intelligence-based automation maintenance of optical network against the service objective of users. Based on the proposed architecture, we also present a self-adapted generation and optimization policy (SAGO) through combination with multiple fine-grained policy in a customized manner. The IDON can convert the service demands into optical network performances, enhance the self-adapted customized service and address the self-optimization control policy with an all-life-cycle maintenance using deep reinforcement learning. The overall feasibility and efficiency of the proposed architecture with SAGO policy are experimentally verified on enhanced SDN testbed.

2. Network Architecture of IDON

In order to promote the network automatics, IDON architecture is illustrated in Fig. 1(a). In the network layer, an amount of terminal devices such as IoT devices have been accessed through radio antennas and connected into the

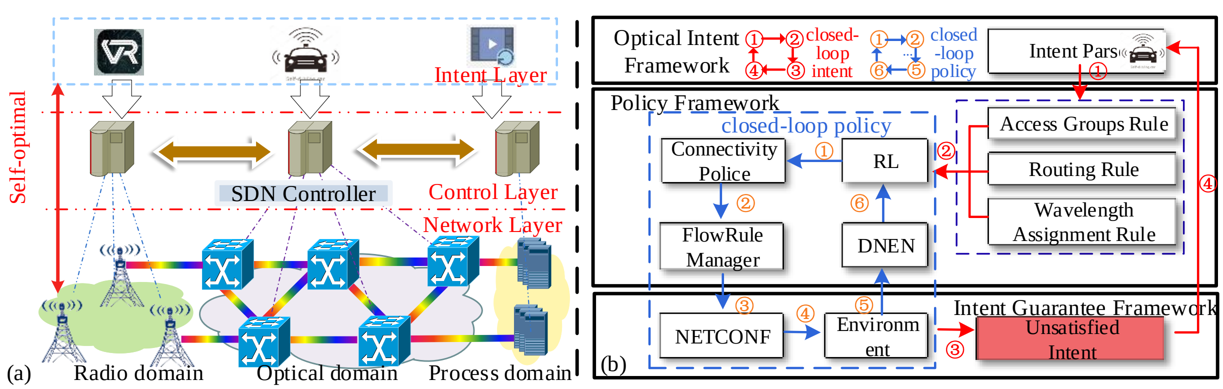

Fig. 1 (a) The architecture of IDON, (b) The orchestration of IDON network. In control layer, each domain has been maintained using software defined controller through its own kind of resources which include radio controller, optical controller and processing controller. In order to implement the software defined control for heterogeneous networks, the protocol agent should be added into the device to enhance the interconnection between controller and switches with OpenFlow protocol. In intent layer, various kinds of applications have been deployed which the user desires to realize and optical network will be used to support such application such as VR and automatic pilot. The intent is only the objective of the user wanted without the network parameters. There are four motivations for IDON. Firstly, the intent should be translated into network service with definitive parameters automatically using artificial intelligence. Secondly, IDON can detect the physical information of optical network which are marked with various categories to estimate whether they are abnormal or healthy. Thirdly, after integrating the intent and physical parameters, the proposed architecture can generate the customized policy automated getting fine-grained strategies together. Finally, the intent may be self-optimized guaranteed with double closed loop feedback.

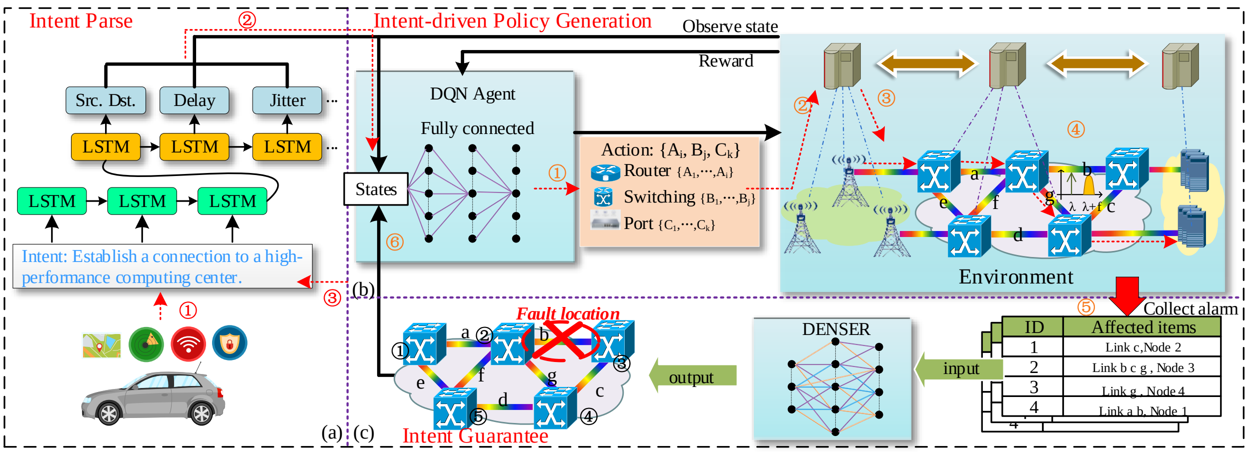

Fig. 2 (a) Intention translation mechanism, (b) Intelligent policy generation mechanism based on RL, (c) Intention guarantee mechanism based on DNEN.

3. Intent-Driven Optical Network Automation

Intention translation mechanism. The premise of implementing intent-driven is to accurately extract the diversified features of the service and intelligently analyze different services with different requirements for communication rate, transmission delay, and bit error rate. High-level intent service requests are defined in a descriptive language, such as “intent: Establish a connection to a high-performance computing center”. The user's network request description will be split into several keywords by long-short time memory (LSTM). Focusing particularly on communication requirements, the approach uses natural language processing (keyword extraction) to construct semantic graphs to understand, interact, and create the required network configuration.

Intelligent policy generation mechanism based on intention driven. Intelligent policy is generated by utilizing reinforcement learning (RL) to combine fine-grained policies of strategy library. The key points include the following two aspects. Firstly, the information model and data model of fine-grained policies are established, and the fine-grained policy is written into the strategy library according to the model. Secondly, the reinforcement learning algorithm is introduced to recombine various fine-grained policies into new strategies. Specifically, the essence of the intelligent policy generation mechanism in the network is to find the combination that satisfies the intent’s requests through the dynamic integration of fine-grained policies.

Intention guarantee mechanism. The construction of the intention guarantee mechanism is the necessary requirement to realize the complete closed-loop of the intention-driven optical network. To this end, the deep neural evolutionary network (DNEN) is introduced [5], which can realize high-precision fault location for large-scale fault sets. During the fault location process, the management system detects that the abnormal state of the network violates the intent constraint, which is called alarm information. Then, the network controller analyzes the received alarm set by configuring the log to obtain the number, location, and type of faults, and implements a topology view of the fault distribution. It is important to note that due to the complexity of the optical network topology, there is an intrinsic link between the fault alarm sets, which are reflected in two aspects. Like the port, switching and routing configuration have the relationship of network topology space. Therefore, when encountering a large amount of alarm information, we must extract deep hidden fault features and accurately find real faults from complex relationships. In short, it can effectively deal with the fault problems in optical networks, maximize the intent of protection, and achieve the complete closed-loop of intent control.

4. Experimental Demonstration and Results Discussion

To evaluate the effectiveness of the proposed architecture, we have constructed a SAGO-IDON platform on a fat-tree topology. Two major components of our testbed are SDON real-time network emulator and the python library ray project that integrates the RL algorithm with the emulator. The RL agent of SAGO collects switch occupancy, jitter, delay, and active flows as the environment state input. While the reward of SAGO execution is obtained by calculating the inverse of the cumulative absolute difference between the current network state and the intended target. The intent translation and SAGO configuration action policy diagrams are shown in Fig. 3(a). The emulator has run 35000 timesteps to prove enough significant stability level of proposed architecture. Each timestep is set to 0.5 seconds to give sufficient time to collect the changing state in the network. This means that each run lasts for about 7 hours under this step size. The proposed architecture is evaluated on the basis of performance metrics such as cumulative reward, configuration time, and queue length.

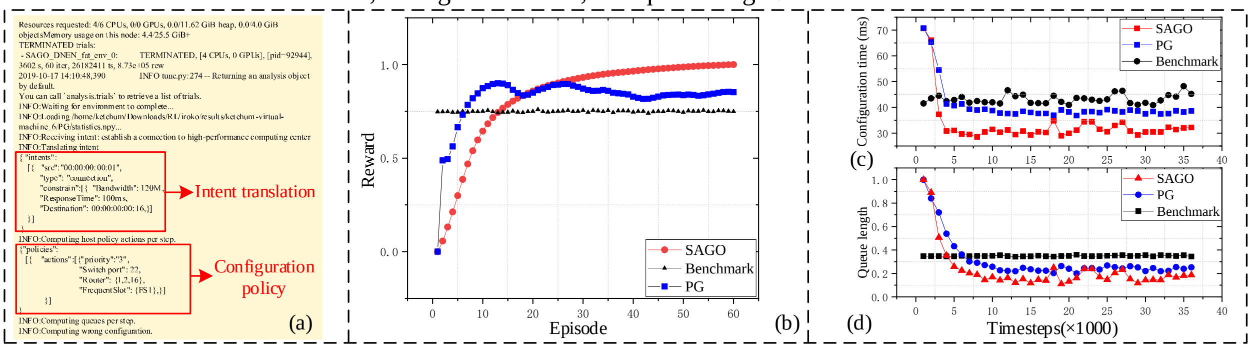

Fig.3(a) Intent translation and SAGO configuration policy, (b) rewards, (c) configuration time, (d) queue length

We first make an analysis on normalized rewards of SAGO and the result is shown in Fig. 3(b). We have compared SAGO with benchmark configuration and policy gradient (PG) algorithm. It can be seen that SAGO achieves the highest reward and continues to improve, while minimizing the queue length on the optical link. This indicates that the SAGO can quickly learn a positive configuration. In the initial training, the reward of SAGO is smaller than the others. This is because SAGO is constantly exploring various configuration strategies and gradually become the best beyond the others until the 35th episode. Then, we evaluate the impact on configuration time and normalized queue length. The results are shown in Fig. 3(c) and Fig. 3(d). It can be seen that the configuration time of SAGO is shorter than PG and benchmark after 5000 timesteps. This is because the RL agent can quickly execute the corresponding policy generation process after intent translation without parsing the flow table for configuration. At the same time, DNEN can locate the wrong configuration at the millisecond level, guaranteeing the closed-loop policy quickly reconfigure operation. With the help of DNEN's fast and accurate positioning, SAGO can reconfigure for failure, avoiding the configuration of nodes on the routing path, which will reduce a lot of configuration time and also reduce the number of intent configuration failures. The variations in queue length with respect to the time steps are shown in Fig. 3(d). As seen in the figure, the queue length of SAGO is obviously shorter than the benchmark and PG. This is because that SAGO takes global IDON into account by introducing future discount factor, maximizing rewards, which mean that the configuration of the intent is considered from the global optimal point of view. Overall, SAGO-IDON has great prospects in realizing zero-touch configuration in the optical transport network operation.

5. Conclusion

This paper presents a novel IDON architecture where SAGO scheme is introduced. Our experiments verify that IDON with SAGO can effectively perform the intent translation and zero-touch configuration. The two closed loops, including closed-loop policy and closed-loop intent, strongly ensure the operation of the zero-touch configuration.

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