SCIENCE CHINA
Information Sciences

• RESEARCH PAPER •
Special Focus on Artificial Intelligence for Optical Communications

June 2020, Vol. 63 160304:1–160304:12
https://doi.org/10.1007/s11432-020-2838-6

# Intent defined optical network with artificial intelligence-based automated operation and maintenance

Hui YANG[1*], Kaixuan ZHAN[1], Qiuyan YAO[1], Xudong ZHAO[1],
Jie ZHANG[1] & Young LEE[2]

[1]*State Key Laboratory of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications, Beijing* 100876*, China;*
[2]*Huawei Technologies Co., Ltd, Shenzhen* 518000*, China*

Received 10 January 2020/Accepted 16 March 2020/Published online 9 May 2020

**Abstract** Traditionally, the operation and maintenance of optical networks rely on the experience of engineers to configure network parameters, involving command-line interface, middle-ware scripting, and troubleshooting. However, with the emerging of newly B5G applications, the traditional configuration cannot meet the requirement of real-time automatic configuration. Operators need a new configuration way without manual intervention at an underlying optical transport network. To cope with this issue, we propose an intent defined optical network (IDON) architecture toward artificial intelligence-based optical network automated operation and maintenance against service objective, by introducing a self-adapted generation and optimization (SAGO) policy in a customized manner. The IDON platform has three key innovations including intent-orient configuration translation, self-adapted generation and optimization policy, and close-loop intent guarantee operation. Focusing specifically on communication requirements, the IDON uses natural language processing to construct semantic graphs to understand, interact, and create the required network configuration. Then, deep reinforcement learning (DRL) is utilized to find the composition policy that satisfies the requirement of intent through the dynamic integration of fine-grained policies. Finally, the deep neural evolutionary network (DNEN) is introduced to achieve the intent guarantee at the milliseconds level. The feasibility and efficiency are verified on enhanced SDN testbed. Finally, we discuss several related challenges and opportunities for unveiling a promising upcoming future of intent defined optical network.

**Keywords** optical network, artificial intelligence, network automation, intent defined network

**Citation** Yang H, Zhan K X, Yao Q Y, et al. Intent defined optical network with artificial intelligence-based automated operation and maintenance. Sci China Inf Sci, 2020, 63(6): 160304, https://doi.org/10.1007/s11432-020-2838-6

## 1 Introduction

Along with the drastic evolution of Internet of Things and high-bitrate applications in beyond 5G (B5G), optical network ecosystem has unprecedented dynamics both of control and resource allocation, resulting in unsatisfactory level of manual operation and maintenance [1]. In such context, the operators are considering to promote the upgrade of their optical network architecture for automatic intelligent operation and maintenance [2]. As one of the transport technologies in B5G, elastic optical network is an important part of optical network architecture, which can dynamically allocate the customized optical fine-granularity spectrum for the user's requirements, and provide the large-bandwidth low-latency connection [3]. In

* Corresponding author (email: yanghui@bupt.edu.cn)

 

B5G scenario, a growing number of emerging services involved time-critical interaction and configuration need the interworking with human behaviour and environment [4]. For instance, automatic pilot, which can assist the vehicle and perform complex collision avoidance under the condition of changing surroundings, involves complex data delivery to processing domain and reliable performance expectation of the transport network [5]. Different from traditional requests attaching the network performance, e.g., bandwidth, jitter and latency, the emerging service from users just provides the operator with the desired effect and reliability without explicit network metrics [6]. In such black-box environment, it is hardly to grapple with the automatic configuration of smart network control. As a result of the complexity of the emerging services, intelligent network control is faced with enormous challenges to adapt diversified services and new ecosystems, especially for optical transport networks. In addition, software defined optical network (SDON) merely focuses on the intelligent control of the optical network with the customized interface after receiving the configuration parameter [7]. To the best of our knowledge, how to convert the user's desired goal into transport network transmission policy has been not resolved, especially in the optical network.

In B5G scenario, users are more concerned with what to achieve, rather than how to carry out on operation of network. User desired goal is defined as intent from operators' perspective, and intent-based networking represents users' intent as high-level intent description [8]. However, it is difficult to accurately translate high-level intent description into a network configuration language after trusted access, guaranteeing a satisfactory level in term of quality of service without manual intervene. Similarly, how to execute close-loop configuration policy after intent translation is still unresolved. Moreover, in case of failure, how to achieve intent guarantee with automatic restore is equally critical. The above flow steps are the most important component of implementing of intelligent networking control for all-life-cycle maintenance [9–11].

On the other hand, artificial intelligent (AI) technology can provide to SDON the capability to automatically learn and promotion in accordance with operation experience without being explicitly programmed [12–14]. It is an irresistible trend to apply AI to assist in the decisions involving network operation and management. However, few researches consider the control issue that how to control network if the controller receives technology-agnostic service objective without anything configuration performance. Thus, it is significant to construct new network architecture toward AI-based optical network automation for implementing of zero-touch operation.

AI is applied to enhance the intelligence of network control, from traffic recognition to fault detection in optical network which is presented in our previous studies [15–18]. In this paper, on the basis of our previous studies, we extend to propose a novel intent defined optical network (IDON) architecture toward artificial intelligence-based automation maintenance of optical network for the users' service objective.

Traditionally, the operation and maintenance of optical networks rely on the experience of operation experts to operate whole network with explicit parameters, involving command-line interface, middle-ware scripting, and troubleshooting. The emerging services make the manual approach unsatisfactory. Therefore, there are three motivations for IDON. Firstly, the users' intent should be automatically converted into networking service with explicit parameters in spite of the variety of services and the complication of network operation procedures. Secondly, after confirming the intent and physical parameters, to achieve the corresponding network performance expectations, the problem that how to self-generate matching network operations without human intervention is still pending. The IDON architecture can generate the self-adapt policy through integrating fine-grained policy together toward the intent goal. Finally, to ensure the effective execution of the intent in the event of a network failure, most methods still fail to response in time. The self-optimization of intent configuration should be achieved through double-closed loop feedback in time.

Our contribution is mainly focused on converting of the user's desired goal without any metrics into transport network transmission policy to achieve zero-touch operation. We also present a self-adapted generation and optimization (SAGO) policy, integrating multiple fine-grained policies in a closed-loop automatic manner. The IDON architecture can convert the service demands into optical network performances, promote the self-adapting customized service, and achieve the self-optimization control utilizing

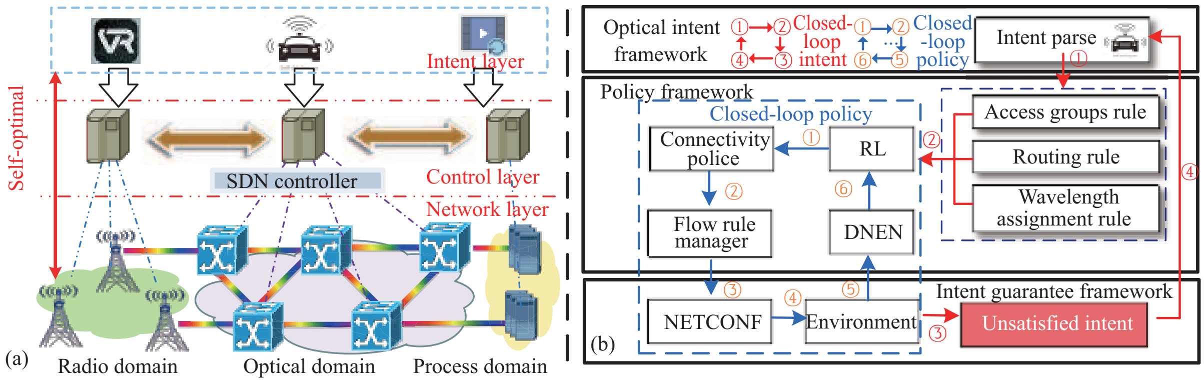


**Figure 1** (Color online) Architecture of IDON.

deep reinforcement learning for all-life-cycle maintenance. The overall feasibility and efficiency of the proposed architecture with SAGO policy are experimentally verified on enhanced SDN testbed. In the rest of the paper, Section 2 describes the overall network architecture of IDON; and the cooperation procedure for IDON multi-domain control is discussed in Section 3; Section 4 presents the performance analysis using SDON testbed. Finally, Section 5 concludes the IDON architecture.

## 2 Network architecture of IDON

The existing network regulation and control system cannot meet the needs of network regulation and control work under the new situation. Based on the contradiction between the dynamic demand of diversified services in optical networks and the rigid transmission system of optical networks, this paper proposes the intent defined optical network architecture based on intention-driven [19]. Research on intelligence policy in optical networks based on intention driven is faced with three challenges. The first challenge is how to effectively extract the diversified characteristics of different services to achieve accurate translation of service intentions. The second one is how to automatically generate transmission strategies under strict constraints of intent to meet service requirements. The third one is how to establish intention guarantee mechanism to realize real-time adaptation of intelligent policies to the network environment. Therefore, this paper starts from the frontier and important requirements in the field of optical networks, and takes the intelligence strategy in the optical network based on intention-driven as the research objective. Firstly, aiming at the problem of low accuracy of service identification, this paper extracts the diversification characteristics of different services based on the deep learning algorithm, and explores the mechanism of service intention translation. Secondly, it focuses on the self-adaption of service transmission strategy in the optical network. In the end, a high-precision fault location algorithm for large-scale alarm sets is proposed, and the strategy guarantee mechanism in optical networks is studied to form a complete closed-loop policy based on intent-orient control.

Toward promoting the automatics of the network, the architecture of IDON is illustrated in Figure 1, including three layers to make the structure efficiently. (1) In the network layer deployed with the radio frequency resources, a mass of IoT terminal devices have been accessed through radio antennas and connected into the network. To transport the data and backhaul to cloud, elastic optical network is used to interconnect wireless and processing domains with the customized spectrum, which can provide the bandwidth for users using fine granularity. The process domain, which contains computing and storage resources in an edge cloud, integrates the functions of signal processing and content cashing. It can pull the calculation elements in a centralized manner and make the procedure more efficient. (2) In the control layer, configuration management of each domain has been maintained using its exclusive software defined controller including radio access controller, optical transport controller and processing controller. To accomplish the software defined control of heterogeneous networks, the protocol agent would be added into the devices so as to boost the intercommunication between controllers and switches

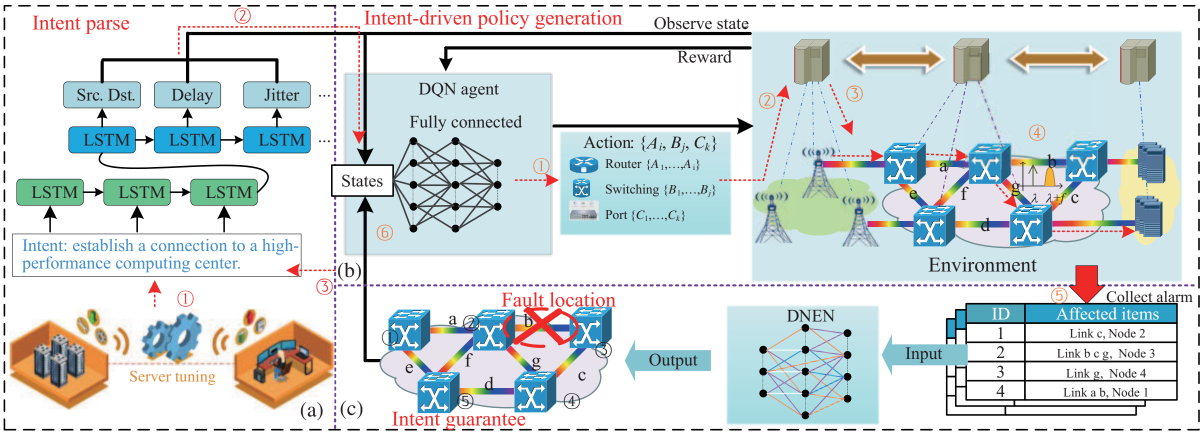


**Figure 2** (Color online) (a) Intention translation mechanism; (b) intelligent policy generation mechanism based on RL; (c) intention guarantee mechanism based on DNEN.

with OpenFlow protocol. (3) In the intent layer, a variety of applications that user desires to realize have been deployed, and optical network would be utilized to meet the demand of such application such as high-definition video, VR and automatic pilot. The user's intent is only the objective of the user wanted without the network parameters. There are four motivations for IDON. Firstly, the users' intent should be automatically converted into networking service with explicit parameters utilizing deep learning. Secondly, IDON can collect the physical information of the optical network which is marked with various operating logs to detect whether the network system is abnormal. Thirdly, after confirming the intent and physical parameters, the IDON architecture can generate the self-adapt policy through integrating fine-grained policy together toward the intent goal. Finally, the self-optimization of intent configuration is achieved through double-closed loop feedback.

## 3 Cooperation procedure for IDON multi-domain control

IDON mainly consists of three steps including intent translation, policy generation, and intent guarantee. First, IDON needs to convert the intent into the configuration language understood by the device. After that, the configuration policy needs to be generated according to the configuration parameters, such as the routing and switching policy. Moreover, when the configuration is completed, the intent guarantee is also needed to ensure the correct configuration of the user's intention in case of failure. It means that a closed-loop policy generation and optimization is required. Similarly, the close-loop intention guarantee is also required for the automatic configuration and implementation of intent [20]. The flow step in the IDON process shown in Figure 2 is elaborated as below.

### 3.1 Services feature extraction and intention translation mechanism

Different services in optical networks have different requirements for communication rate, transmission delay and bit error rate, and it is difficult to unify them. The advance of 5G accelerates the trend of services' diversification and trusted multi-domain collaboration [21]. How to quickly extract the diversification characteristics of services and intelligently analyze the intentions of different services is the premise to realize intention driven.

In order to solve the above problems, the IDON first introduces a multi-feature extraction method based on deep neural network algorithm, which explores the intrinsic relationship between services' characteristics and intentions. It then constructs a mapping relationship model between them and establishes a connection relationship from services characteristics to network parameters, realizing rapid extraction of diversified characteristics of different services and accurate identification of service intentions. The

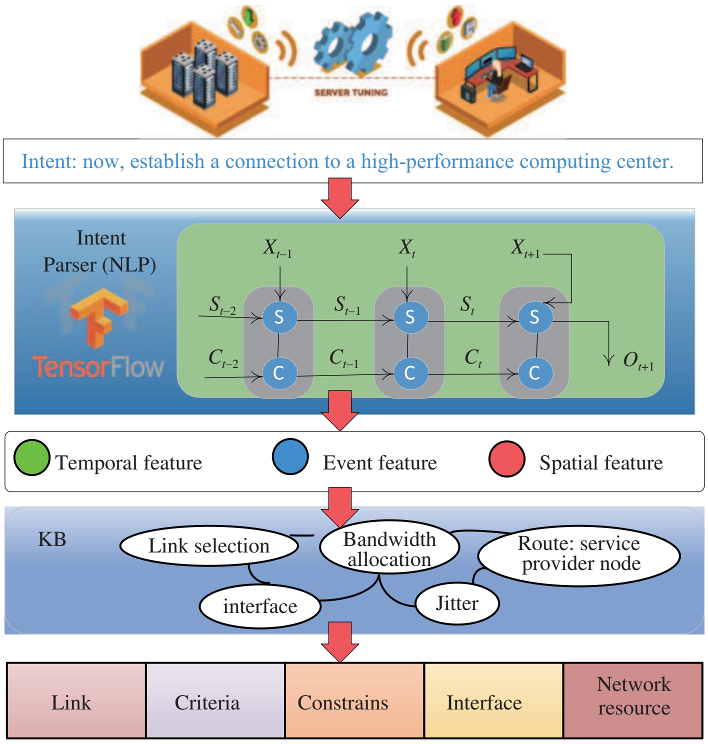


**Figure 3** (Color online) The process of intent translation.

result of intention translation lays a crucial foundation for intelligent policy generation. The flow steps in the intent translation process between users and the network shown in Figure 3 are elaborated as below.

First, high-level service requests are defined in a descriptive language, such as "I am requesting a connection to high-performance calculation center". The intent translation uses natural language engineering to define requests and convert them into network commands, reconfiguring resources, preferences, and policies. 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. The user's intent request description will be split into several keywords by long-short time memory (LSTM). The keywords then are mapped into the following configuration aspects which define requirements of intent translation, such as jitter, bandwidth and delay.

Link: Link selection from source node to sink node.

Criteria: Transmission protocol standard.

Constrains: Quality of service constraints, such as delay, jitter, etc.

Interface: Switch port selection.

Network resource: Requirement of spectrum and power resources.

According to the keywords extracted by the LSTM, the process of mapping the keywords to the network constraints can be described as follows. The proposal first searches for the corresponding network constraints, and queries the corresponding network configuration parameters in accordance with the keyword extraction results in the knowledge base (KB). For instance, "I" is translated into source address "source: 10.0.0.1", "high-perform calculation center" is translated into service provider address "service provider node: 10.0.0.2" and corresponding communication requirements such as 120 M bandwidth, and "requesting a connection" is translated into "establish connection between the source node and the service provider node". It is then rendered as OpenFlow rules and connected to the network configuration and transport tools to allow the transfer of OpenFlow rules to configure the user's intent. In the process of intent translation, not only the configuration operation intricacy is abstracted (e.g., "I am requesting a connection to high-perform calculation center" without explicitly giving delay, jitter and service provider nodes along the route), but the controller still understands the intent language and configures the connection at the underlying network to meet the requirements of users' intent. In case of failure to satisfy the requirement of intent, the intent will be automatically re-mapped to the constraint and the network will be reconfigured to satisfy the requested connectivity without any users' intervention. In short, the intent translation mechanism provides reliable, simple, and technology-independent communication between users and the network.

After converting the user language into the network configuration rule, Subsection 3.2 describes the implementation of close-loop policy generation under the constraint of intent.

### 3.2 Intelligent policy generation mechanism based on intention driven

When different intentions are mapped to the understandable network parameters of the optical network, the intent-driven intelligent transmission strategy on secure control is needed to be designed, and the intelligent strategy adapted to the intentions is also necessary to be solved in the optical network [22–25]. Aiming at the above problems, the proposed IDON realizes the combination of fine-grained policies and generates new policies utilizing deep reinforcement learning (DRL) on the basis of fine-grained policies in the policy library [26].

The key points of intent-driven policy generation mechanism include the following two aspects. Firstly, the information model and data model of fine-grained policy are established, and the fine-grained policy is written into the policy library according to the model. Secondly, the reinforcement learning algorithm is introduced to recombine various fine-grained policies into new policies. To be clear, the essence of the intelligent policy generation mechanism in the network is to find the combination that satisfies the intent's requests through dynamic integration of fine-grained policies. In addition, there are thousands of atomic strategies of network configuration. In such case, deep Q network (DQN) is an effective solution due to its excellent reinforce composition action characteristics. The aim of DQN is to find the appropriate component policy to best meet the requirement of user's intent. Some important definitions related to DQN are given below.

**Definition 1** (Fine-grained policy)**.** A fine-grained policy implements the configuration of some functional nodes. For instance, fine-grained strategies include bandwidth configuration (BW_config), Routing selection (Routing_sel), switching selection (SW_sel), service provider node selection (Ser_prov), etc. BW_config includes sub policies such as dynamic bandwidth allocation (DBA) and fixed-bandwidth allocation (FBA). The Routing_sel policy includes routing policies such as greedy routing and shortest routing.

**Definition 2** (Network environment)**.** The environment consists of network topology and node equipment, internet service provider (ISP) and other components that implement network functions.

**Definition 3** (Policy action)**.** According to intent logic, fine-grained policies with different functions are integrated into a loosely coupled, scalable, prolongable set of configurations, namely configuration policy action. In our example, an action consists of five fine-grained policies, of which more can be added. An policy action can be formalized as $a =$ (BW_config, Link_sel, SW_sel, Port_sel, Ser_pro_sel).

**Definition 4** (Network environment state)**.** State $s$ refers to the stage in which the network is running. $s$ consists of performance indicators and it can be formalized as $s =$ (delay, jitter, packet loss probability, connectivity rate, provider node configuration). The state of network indicates whether the intent constraint is satisfied.

**Definition 5** (Configuration reward)**.** Configuration reward is a reward feedback function that is calculated after taking a configuration policy action. Configuration score is the reward from the $s$ to $s'$ state after configuration operation. The goal of selecting the best policy combination action is to find the combination strategy with the highest cumulative reward. The more rewards DRL get, the better the combination of fine-grained policies chosen by the DRL. Therefore, getting as many rewards as possible is the standard of the fine-grained-based policy combination.

The following is a detailed description of the specific process of fine-grained policies composition based on DQN. A policy library is first created with thousands of fine-grained policies, including BW_config, Link_sel, SW_sel, Port_sel, Ser_pro_sel, etc. Then, after building the fine-grained policy library, we use

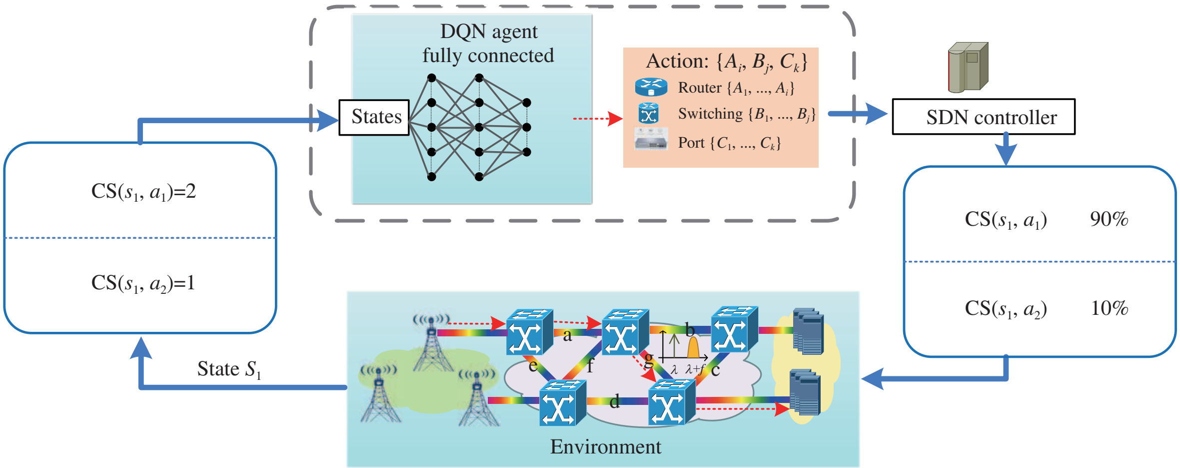


**Figure 4** (Color online) The process of policy generation based on RL.

DQN to combine the fine-grained policies into one configuration action. DQN is a combination of neural network and reinforcement learning (RL). Its mathematical essence is a model for state migration using Markov decision process (MDP). The purpose of the neural network is mainly to summarize the state-action pairs and the corresponding configuration score. The automatic policy configuration needs to map the observed state $s$ to the configuration action $a$ utilizing DQN. At each time step, current state $s$ is used as the input of the neural network, and then DQN obtains the configuration score of the combined policy after the neural network analysis. And it outputs the action with the largest configuration score as the next action according to the Q-learning principle. Next, an iterative process is performed to learn the configuration score of the policy combination actions in any state. As a result of reinforcement learning, the DQN agent selects an action from the optimum legal combination of fine-grained policies in accordance with the network state and constraints of intent translation.

We take one configuration strategy shown in Figure 4, which is one of combinations of the fine-grained strategies. It is assumed that the network is in state $s_1$, and there are two combinations $a_1$, $a_2$ of fine-grained policy actions. In the $s_1$ state, the potential reward for taking $a_1$ is higher than $a_2$ based on past experience. Here, we can use a configuration score (CS) table with $s$ and $a$ instead of the potential reward. In the DQN memory CS table, $\mathrm{CS}(s_1, a_1) = 2$ is greater than $\mathrm{CS}(s_1, a_2) = 1$, so the DQN agent decides to choose $a_1$ as the action to take. Now that state $s$ is migrated to $s_2$, we still have two identical choices, and repeat the above procedure. In the CS table, DQN agent compares the value of $\mathrm{CS}(s_2, a_1)$, $\mathrm{CS}(s_2, a_2)$, and then chooses the larger one. Then the environment reaches $s_3$ after acting and repeats the above decision process here. The CS table finally indicates in what way it is changed and promoted. According to the estimation of the CS table, because the CS value of $a_1$ is relatively large in $s_1$, the agent executes $a_1$ in $s_1$ through the previous decision method, and arrives at $s_2$. We multiply the $\mathrm{CS}(s_1, a_2)$ obtained by an attenuation value $\gamma = 0.9$ when it reaches $s_2$. Getting the real reward $R$ from network environment, the agent takes this as the value of $\mathrm{CS}(s_1, a_2)$ in reality. We also have the estimation value of $\mathrm{CS}(s_1, a_2)$ in the CS table. So, we can update $\mathrm{CS}(s_1, a_2)$ based on the difference between the estimation and the reality. Multiply this difference by a learning efficiency alpha, and plus the value of the old $\mathrm{CS}(s_1, a_2)$ to be the new value. Moreover, epsilon greedy $\epsilon$ is used in decision making one strategy. Epsilon is equal to 0.9, indicating that agents choose the best action in optimal CS table with 90% probability, and it will provide the opportunity with 10% probability for the combination of other strategies using the random selection action.

Finally, the action is transmitted to the controller. If the selected action is successfully executed without against constraint of the intent, then modify the network environment internal state. The agent receives a reward $R$ indicating a change in the configuration score. In the case of violation of the constraint, the reward becomes a negative number for penalty. The state $s$ maintains its stage and the DQN reselects the policy combination and executes it. The iteration does not terminate until the reward converges. In the above steps, the DQN agent learns through the interaction with the environment in a trial and error manner.

In addition, we use a technique called experience replay. In the process of multiple episodes, the agent uses e-greedy to select the action at each step, and generates experience $e_t = (s_t, a_t, r_t, s_{t+1})$. $e_t$ will be stored in a memory dataset $D_t = (e_1, \ldots, e_n)$. During the loop, we apply Q-learning principle to sample of experience library, which is randomly extracted from the stored memory and can be defined as $(s, a, r, s') \sim U(D)$, randomly extracted from the stored memory. The model ultimately learns how to combine the strategies to satisfy each intent constraint in each state. Under the constraints of the intent translation, the DQN agent learns in an iterative manner through interaction with the environment, seeking for combination actions of fine-grained policy that can achieve those intent goals.

Finally, after the above steps, we get the network configuration policy, and then send the policy to the controller NETCONF for network configuration. However, the implementation of the above procedure is not enough. IDON also needs a guarantee mechanism to ensure the realization of the intention in case of failure.

### 3.3 Optical network intention guarantee mechanism

Due to the characteristics of high bandwidth and wide coverage in B5G, the number of optical network nodes and links is increasing, and the network structure is becoming more and more complex, resulting in more risk of failure [27]. In case of failure, how to guarantee the intent is also a key for close-loop zero-touch operation. When intent-driven generation of intelligent policies is launched and executed, it may face the difficulty of not adapting to the abrupt optical network environment. Therefore, the construction of intention guarantee mechanism is the necessary requirement to realize the complete closed-loop of intention-driven optical network.

To this end, the intent guarantee mechanism based on deep neural evolutionary network (DNEN) is introduced, ensuring a high-precision fault location with large-scale fault sets collected from network [16]. It can effectively deal with the fault problems in optical networks, maximizing the protection of intent, and achieve the complete closed-loop of intent control.

The monitor module of the controller monitors the abnormal state which breaches the constraints of intent in the network, namely alarm information. The controller then analyzes the alarm set collected from the configuration log to obtain the type, location, and the number of failures, and constructs an abstracted topology view of the fault distribution. It is noted that there is an intrinsic relation among the fault alarms for the complexity of the optical network topology, which is embodied in two aspects [28]. First, the fault can continuously cause multiple alarm messages. For instance, the bandwidth configuration does not meet the intent constraint, resulting in resource alarms, connection alarms, routing alarms, etc., meaning that other faults can be triggered by a fault. Secondly, due to the connectivity of the network topology, the alarm information has a certain relationship in the space dimension. For instance, the port, switching, and routing configuration have the relation in terms of the network topology space. Therefore, when encountering a large amount of alarm information, deeply hidden fault features must be extracted and real faults should be accurately found from complex relationships. Most of deep neural networks use gradient descent to train models. In the process of the gradient descent, the neural networks easily tend to be trapped by local optimization. However, DNEN constantly tries to mutate, and modify the weight, resulting in changing the training results of the neural network. It finally retains the well-performed model, and eliminates the poorly behaved models. As a result, it can jump out of the local optimization to find the global optimum. Therefore, DNEN with excellent global search capability can be well applied to the fault location during the intent configuration in optical networks.

The specific steps of applying the DNEN to fault location featuring sophisticated relation shown in Figure 5 are illustrated as follows. In the control plane, the central controller collects operation and maintenance data, including alarm information from all transport and control nodes. Due to the connectivity of the network topology, an enormous amount of alarm information would be collected by the controller when the network configuration operation fails to meet the requirement of intent constraints.

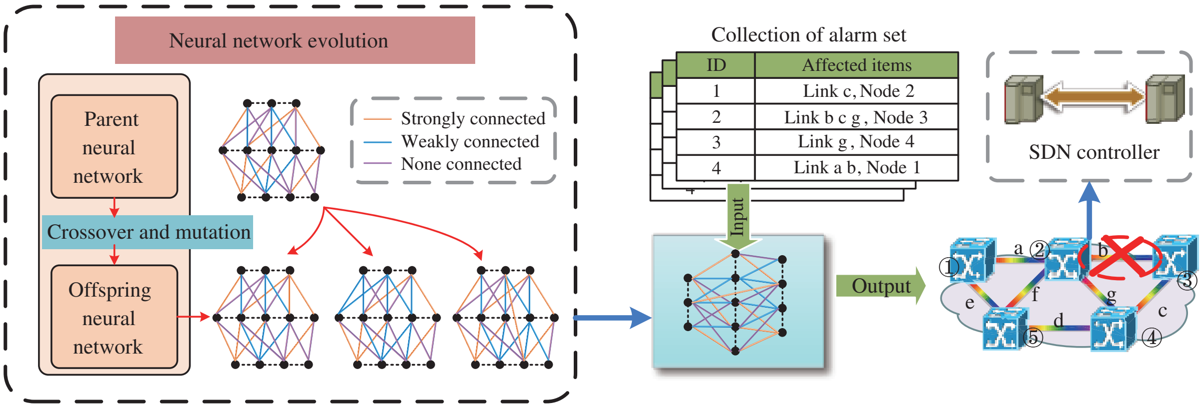


**Figure 5** (Color online) Illustration of DNEN scheme.

The mutation is the most important step in the evolutionary process of DNEN. Figure 5 shows the initial neural network structure and gene coding for the more precise location of configuration fault in DNEN. The first step is tantamount to initialize the structure of the neural network and encode the genome. Moreover, in order to satisfy the randomness of DNEN, a large number of neural networks are generated as the initial population. The normal distribution method is used to perturb the neural network weight parameters in DNEN. After that, the reward and utility of fault location will be used to update the weight parameters of neural networks. The neural network connection weights and connection forms have evolved, and we can obtain neural network structures that comply with the requirements of the final evolutionary genetic code. A neural network with higher adaptability has the advantage of breeding offspring and maintaining good features. This procedure has continued until the adaptability of the new neural network meets the requirements of extraction and precise for fault location.

Owing to the constant evolutionary state, the neural network structure of DNEN is different from the traditional multilayer neural network [16, 29]. Through evolutionary neural networks, we can find faults during the configuration process and re-select configuration policies to safeguard users' intent. DNEN not only makes fault location more precisely, but also ensures that each intent has a guarantee mechanism to execute in case of failure [30].

## 4 Performance analysis and results discussion

To verify the efficiency of the proposed IDON architecture, we have built a SAGO-IDON platform on SDON testbed with a fat-tree topology, which includes access domain optical domain and computing domain as well as 16 hosts with discrete intent event simulation. OpenAI Gym is also utilized to assemble core tools including network topology, discrete intent event generator, and monitor. Two major components of our platform are SDON real-time network emulator and the python library ray project that integrates the SAGO with the network emulator. The SAGO collects occupancy of switch, jitter, delay, and active flows as the environment state input. The emulator has run 35000 timesteps so as to prove enough significant robustness and stability level of proposed IDON architecture. Each timestep is set to 0.5 s to give enough time to collect the changing state of the network, meaning that it lasts for about 7 h under this step size in each running. The experimental steps are shown as follows. The intent is to input the LSTM model constructed by Keras for semantic segmentation and then map to network parameters. The parameter result of the intent translation is sent to the RL model, in line with the parameter, the RL selects an appropriate configuration action to generate corresponding flow rule for NETCONF. The monitor feedbacks the real-time states of the network to RL model. The configuration operation would finish when achieving the optimal configuration reward calculated based on the network status and intent expectation. Once failures appear and affect the intent configuration, DNEN locates the fault position according to the collected alarm set. Moreover, the location result is to be sent to the RL model for reselecting the configuration action. Once the running is accomplished, the proposed

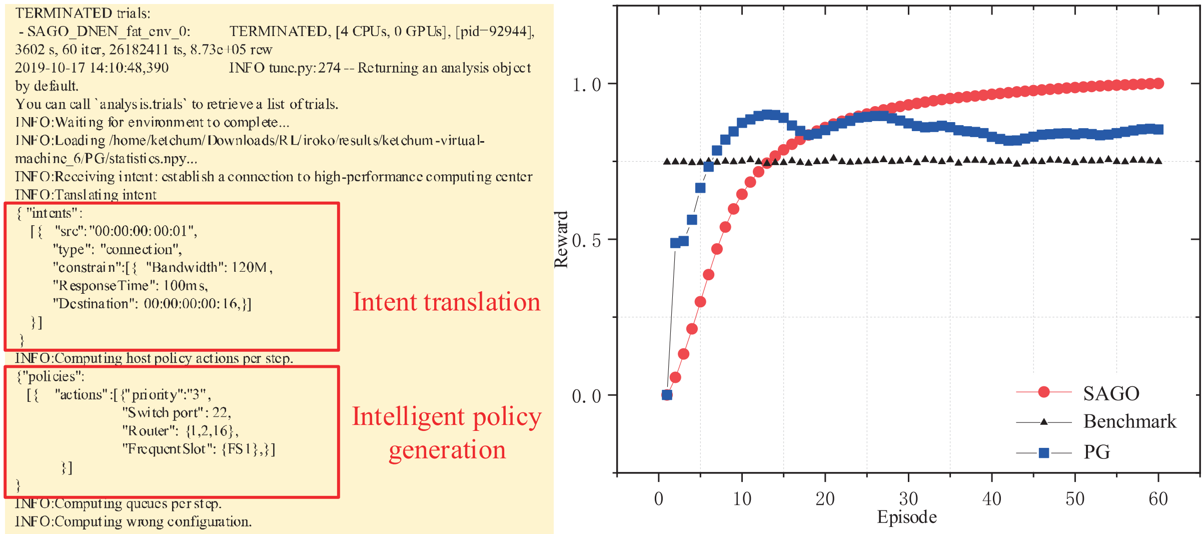


**Figure 6** (Color online) Illustration of DNEN scheme.

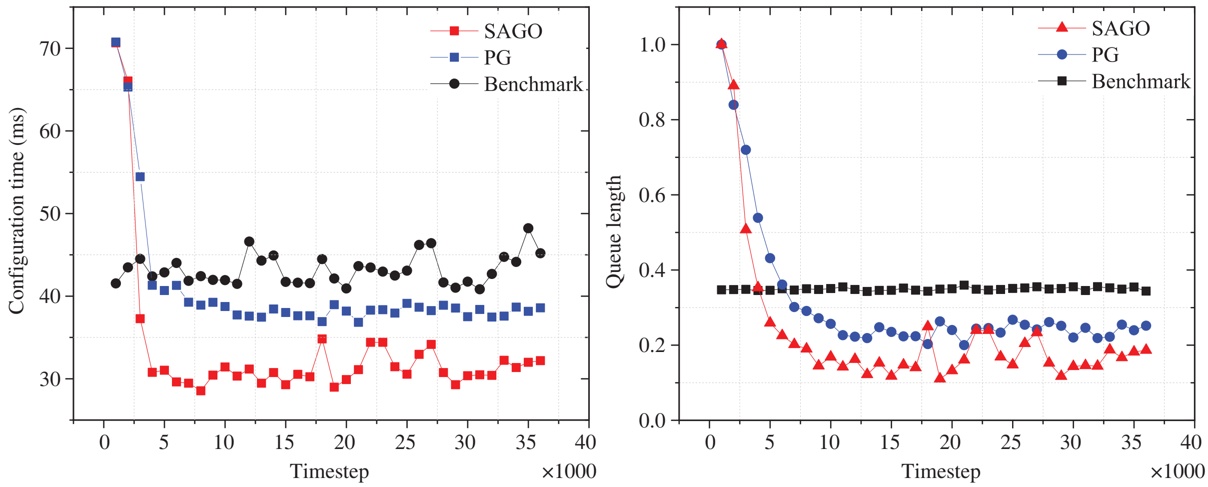


**Figure 7** (Color online) Illustration of DNEN scheme.

architecture is verified on the basis of performance metrics such as cumulative configuration rewards, configuration time, and queue length.

**Cumulative rewards of SAGO configuration.** The results of intent translation and SAGO configuration action policy are shown in Figure 6(a). We can see that the result of intent translation is to map the natural language to several constraints such as source node destination node, delay bandwidth, jitter, etc. Then, according to the result of the intent translation, IDON executes the intelligent automatic operation. The variations in cumulative rewards with respect to training episodes are shown in Figure 6(b). As seen in this figure, it can be seen that SAGO gets the highest configuration rewards, which indicates that the proposal can learn a positive policy under the constraints of intent translation. SAGO also has been compared with the policy gradient (PG) network and benchmark configuration. In the initial training, the performance of the proposal is not well-perform than the others. This is because SAGO is constantly exploring various configuration policies. But it gradually learns how to configure in the best way and outperform the others until the 30th episode.

**Impact on configuration time.** Figure 7(a) presents the variation on configuration time with the passage of timestep. It can be seen that the configuration time of SAGO is shorter than PG and benchmark after 5000 timesteps. This is because the SAGO can quickly execute the corresponding policy generation process after intent translation without parsing the flow table for configuration. Moreover, DNEN can locate the position of fault configuration at the millisecond level, ensuring the reconfiguration of closed-loop operation in case of failure. With the aid of DNEN's fast and accurate fault location, SAGO can reconfigure the network for failure in goal manner, avoiding the configuration of nodes on the routing path. Thus, the proposal cuts a large amount of configuration time as well as decreases the risk of configuration failure.

**Impact on queue length of switching.** The variations in queue length of switches, namely pending intent services, with respect to the time steps are shown in Figure 7(b). As seen in the figure, after intelligent control of SAGO-IDON, the queue length of the proposal is distinctly lower than the benchmark method and PG. This is because that SAGO takes global optimization of network system into account through introducing the evaluation criterion of configuration rewards, maximizing rewards of configuration operation. It means that the intent-driven intelligent control is considered from the global optimal point of view in IDON with SAGO. Overall, SAGO-IDON is endowed with a promising future in achieving zero-touch control of the optical transport network operation.

## 5 Conclusion and future work

This article presents a novel intent defined optical network architecture for achieving zero-touch operation, which can solve the intent-based networking operation and maintenance issue without the manual intervene. We have investigated and presented the functional entities of the architecture and interworking procedure in optical network automatic operation. The performances are demonstrated on the testbed for intent-based control. 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 safeguard the operation of the zero-touch configuration.

**Acknowledgements** This work was supported in part by National Natural Science Foundation of China (Grant No. 61871056), Young Elite Scientists Sponsorship Program by CAST (Grant No. 2018QNRC001), Beijing Natural Science Foundation (Grant No. 4202050), Fundamental Research Funds for the Central Universities (Grant Nos. 2018XKJC06, 2019PTB-009), Fund of SKL of IPOC (BUPT) (Grant Nos. IPOC2018A001, IPOC2019ZT01), ZTE Research Fund, and Key Laboratory Fund (Grant Nos. 6142411182112, 614210419042, 61400040503, CEPNT-2017KF-04).

**References**

1 Yang H, Zhao X, Yao Q, et al. Accurate fault location using deep neural evolution network in cloud data center interconnection. IEEE Trans Cloud Comput, 2020. doi: 10.1109/TCC.2020.2974466
2 Musumeci F, Rottondi C, Nag A, et al. An overview on application of machine learning techniques in optical networks. IEEE Commun Surv Tut, 2019, 21: 1383–1408
3 Casellas R, Martinez R, Vilalta R, et al. Control, management, and orchestration of optical networks: evolution, trends, and challenges. J Lightw Technol, 2018, 36: 1390–1402
4 Tuncer D, Charalambides M, Pavlou G. Management application interactions in software-based networks. IEEE Netw, 2019, 33: 149–155
5 López V, Jiménez R, de Dios O G, et al. Control plane architectures for elastic optical networks. J Opt Commun Netw, 2018, 10: 241–249
6 Kazemi H, Safari M, Haas H. A wireless optical backhaul solution for optical attocell networks. IEEE Trans Wirel Commun, 2019, 18: 807–823
7 Aguado A, Davis M, Peng S, et al. Dynamic virtual network reconfiguration over SDN orchestrated multitechnology optical transport domains. J Lightw Technol, 2016, 34: 1933–1938
8 Szyrkowiec T, Santuari M, Chamania M, et al. Automatic intent-based secure service creation through a multilayer SDN network orchestration. J Opt Commun Netw, 2018, 10: 289–297
9 Choi J S, Chun S J. Performance analysis of a hierarchical inter-domain provisioning framework for multi-domain software-defined optical transport networks. J Lightw Technol, 2019, 37: 3834–3843
10 Yang H, Zhang J, Zhao Y, et al. CSO: cross stratum optimization for optical as a service. IEEE Commun Mag, 2015, 53: 130–139
11 Yang H, Yuan J, Yao H, et al. Blockchain-based hierarchical trust networking for JointCloud. IEEE Internet Things J, 2020, 7: 1667–1677
12 Ayoubi S, Limam N, Salahuddin M A, et al. Machine learning for cognitive network management. IEEE Commun Mag, 2018, 56: 158–165

13 Zibar D, Wymeersch H, Lyubomirsky I. Machine learning under the spotlight. Nat Photon, 2017, 11: 749–751
14 Liu S, Niu B, Li D, et al. DL-assisted cross-layer orchestration in software-defined IP-Over-EONs: from algorithm design to system prototype. J Lightw Technol, 2019, 37: 4426–4438
15 Yu A, Yang H, Xu T, et al. Long-term traffic scheduling based on stacked bidirectional recurrent neural networks in inter-datacenter optical networks. IEEE Access, 2019, 7: 182296–182308
16 Zhao X, Yang H, Guo H, et al. Accurate fault location based on deep neural evolution network in optical networks for 5G and beyond. In: Proceedings of Optical Fiber Communication, 2019. M3J.5
17 Yang H, Zhan K, Kadoch M, et al. BLCS: brain-like based distributed control security in cyber physical systems. 2020. ArXiv: 2002.06259
18 Yao Q, Yang H, Yu A, et al. Transductive transfer learning-based spectrum optimization for resource reservation in seven-core elastic optical networks. J Lightw Technol, 2019, 37: 4164–4172
19 Yang H, Zhang J, Ji Y, et al. C-RoFN: multi-stratum resources optimization for cloud-based radio over optical fiber networks. IEEE Commun Mag, 2016, 54: 118–125
20 Ji Y F, Zhang J W, Zhao Y L, et al. Prospects and research issues in multi-dimensional all optical networks. Sci China Inf Sci, 2016, 59: 101301
21 Yang H, Liang Y, Yuan J, et al. Distributed blockchain-based trusted multi-domain collaboration for mobile edge computing in 5G and beyond. IEEE Trans Ind Inf, 2020. doi: 10.1109/TII.2020.2964563
22 Ji Y F, Zhang J, Wang X, et al. Towards converged, collaborative and co-automatic (3C) optical networks. Sci China Inf Sci, 2018, 61: 121301
23 Yang H, Zhang J, Zhao Y, et al. SUDOI: software defined networking for ubiquitous data center optical interconnection. IEEE Commun Mag, 2016, 54: 86–95
24 Gu R, Zhang S, Ji Y F, et al. Network slicing and efficient ONU migration for reliable communications in converged vehicular and fixed access network. Vehicular Commun, 2018, 11: 57–67
25 Yang H, Liang Y, Yao Q, et al. Blockchain-based secure distributed control for software defined optical networking. China Commun, 2019, 16: 42–54
26 Ferreira P V R, Paffenroth R, Wyglinski A M, et al. Multi-objective reinforcement learning for cognitive satellite communications using deep neural network ensembles. IEEE J Sel Areas Commun, 2018, 36: 1030–1041
27 Yang H, Zhang J, Ji Y, et al. Experimental demonstration of multi-dimensional resources integration for service provisioning in cloud radio over fiber network. Sci Rep, 2016, 6: 30678
28 Yang H, Yao Q, Yu A, et al. Resource assignment based on dynamic fuzzy clustering in elastic optical networks with multi-core fibers. IEEE Trans Commun, 2019, 67: 3457–3469
29 Yang H, Wang B, Yao Q, et al. Efficient hybrid multi-faults location based on hopfield neural network in 5G coexisting radio and optical wireless networks. IEEE Trans Cogn Commun Netw, 2019, 5: 1218–1228
30 Zhan K, Yang H, Yao Q, et al. Intent defined optical network: toward artificial intelligence-based optical network automation. In: Proceedings of Optical Fiber Communication Conference, San Diego, 2020. T3J.6