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Artificial intelligence-driven autonomous optical networks: 3S architecture and key technologies

Yuefeng JI[1*], Rentao GU[1], Zeyuan YANG[1], Jin LI[2], Hui LI[1] & Min ZHANG[2]

[1]*State Key Laboratory of Information Photonics and Optical Communications, School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing* 100876*, China;*
[2]*State Key Laboratory of Information Photonics and Optical Communications, Institute of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications, Beijing* 100876*, China*

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Abstract In the optical networks, the dynamicity, the complexity and the heterogeneity have dramatically increased owing to the deployment of advanced coherent techniques, and the optical cross-connect technologies and diverse network infrastructures pose great challenges in the optical network management and maintenance for the network operators. In this review, we propose a "3S" architecture for AI-driven autonomous optical network, which can aid the optical networks operated in "self-aware" of network status, "self-adaptive" of network control, and "self-managed" of network operations. To support these functions, a number of artificial intelligence (AI)-driven techniques have been investigated to improve the flexibility and the reliability from the device aspect to network aspect. Adaptative erbium-doped fiber amplifier (EDFA) controlling is an example for the device aspect, which provides a power self-adaptive capability according to the network condition. From the link aspect, adaptive fiber nonlinearity compensation, optical monitoring performance and quality of transmission estimation are developed to monitor and alleviate the link-dependent signal impairments in an automatic way. From the network aspect, traffic prediction and network state analysis methods provide the self-awareness, while automatic resource allocation and network fault management powered by AI enhance the self-adaptiveness and self-management capabilities. Benefit from the sufficient network management data, powerful data-mining capability and matured computation units, these AI techniques have great potentials to provide autonomous features for optical networks, including the network resource scheduling and the network customization.

Keywords artificial intelligence, optical networks, self-aware, self-adaptive, self-managed

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1 Introduction

To meet ever-increasing capability requirements driven by numerous end users and emerging bandwidth-hungry Internet applications including the 4K/8K high-definite video, the virtual reality/augmented reality (VR/AR), social applications and the cloud computing [1, 2], novel emerging technologies, such as advanced lasers and amplifiers, flexible grids, reconfigurable optical add-drop multiplexers (ROADMs) and coherent technologies have been deployed in the optical communications recently [3]. The dynamic optical signal path, high spectral efficiency, multi-layer service, complex networking stacks and diverse network state information are available, which have drastically improved the dynamicity, complexity, flexibility and heterogeneity of the optical networks [4, 5].

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

In the dynamic optical networks, the link information is time-variant and unforeseeable owing to the dynamic optical switching, where the complicated link-dependent impairments of transmitted signal impacted by the fiber Kerr effects are difficult to be compensated [6]. Meanwhile, the manual-designed static safety-margin for the advanced modulation formats leads to wastage of network resources owing to the lack of the quality of transmission information. To compensate link-dependent signal impairments and to sense real-time conditions of physical infrastructure, adaptive impairments compensation (AIC) and efficient optical performance monitoring (OPM) techniques should be proposed. Moreover, the unprecedented increase of network complexity has been introduced by numerous adjustable system and network parameters including the amplifier operating point, modulation format, baud rate, coding schemes, routing selection and resource allocation [7]. To decrease the network operation expenditure (OPEX), more flexible configuration schemes (FCS) with the full consideration of complicated network state constraints are necessary to enable the automatic network controlling and management. Besides the improvement of dynamicity and complexity, diverse transmission media are co-existed in the multi-domain heterogeneous optical network. The heterogeneity of the optical network is increased, where the conventional static design approach is not effective owing to highly time-varied service and operational demands. With the growing heterogeneity of the optical networks, how to guarantee high reliability of optical network is significant. Benefit from the development of the software defined network (SDN) and network function virtualization (NFV) platforms, numerous data collectors have the potential to be deployed in optical networks, massive data ranging from the quality of signal, network traffic loads, network fault data, the service configuration data to the end user behaviors information can be gathered and stored in the network maintenance logs, which can be further analyzed to discover the intrinsic patterns and enable intelligent and adaptive operations such as the traffic load balance (TLB), cognitive resource allocation (CRA), device fault management (DFM), network alarm compression (NAC). Therefore, to enable the adaptive pattern learning, nonlinear impairments compensation, network devices controlling, intelligent resource allocation and automatic network fault management, it is significant to take full advantages of the massive raw data from the multi-layer and multi-domain network architectures through powerful data analysis tools and propose more automatic techniques with less manual interventions and expert experiences. The operation of optical networks should work in an autonomous manner.

Recently, artificial intelligence (AI) has made tremendous breakthroughs since 2012, from the image recognition, natural language processing, data mining to the automatic decision, such as the game playing and unmanned car driving, enabled mainly by the massive training data, advanced algorithms and matured computation processors [8, 9]. AI is capable of extracting the complicated functional relationship among correlated variables and accomplishing the data-driven tasks with less manual interventions, which is specialized in addressing the problems that complicated functional relationships are needed to be modeled. But the underlying principles of physic and mathematics are too complex to be described through the conventional numerical analysis and expert modeling.

In this study, we propose a “3S” architecture of the AI-driven autonomous optical networks and review the major applications of the AI techniques in the optical network systems. In 3S architecture of the AI-driven autonomous optical networks, the advantages of AI techniques can be leveraged to enable the intelligent and autonomous operation of optical networks. With the aid of AI techniques, the optical networks can perform in a self-learning manner, with the “self-aware” of network status, the “self-adaptive” of network actions and control policies, and the “self-managed” of network operation, especially failure management. Enlightened by the powerful data analysis capability, AI has been introduced into the optical networks to comply with the ever-increasing dynamicity, complexity, flexibility and heterogeneity of the optical networks. The typical AI-driven applications ranges from the erbium-doped fiber amplifier (EDFA) controlling [10–12], nonlinearities compensation [13–15], optical performance monitoring [16–22], quality of transmission estimation [23–26], network device fault management [27–31], network alarm compression [32, 33], network attack detection [34–36] to the network resource orchestration [37, 38] for perceiving the timely conditions of the physical infrastructure, reducing the effects of signal impairments, configuring the network devices and schemes, enabling automatic network fault management and orchestrating the network resource for end-to-end services. The AI has great potential to realize these targets and improve the degree of intelligence of the optical networks dramatically.

The remainder of this article is organized as follows. In Section 2, the historical evolution of intelligent optical networks is introduced. In Section 3, the 3S architecture of the proposed AI-driven optical networks is specifically described. In Section 4, key AI-driven techniques for optical networks are evaluated, which have the potential to be applied in the near future. In Section 5, the challenges hidden from the AI-driven applications and the outlook for the furthering related researches are discussed. Finally, the AI-driven optical networks are drawn conclusion.

2 The evolution of intelligent optical networks

In this section, we will review the development process of the intelligent optical communications. Different optical network architecture and technologies, which introduce flexibility and intelligence into optical network operations, are compared and analyzed from characteristics, advantages and performance. The network architectures include wavelength division multiplexing (WDM) networks [39, 40], automatically switched optical network (ASON) [41] and its variants, software defined optical network (SDON) [42], and finally, the optical communication system that incorporates with machine learning (ML) which is the main content of this study.

Initially, WDM optical network is a point-to-point network form. The nodes of the network are connected by optical fiber and data transmission is carried out by WDM technology. The huge bandwidth brought by WDM technology has successfully solved the bandwidth bottleneck problem in the process of network transmission. However, like the data still needs to be processed with an optical-electric-optical (OEO) conversion mode at the original WDM optical network nodes. Thus, the point-to-point WDM is still unable to overcome the bottleneck of nodal switching rate. As the number of WDM wavelengths and the rate of single-wavelength data transmission increased, this bottleneck becomes more prominent until the advent of all-optical switching devices.

In order to solve the bottleneck problem of optical-electric conversion at nodes of point-to-point WDM optical network, an all-optical switching device is represented by optical add-drop multiplexer (OADM) and optical cross connection (OXC) appeared in the early 1990s, thus avoiding OEO conversion at network nodes and realizing all-optical transparent exchange of wavelength granularity. After the adoption of these all-optical switching devices, point-to-point WDM optical network evolved into wavelength routing optical network [40]. However, the original wavelength routing optical network only has the function of static configuration of transmission resources, which cannot meet the dynamic needs of various new services. Moreover, with the expansion of optical network scale, the management and maintenance costs of optical network gradually increase, and the service quality is difficult to guarantee. In order to realize the high flexibility, expansibility and service quality of the optical network, it is necessary to introduce intelligent control and management functions for the optical network, so as to realize the dynamic optimal allocation of transmission resources according to the business request and the state of the optical network.

ASON was proposed to combine optical layer networking technology with IP-based network intelligence technology to form the so-called "intelligent optical network". ASON added control plane to the traditional wavelength routing optical network transmission plane and management plane, and introduced routing, signaling, link management and other protocols to automatically complete the data exchange, transmission and other functions [41, 43]. Then, the optical network becomes a dynamic reconfigurable intelligent network. With the continuous expansion of the optical transmission network scale and the increase in type and number of devices, the development of optical network presents an obvious trend of heterogeneous, forming a multi-domain heterogeneous optical network. However, the routing calculation of the ASON architecture and the connection control process are highly correlated with the transport mechanism. Major modifications are required to support new switching devices or modes that may emerge in the future, so network construction costs, scalability, and smooth network upgrade capabilities will be greatly limited. The emergence of SDN provides a good way to solve this problem.

In 2009, researchers from Stanford University proposed the concept of SDN based on OpenFlow, whose core idea is the decoupling of network control plane and data plane. If this idea is introduced into optical network, it may fundamentally solve the problems of optical network scalability, flexibility and smooth upgrade. However, owing to the historical reasons for the development of optical network and the characteristics of optical (circuit) switching itself, the current optical network has a strong heterogeneity compared with IP network, which is manifested in the differential composition and representation of network resources under different transmission systems, different routing computing limitations and different connection control methods. Therefore, simply transplanting OpenFlow-based SDN technology into optical network is difficult to solve the problems of heterogeneous interconnection, expansibility, flexibility and smooth upgrade in optical network at the same time [42].

The main advantages of the SDON architecture are reflected in the following aspects.

(1) Reduce network construction and operating costs. The separation of control plane and data plane of SDON can avoid the repeated construction of network nodes, greatly reducing the cost of network construction. In addition, the SDON architecture can support the automatic operation and management of the network, reducing the need for manual operation, thus reducing the cost of network operation.

(2) Support connectivity of heterogeneous networks. The SDON architecture can not only realize the interconnection between different equipment providers and different types of existing switching equipment, but also support new switching equipment, switching modes and new services that may appear in the future through the construction of unified virtual resource matrix, unified virtual control state machine and other entities.

(3) Support smooth network upgrade. The separation of the control plane from the data plane enables the upgrade of the network (including the upgrade of the underlying switching equipment and the upgrade of the upper application) by means of software, ensuring that the existing network services and hardware will not be affected.

(4) Support more flexible routing calculation. It provides a unified virtual resource interface and a flexible routing computing interface to utilize network resources and optimize routing on demand.

(5) Provide a flexible experimental environment for network innovation. Through the software programming of the unified virtual control state machine and the use of the flexible routing computing interface, the complex routing and connection control strategy can be realized in the real network environment, shortening the development cycle and reducing the development cost.

To further improve the intelligence and automation level in optical networks, intelligent algorithms should be brought into the optical networks for intelligent and autonomous operations. The AI modules should be embedded in the control layer to support the self-learning manner, which include the aspects of self-aware, self-adaptive, and self-managed. The recent arising monitoring technique, telemetry, can collect real-time packet and network state data. These network features are uploaded for further prediction and estimation. The AI based decision-making method can aid the operation and control of the optical networks.

3 The 3S architecture of AI-driven autonomous optical networks

The 3S architecture of AI-driven optical networks is illuminated in Figure 1. The fundamental functional elements are used to execute information collection, data preprocessing, and control command sending. An AI module is adopted in the control layer to introduce intelligence in the optical networks for self-learning. The AI layer contains 3S modules: self-aware, self-adaptive, and self-managed, which enables novel features in the application layer including the network customization.

3.1 Data processing for AI

The AI module should obtain the network states to perform intelligence. The data processing in network controller is responsible for collecting the network states and preprocesses this state information to support the AI-driven modules for analysis and decision. The raw data that describe the network states, which may

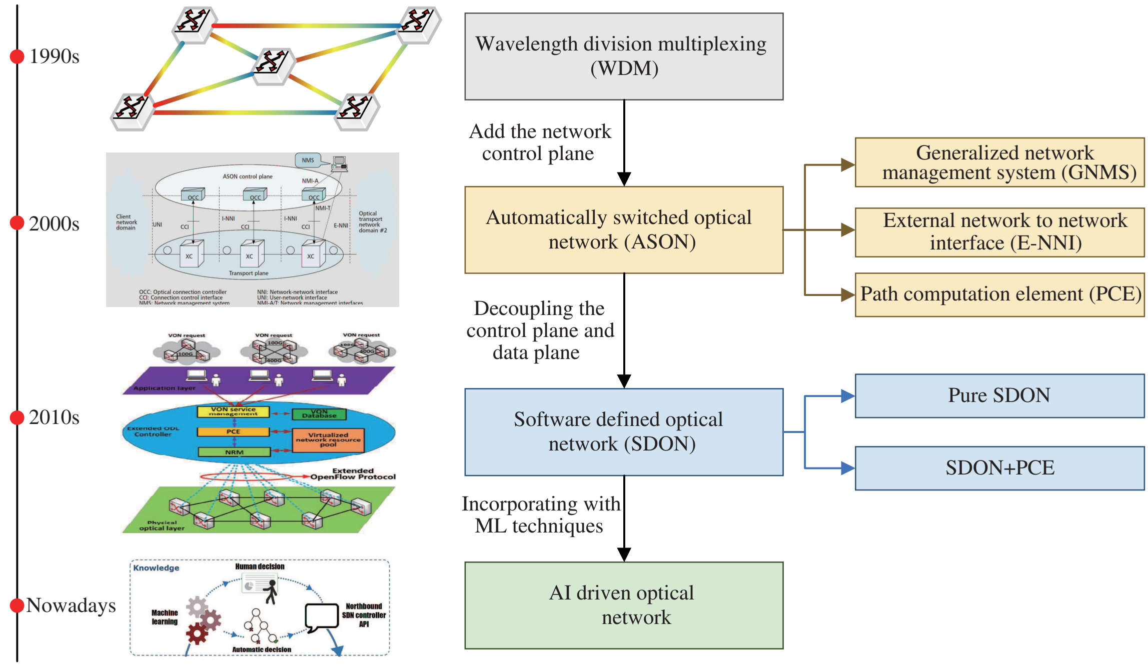

Figure 1 (Color online) The evolution of optical networks.

include traffic data, network topology, link status, and resource status, are collected from the underlying optical networks in data plane with telemetry techniques from southbound interface (SBI). The control plane first receives these data and uploads to the data processing modules in perception function for data preprocessing. The data aggregation module deals with heterogeneous data from different vendors and ISPs with data alignment to obtain a uniform data. Then the data are desensitized in data desensitization module to leave out or mask the privacy information for privacy protection. The desensitized data are labeled with data labeling under specific rules, and features are extraction with feature engineering module. The features and corresponding labels are used as structural data for AI algorithm training. In addition, a database should be adopted to store the raw data from networks and instances for training.

3.2 AI-driven self-aware functions

The self-aware functions are realized through AI based modules to predict and estimate network parameters. The self-aware of network status include AI-based network traffic prediction, AI-based optical performance monitoring, and AI-based quality of transmission (QoT) estimation of lightpaths.

Traffic prediction. The traffic prediction module receives the historical traffic volume in a certain time window from the perception module. The structural traffic data are input into the trained AI-based model and the AI models; i.e., artificial neural networks (ANN), recurrent neural networks (RNN) and the long short-term memory (LSTM), are capable of providing the predicted traffic volume. The resource allocation function receives the predicted traffic value and computes the optimal policies under the future traffic to release the proactive service provisioning schemes.

Optical performance monitoring. The major optical performance parameters include the chromatic dispersion (CD), polarization-mode dispersion (PMD), optical signal-to-noise ratio (OSNR), optical fiber nonlinearity and modulation formats. The signal parameters are first collected with telemetry and preprocessed into the forms of different transformed features such as the asynchronous amplitude histograms (AAH), direct detection and asynchronous sampling plot (DASP) and asynchronous delay-tap plot (ADTP). The supervised learning models are used to learn the relationship between the input features and signal parameters.

QoT estimation. The QoT performance of link and lightpath should be known to perform a precise resource allocation (such as modulation format allocation) with low margin. However, the traditional QoT estimation method usually relies on analytical ways, where the knowledge of transmission parameters such as the type of fiber and noise figure of amplifiers is required and this information may be difficult to obtain in real optical networks [44]. AI-based method can learn the nonlinear relationship between lightpath features and lightpath QoT performance. The lightpath features are extracted by feature engineering module with human knowledge or automatic feature selection. The features correspond with the QoT values are input into the ML models and the trained ML models can estimate the lightpath QoT with the input features and give references for resource allocation.

3.3 AI-driven self-adaptive functions

Self-adaptive network control changes the traditional static management mode of the network and enables the operation of the network to adapt the changes in the network state through AI. AI-based self-adaptive includes AI-based nonlinear compensation of optical signals, AI-based EDFA control, and AI-based optical network resource allocation.

EDFA controlling. The optical network devices should be operated under diverse network sates and constrained conditions. The real-time maintenance data consisting of the network experiment running parameters and experiment performances are monitored by the distributed monitors deployed in diverse key network experiments. The historical maintenance data comes from all distributed network device nodes, and is stored into the dataset. Taking the EDFA for example, the experiment running parameters include the amplifier input power and amplifier output power, and the experiment performances are constituted by the average gain (AG), noise figure (NF) and gain flatness (GF) of the EDFA. To control the network experiment adaptively to comply with service requirements, the AI techniques are adopted to model the nonlinear functional relationship between the experiment running parameters and the experiment performances to further provide optimized controlling operation points.

Nonlinearities compensation. Optical fiber nonlinearities are the dominant limitations for long-reach coherent systems working at advanced modulation formats. To alleviate the effects of the fiber nonlinearities, AI-based modules are selected for the adaptive nonlinearity compensation without the channel information, where the historical distorted symbols and the corresponding original symbols are collected and optimal decoders enabled by the supervised learning are trained by these symbols in the SDN controller. To accelerate the signal procedure, the well-trained decoders are downloaded into the local transceivers to realize the adaptive optical fiber nonlinearities compensation.

Resource allocation. The resource allocation is difficult in optical networks from two aspects. On the one hand, the dynamic of network is enhanced by the dynamic traffic and operations of network devices. On the other hand, the resources in optical networks are multi-dimensional, which are constituted of optical links, fiber cores, wavelengths, spectrums and modulation formats. The traditional network resource allocation is based on manual based configuration, using a large number of redundant resources or margins to cope with the traffic needs under the extreme condition of the networks. However, in the current network scenario, there is an exponential growth trend in the network traffic. In such condition, the optical network should be able to dynamically configure the network resources to each traffic according to specific network traffic volume. As is depicted in Figure 2, the optical network should obtain the traffic value from traffic prediction module to give an efficient configuration in a proactive way. The resource allocation also receives the estimated QoT value for impairment-aware resource allocation and modulation format assignment. The allocation scheme can be used as policies of path computational element in controllers.

3.4 AI-driven self-managed functions

The application of AI in network management mainly focuses on automatic fault management, including AI-based fault prediction, fault detection and fault location. One of the typical examples is failure management. The failure management tasks include failure prediction, failure detection and failure localization. The AI-based failure prediction module receives the information on network signals, links and devices from perception functions and further predicts whether there will be failures in network with

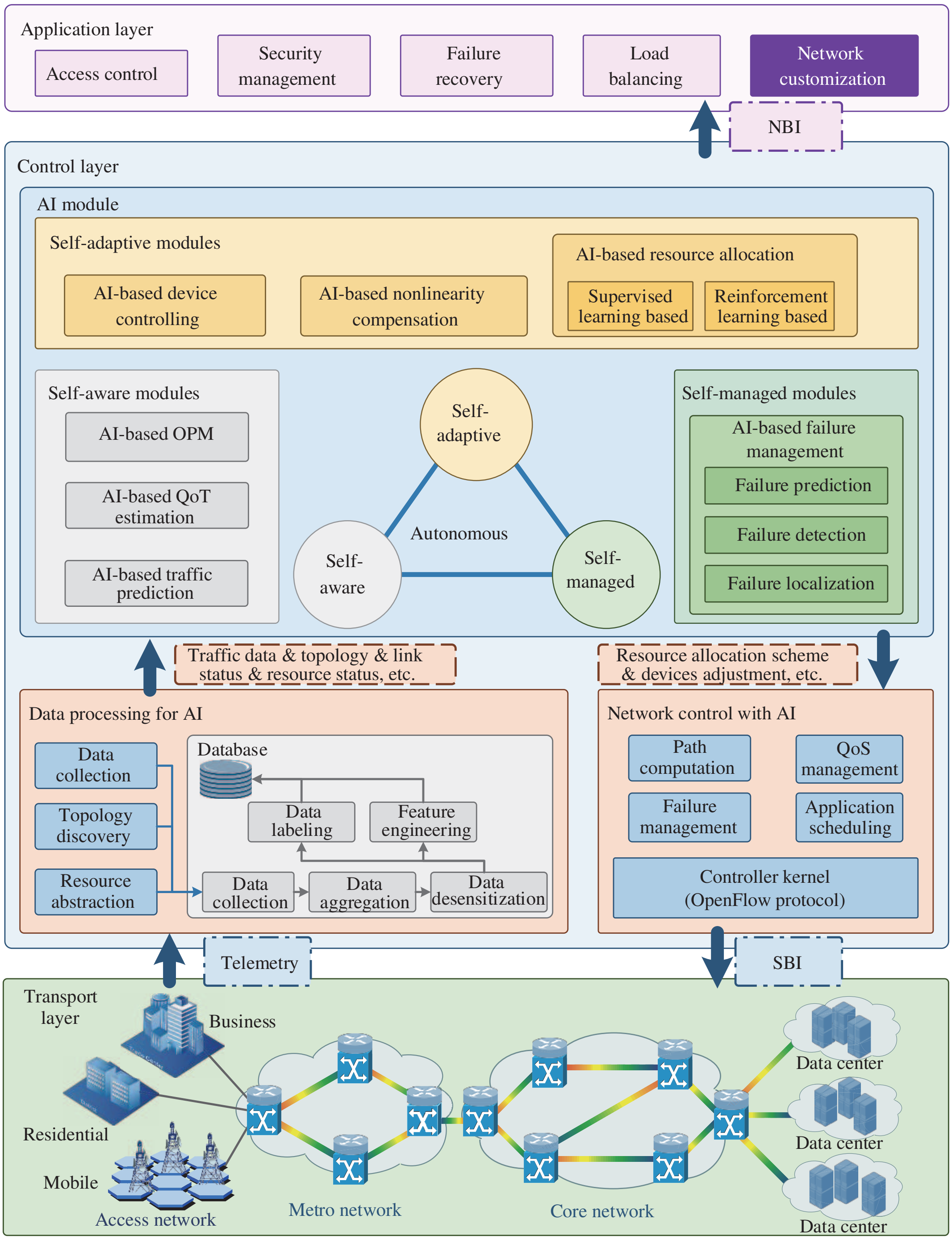

Figure 2 (Color online) The 3S architecture of AI-driven autonomous optical networks.

AI models or not. In the AI-based failure detection, classification models are used to identify the classes of failures already occurred. The AI-based failure localization faces the challenges that the large number of alarms appears in current optical networks and the true failure is not explicit. The AI methods are used to localize the real failures with the information of alarms. The predicted failures, failure type, and true failure localization are output to the failure management module in controller functions.

4 Enabling technologies in AI-driven autonomous optical networks

As shown in Figure 2, 3S architecture of AI-driven optical networks cannot be implemented by local innovations. It needs many key supporting technologies from device aspect, link aspect, to network aspect. For now, many researches investigate AI powered approaches on the above three levels, which will enable the optical networks to become self-aware, self-adaptive and self-managed.

4.1 Enabling technologies in device aspect

Recently, some adaptive techniques based on machine learning have been applied to configure optical network devices automatically, according to the device status and the network requirement. In the reconfigurable dynamic optical networks, the EDFA is one of the key components, which is capable of extending the transmission distance between the source node and the destination node by augmenting the power of the transmitted optical signal in the optical domain [45]. In the EDFA, the amplified spontaneous emission (ASE) noise is added and the non-flat gain spectrum exists. Moreover, the EDFA characteristics including the average gain (AG), noise figure (NF) and gain flatness (GF) depend on the input power, the pump power and the operating point. Owing to the time-varied input power in reconfigurable dynamic optical networks, the operating point of the EDFA should be adjusted adaptively to maintain the expected input and output power of the optical paths. Enlightened by the powerful self-learning capability, machine learning techniques are capable of providing adaptive operation of EDFAs for the dynamic input power and non-flat gain spectrum.

A few adaptive EDFA operation point adjusting techniques based on machine learning have been proposed for the dynamic reconfigurable optical networks. In [10], the multi-layer perceptron (MLP) is utilized to adaptively configure the parameters of each EDFA in the EDFA group to obtain the expected power performances of the corresponding optical path. In the MLP, the inputs of the MPL are the input and output power of the EDFA and the outputs of the MLP are the NF and the GF of the corresponding EDFA. The target of the adaptive EDFA based on the MLP is to select the optimal operating point, where lies the best tradeoff between the NF and the GF. The hypothesis in this study is that the optimal configuration for each EDFA may not result in the global optimal option for the complete optical path. Thus, the replaceable approach is to keep the balance among neighbor amplifiers. The configuration parameters of the EDFA are updated iteratively until the minimum noise figure and frequency response fluctuation are obtained. The proposed approach is verified experimentally that the expected input and output power in optical links can be obtained, where the power performances are maintained near 3 dBm within 0.1 dB deviation.

Moreover, Huang et al. [11] used a low-overhead machine learning algorithm called kernelized Bayesian regression (KBR) to describe the dependent power excursions among cascade EDFAs in the entire optical path. The KBR algorithm with radial basis function (RBF) is trained with historical channel sates, i.e., snapshots of the networks, and the power statistical deviation. The trained model is capable of predicting best slots selection to obtain minimum power deviation among neighbor links through adding or dropping certain wavelength. Further, in [12], the same group extended the previous study and proposed a ridge regression model to adjust the power of EDFA automatically. The trained model is able to determine power excursions of cascade EDFAs while various defragmentation approaches are adopted and then provide a dynamic power adjustments method for different defragmentation process, where it specifies whether the contribution will increase the discrepancy among post-EDFA powers or not. Thus, the power excursion problem after the dynamically changing spectral configurations can be addressed. It is verified that the ML-based method can output the appropriate channel selection to realize minimum power excursion (<1%) generally.

In dynamic optical networks, owing to the switched lightpaths and time-varied input power, the NF and the GF of EDFAs rely on the operating point and internal parameters of the amplifier, where the random noise is added and a non-flat power gain impact is caused. The MLP based EDFA controlling scheme is straightforward and is capable of adjusting the parameters of each EDFA among the EDFA sets in the optical link. The proposed schemes depend on the simplified hypothesis that the optimal configuration parameters of signal EDFA may not cause the global optimal configuration sets for the whole optical link. However, the stability and interpretability of the MLP need to be improved for the robust EDFA controlling. The proposed technique may not be able to realize the expected powers of the optical link, which is significant for the applicable scenarios. For EDFA controlling, the energetic consumption of the amplifier can be served as the other performance indexes and a power attenuator can be deployed at the receiver side in the optical links to alleviate the constraints about the expected output power.

4.2 Enabling technologies in link aspect

The enabling technologies in link level problems in optical network inlcude fiber nonlinearity compensation, OPM, and QoT estimation. The former two technologies focus on the optical signals performance monitoring and enhancement, and QoT estimation focuses on the performance of lightpaths which are consist of several links.

4.2.1 *Fiber nonlinearities compensation*

With the development of the digital signal processing (DSP) based algorithms, optical fiber linear impairments such as the CD and PMD can be effectively compensated in the modern coherent systems with advanced modulation formats. For the long-reach coherent systems with higher modulation formats, the optical fiber nonlinearities degrade the quality of the optical signal severely and are regarded as the major limitations for the capacity and transmission length improvement [46]. Therefore, it is significant to compensate the nonlinear optical fiber impairments to extend the transmission distance and enlarge the system capability. To compensate the fiber nonlinearities, various approaches have been proposed. Typical approaches consist of the digital back propagation (DBP), maximum-likelihood sequence estimation (MLSE), nonlinear polarization crosstalk cancelation (NPCC) [13, 47–50]. However, some of these typical approaches suffer from the computation complexity and some approaches are limited by the known optical fiber channel information, which is not effective in the dynamic optical networks owing to the time-varied optical paths. Therefore, more efficient and adaptive fiber nonlinearities compensation techniques should be proposed.

Recently, there have been a few researches using machine learning techniques for the optical fiber nonlinearities compensation. Nonlinear phase noise (NLPN) caused by the interaction between ASE noise from optical amplifiers and optical fiber Kerr nonlinearity effect is the dominant impairment. In [14, 51], as shown in Figure 3, support vector machines (SVMs) are utilized to generate optimal decision boundaries for the nonlinear phase noise (NLPN) mitigation. During the training phase of the SVM, the target is to search the distorted symbols in the constellation diagram of the received signal closest to the separating hyperplane, i.e., support vectors, and ensure it is as far away from the separating boundary as possible according to the structural risk minimization theory. After the training phase, the optimal decision boundaries created by the support vectors are capable of classifying the category of the distorted received symbols and combating the effects of the NLPN. The simulation results verify the effectiveness of the SVM-based NLPN compensation approaches, and the launch power dynamic range is increased by 3.3 dBm for 8PSK and 1.2 dBm for QPSK. The maximum transmission distance for 8PSK is increased by 480 km. Compared with MLSE, the M-ary SVM can perform better performances on the bit error rate (BER) and the transmission distance without any prior information of the transmission link. Other SVM- related stuides with different complexities and performance concerns are reported in [52, 53] with a 0.5–2 dB gain in Q-factor compared to linear equalization methods. SVM is originally a binary classifier, the combination of multi-SVMs is necessary for the nonlinearity compensation of signal with advanced modulation formats. To decrease the complexity of nonlinearities compensation approach, other machine learning based methods have also been researched.

In [54], the expectation maximization (EM) algorithm was utilized to compensate multi-impairments including the fiber nonlinearity, inphase and quadrature (I/Q) modulator imperfections and laser linewidth. Through the EM algorithm deployed after the DSP modules consist of I/Q imbalance compensation, CD compensation, clock recovery, joint polarization demultiplexing and carrier recovery, the nonlinear decision boundaries are also determined automatically to identify the category of the distorted symbols

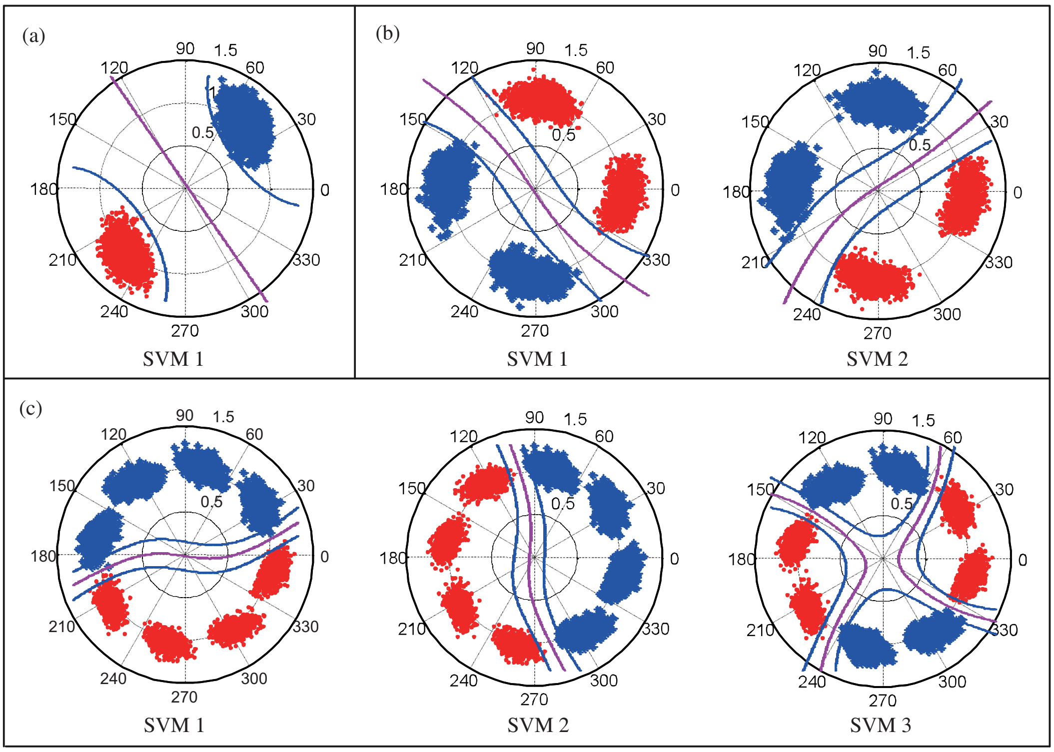

Figure 3 (Color online) The nonlinear decision boundaries created by SVM-based classifiers for (a) BPSK, (b) QPSK and (c) 8PSK systems [14] @Copyright 2015 IEEE.

in the constellation points and combat the impacts of these impairments. The effectiveness of EM for combating NLPN is experimental verified and 3 dB power tolerance can be obtained for a dispersion managed polarization multiplexed 16-QAM system operating at 14 Gbaud for a dispersion unmanaged system, the corresponding power tolerate decreases to 0.5 dB. In [55], an ANN was deployed after CD compensation for the fiber nonlinearities compensation, where the training mechanism called extreme learning machine (ELM) is adopted to avoid iterative weights and biases updates [56]. In [15], as shown in Figure 4, a k-nearest neighbors (KNN) based approach is designed as a classifier, which is capable of recognizing the category of the distorted symbols; i.e., different categories in the constellation diagram denote various symbol with certain amplitude and phase information, and then recovering corresponding binary information to relief the effects of the fiber nonlinearities for three kinds of link scenarios including the zero-dispersion link (ZDL), dispersion managed link (DML), and dispersion unmanaged link (DUL). Compared with the MLSE, better performances in terms of the linewidth tolerance, launch power range and transmission distance can be achieved in the KNN, especially for laser phase noise and nonlinear phase noise mitigation in ZDL or DML. Moreover, the distance-weighted KNN (DW-KNN) is able to further improve the system performances.

For the fiber nonlinear impairments compensation, various techniques including the DBP, MLSE, NPCC, nonlinear pre- and post-compensation (NPC) and machine learning based approaches have been proposed. In the DBP and MLSE, high computation complexity limits the processing speed and the achievable gain in the nonlinear tolerance is dependent on particular transmission scenarios. Moreover, the specific fixed fiber link information is needed in these electronic methods, which may not be effective for dynamic and reconfigurable optical network link. For the expectation maximization-based algorithm, it can improve the nonlinearities tolerance of the optical fiber communication systems. However, compared to the dispersion unmanaged link, the signal propagation in the dispersion managed link is affected. It is essential to investigate the benefits of EM for dispersion unmanaged link as well. Efficient and applicable algorithms for the optical fiber nonlinearity compensation are still open for research.

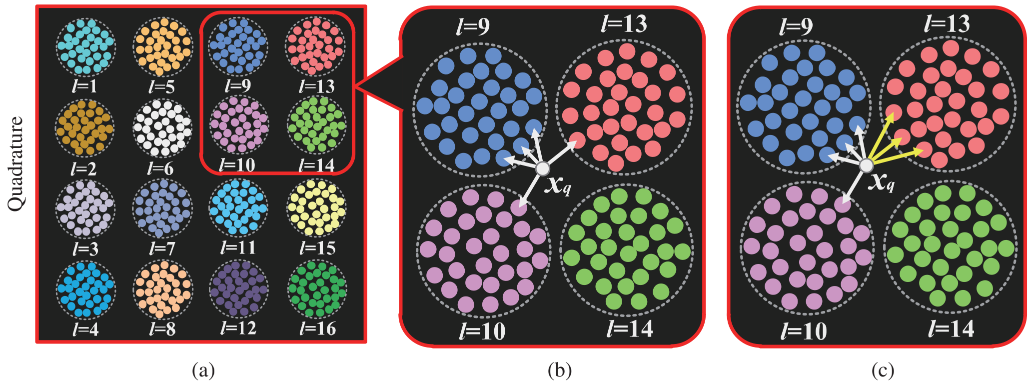

Figure 4 (Color online) (a) 16QAM constellations with the corresponding labels; (b) KNN-based decoders when k is valued in 5; (c) DW-KNN-based decoders when k is 7 for the nonlinearity compensation [15] @Copyright 2016 IEEE.

4.2.2 *Optical performance monitoring*

With the advent and deployment of the reconfigurable optical add-drop multiplexers (ROADMs), the flexible grid and advanced coherent technologies, the dynamic signal path and high spectral efficiency are available, where the flexibility, complexity and dynamicity of optical networks have been improved drastically [6]. In the dynamic optical networks, the link information is time-variant and unforeseeable owing to the dynamic optical switching, where the complicated link-dependent impairments of transmitted signal are difficult to be compensated. Meanwhile, the manual-designed safety-margin for the advanced modulation formats leads to wastage of network resources. To compensate link-dependent signal impairments, achieve optimum resources utilization and enable automatic network management, it is necessary to sense the real-time condition of physical infrastructure and adopt the OPM techniques to estimate and measure diverse physical parameters of transmitted signals and various components of optical networks. In the OPM, the major monitoring parameters include CD, PMD, OSNR, optical fiber nonlinearity and modulation format. Moreover, accuracy, sensitivity, dynamic range, cost-effectiveness, multi-impairment monitoring are crucial demands of the OPM.

The classical OPM approaches can be roughly divided into four kinds of methods including the spectrum-analysis-based method, polarimetry-based method, pilot-tones-based method and measurement-based method. However, external devices are necessary for estimating particular parameters in these optical performance monitors generally. Recently, machine learning techniques have been widely used in the image recognition, natural language processing, data mining and automatic decision. Compared with the traditional DSP techniques, machine leaning algorithms have special advantages in learning the complex relationship that is difficult to be investigated owing to significant computational complexity. Benefit from the powerful data discovery capability, machine learning techniques have been widely utilized in the optical communication. To decrease the cost of OPM and improve the flexibility, the OPM techniques based on the AI have attracted a lot of attention, where multi-tasking data driven machine learning algorithms are available and flexible digital signal processing techniques can be deployed in the receiver without extra devices.

(1) OSNR and modulation format monitoring. OSNR is one of the most significant parameters that should be monitored in optical networks owing to the direct relationship between the BER and OSNR [57], which can be served as the crucial QoT indicator for thesuperiors routing selection, resource allocation and network fault management. The OSNR monitoring methods using ML can be coarsely divided into two categories according to the applied situations. Some methods are specially designed for the OSNR monitoring at the intermediate node, where the monitoring techniques should be low-cost because of the limited DSP resources and the wide deployment requirements. To decrease the hardware cost and the complexity of OSNR monitors at the intermediate node, different techniques including the direct detection and asynchronous sampling (DDAS), asynchronous amplitude histograms (AAH) [22] and asynchronous delay-tap sampling (ADTS) [58] have been proposed, where the low-cost direct detection and low-speed

asynchronous sampling are adopted to avoid expensive coherent detection high-speed analog-to-digital converter (DAC) and complex clock recovery. What's more, diverse modulation formats are coexisted in the reconfigurable optical networks and the DSP and QoT requirements of optical signal with varied modulation formats are different with each other. Therefore, the modulation format is also one of necessary parameters needed to be monitored and it is always monitored together with the OSNR in the ML-based approaches.

In [22], numerous AAH data of the directly detected signal with diverse OSNR are gathered as the dataset through the simulation setup. During the training step, the mapping relationship between the AAH and the corresponding OSNR is learned via the error back propagation mechanism of the DNN. After the training phase, the AAH data from new directly detected signal are fed into the trained DNN and the predicted OSNR is then output. Through comparisons between the predicted OSNR and the true OSNR, the estimation error can be measured. The average root-mean-square OSNR estimation error is around 0.45 dB in [17]. Besides the AAH, the ADTP is also used to extract the OSNR information for OSNR monitoring as the immediate node. The ADTP is generated through the ADTS, where the direct detected signal is asynchronously sampled in pairs with a fixed time delay and the amplitude statistical information in the sample pairs is further plotted as an ADTP. In [17], asynchronous delay-tap plot (ADTP) analyzer using convolutional neural network (CNN) is proposed for the cost-effective OSNR monitoring at the immediate nodes. CNN is a kind of neural networks that is superior in image processing. With weight sharing and convolutional computing of matrix, it can reduce the parameters between layers. CNN is applied to analyze ADTP images that are converted from two-dimension digital vectors, where the trained CNN is adaptive for ADTP with different sampling rate since the ADTP images can be resized flexibly. In this approach, the maximum OSNR monitoring deviation is less than 0.45 dB and 1920 ps/nm accumulated CD can be tolerated. In [16], the transmitted optical signal after the filter is directly detected by a photodetector (PD) and the asynchronous single channel sampling (ASCS) scatter plots are generated and then sent into the PCA for the feature extraction. In the ASCS plots, only single-tap sampling is needed compared to the ADTS which uses two-tap sampling for the acquisition of delay-tap sample pairs. The OSNR and modulation format information of the extracted feature data can be recognized through the Euclidean/Manhattan distance comparisons among the feature data with known OSNR and modulation format in the dataset. The OSNR monitoring estimation errors for NRZ-OOK, NRZ-DPSK, and RZ-DPSK signals are 0.65 dB, 1.04 dB, and 1.3 dB respectively and the overall modulation format identification accuracy is 98.46%.

Other methods are proposed for the OSNR monitoring at the end node, in which the OSNR can be extracted from the received signal after dispersion and phase compensation and the DSP is sufficient in the receivers. Benefit from the advanced DSP technologies, the linear impairments can be fully compensated in coherent receivers and the transmission performance is mainly determined by OSNR [59]. In [60], the DNN is utilized to extract OSNR and modulation format information from AHHs obtained after constant modulus algorithm (CMA) equalization, where three kinds of modulation formats including the quadrature phase-shift keying (QPSK), 16-ary quadrature amplitude modulation (16-QAM), and 64-QAM can be identified with free error rate and the mean OSNR estimation errors is 1.2 dB, 0.4 dB and 1 dB respectively. In [61], the data with four branches serve as the input, where each input branch contained 512 time-concatenated data is sampled with 40 GS/s after the coherent detection. The DNN with three-hidden layer is utilized to learn the relationship between input and the corresponding OSNR. The experimental results show that the OSNR differences are less than 0.5 dB for 14/16 GBaud DP-QPSK/64QAM systems. In [18, 20], as shown in Figure 5, OSNR estimation and modulation format identification are realized through the CNN as the perspective of image recognition, where eye diagrams and constellation diagrams are adopted for the OSNR and modulation format monitoring, and intensity modulation and direct detection (IMDD) systems, respectively. For the eye diagrams analysis, the OSNR estimation accuracy is 100% and four widely-used modulation formats in the IMDD systems, i.e., RZ-OOK, NRZ-OOK, RZ-DPSK, and 4PAM, are recognized with free error. For the constellation diagrams analysis, the OSNR estimation errors for all the signals are less than 0.7 dB and 100% accuracies are achieved for six typical modulation formats including QPSK, 8PSK, 8QAM, 16QAM, 32QAM, 64QAM.

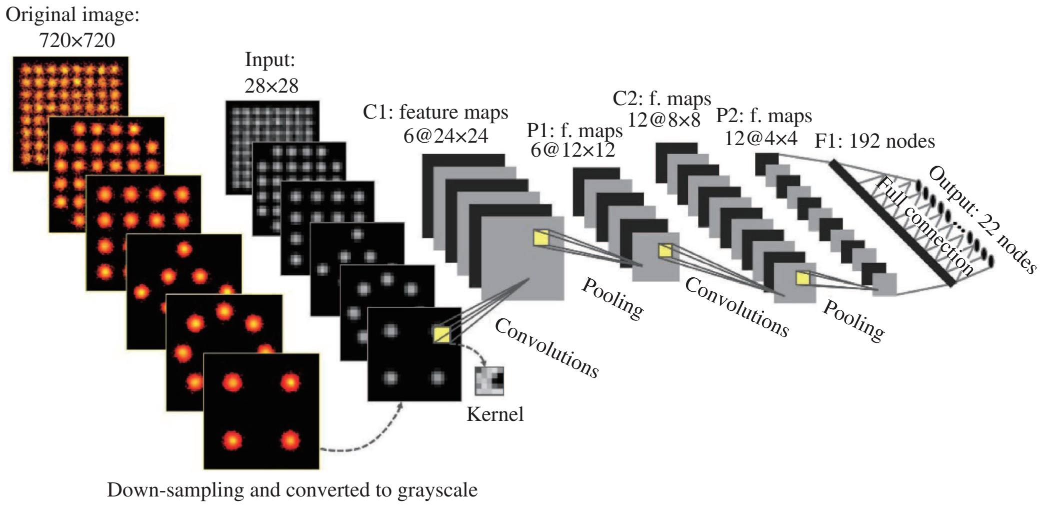

Figure 5 (Color online) Schematic diagram of CNN-based constellation diagram analyzer for the OSNR estimation and modulation format identification [20].

The advantages of AAH-based monitoring techniques are that less deployment complexity is obtained and they are transparent to modulation formats and data rates. However, the major drawback is that the effects of various impairments are mixed, which limits the independent monitoring ability. Moreover, the number of samples affects the monitoring accuracy of AAH-based techniques significantly. The balance between accuracy and monitoring speed should be investigated. For the ADTP based monitoring techniques, the similar information in the eye-diagram can be obtained, where the specific shape of an ADTP includes the modulation format, bit rate, tap-delay and different signal distortions information such as the ASE noise, CD and PMD. The special advantage of ADTP-based techniques is that multiple impairments can be estimated simultaneously. For the ML-based OSNR monitoring techniques, the estimation accuracy needs to be further improved, which is essential for the adjustment of modulation format, powers and symbol rates of different subcarriers in the EON. Moreover, the monitoring function should be extended to multi-impairment monitoring including the wavelength, OSNR, CD, PMD to decrease the cost of OPM in the optical networks.

(2) Fiber nonlinearities estimation. The effects of the optical fiber nonlinearity derive from the power dependence of refractive index, where large power of the optical signal causes the interference and crosstalk between different WDM channels and further degrades the quality of signal with advanced modulation formats. The influence of inter-channel nonlinear distortions such as cross-phase and cross-polarization modulation (XPM and XPolM) and four-wave-mixing (FWM) can be modeled as a stochastic process related with the auto-correlation function (ACF) and the ACF is a function of the physical layer parameters including input power, channel spacing, span length and propagation distance. In [62], as shown in Figure 6, an inter-channel nonlinearity monitoring technique based on the principal component analysis (PCA) and neural networks (NN) is reported, where NN is utilized to learn the nonlinear mapping between the ACF and input physical layer parameters and the trained NN is able to output the ACF of a new set of physical layer parameters. To decrease the complexity of the NN, PCA is adopted to reduce the dimension of the ACF, where three coefficients are finally used to replace the ACF. During the testing phase, the trained NN is able to predict these three coefficients with mean squared error (MSE) valued in 7.8E−3. In [63], ANN-enabled nonlinear noise monitoring according to amplitude noise covariance (ANC) and phase noise covariance (PNC) related to the received waveform is proposed and the monitoring accuracy is improved obviously. In [64], the artificial neural network (ANN) is used to calibrate the deviations in Gaussian-noise (GN) model and then the ML is adopted to estimate fiber nonlinear noise variance and model the nonlinear optical link for the heterogenous dynamic optical networks, where the system features including the span number, maximum and average span length, launch power,

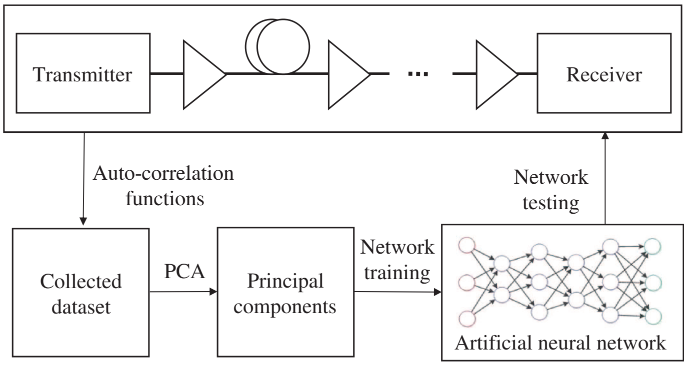

Figure 6 The fiber inter-channel interference analyzer based on the PCA and NN [62].

link length, chromatic dispersion, number of WDM channel, average gamma and alpha of fiber span and the noise covariance features including the ANC, PNC and the indexes about the ANC and PNC across neighboring symbols serve as the input of the ANN engine and the corresponding signal-to-noise ratio (SNR) work as the output. The NLI estimation accuracy is significantly improved and the SNR monitoring deviations are within ±1.1 dB. Moreover, in [65], a small ANN is trained to establish the nonlinear relationship between the linear and nonlinear SNR of the received signal and the input features consist of the nonlinear phase noise and second-order statistical moments. The standard error for the linear and nonlinear SNRs is verified by numerous simulations and valued in 0.04 and 0.20 dB, respectively. In the proposed technique, the temporal properties of the time-varying ISI matrices are exploited and not depended on the GN model.

For the modeling and monitoring of optical fiber nonlinearities, different approaches have been researched, including the nonlinear Schr dinger (NLS) equation and the split-step Fourier method (SSFM). However, the computation complexity is too high to apply them as the real-time planning tool. The simplified GN model makes it a promising technique for network planning, but the accuracy should be guaranteed for the dynamic links. For the ML-based nonlinear noise monitoring with ANC and PNC, a significant improvement in monitoring accuracy is realized. It is still difficult to maintain the monitoring accuracy in complicated link conditions because of the limited information in the coherent receiver.

(3) Chromatic dispersion estimation. In reconfigurable optical networks, dynamic path may introduce variable amounts of accumulated CD. Traditional fixed CD compensation techniques are not effective, where the known value of the CD is needed to be sent into the frequent domain equalizer [66]. Thus, CD is necessary to be monitored for the adaptive CD compensation to guarantee the transmission of quality in high-speed dynamic networks. Furthermore, PMD is another dispersive impairment that needs to be monitored for the reason that the PMD effects are stochastic, time-variant, temperature related and data rate dependent, which is a major limitation in fiber-optic networks operating at data rates above 40 Gbit/s [56, 67]. What't more, in the PMD monitoring, the main target is to ensure whether it is greater than certain maximum value or not to guarantee it can be compensated by the adaptive filter [68]. Therefore, CD and PMD are key dispersive impairments parameters that need to be monitored in dynamic optical networks.

There are a number of approaches based on ML proposed for the CD and PDM monitoring. For the ML-assisted CD monitoring, the key issues are to discovery appropriate CD-sensitive features and decrease the monitoring complexity, where the parameters extracted from the eye diagrams [69, 70], asynchronous amplitude histograms (AAH) [71, 72] and asynchronous delay tap plots (ADTP) [73–75] are exploited to monitor the CD information. In those techniques, the typical machine learning algorithm called artificial neural network is used to discovery the underlying relationship among CD-sensitive features and the accumulated CD. The dynamic monitoring range is generally within 800 ps/nm. To enlarge the CD monitoring range, new feature, i.e., the error vector magnitude (EVM) of the distorted signal after the coherent detection, is utilized to estimate the accumulated CD [76]. The strong correlation between the accumulated CD and the EVM is observed, where the signal constellation is compact when the small CD is accumulated and contrarily the signal constellation is scattered when the accumulated CD is large. The DNN is utilized to estimate the CD through the EVM. Benefit from more CD-sensitive features, the CD monitoring range is extended into 2000 ps/nm, the mean estimation error is less than 20 ps/nm and the complexity of the estimated approach is decreased obviously compared to the traditional CD scanning and frequent domain equalization approach. For the ML-assisted PMD monitoring, PMD is usually monitored together with the CD estimation.

For the CD monitoring, the monitoring range of the CD estimation method based on the coefficients of adaptive filer is near several hundred ps/nm, which is limited by the length of filter taps. For the CD monitoring based on the machine learning, the CD estimation range is extended to several thousand ps/nm, which is effective and low-complexity in the long-reach coherent passive optical network. For the coherent long-haul optical transmission systems, the CD compensations are not deployed in the links and the accumulated CD is up to tens of thousands ps/nm at the intermediate nodes. The monitoring range of CD estimation method using the CD scanning and numerous frequency domain equalization is not limited in theory, but the complexity is too high to realize the fast signal processing, which is important for the subsequent DSP modules deployed in the receivers. Therefore, the adaptive CD monitoring techniques with larger monitoring range and low complexity are still in demand.

4.2.3 *AI based quality of transmission estimation*

In actual optical network operation, in order to ensure reliable optical connection, it is necessary to reserve a large system margin to cope with the possible uncertainties in the network. These redundancies may cause a low utilization of the network resources. Besides, the modulation format assignment in EON needs the link performance in advance to select proper modulation format. Thus, an accurate monitoring of QoT is needed. With an accurately estimated QoT vaule, the system uncertainty and the redundant margin can be reduced. Compared with OPM, QoT does not only focus on the physical layer, but also consider a more general concept, including the influence of link layer and even network layer.

Traditional QoT estimation methods are mostly based on approximated analytical models which provide an accurate estimation but require information of networks parameters. In a real network, these parameters may be difficult to obtain. The approximated models with these inaccurate parameters might cause significant underutilization of network resources. Other analytical estimation approaches, such as split step Fourier transform based methods, are with high computational complexity which hinders the practical use.

ML based methods have been used to estimation QoT to overcome the complexity and time-consuming computations of conventional analytic QoT estimation methods. Barletta et al. [24] classified whether the BER of a lightpath meets the performance requirement. The problem is modeled as a classification tasks and random forest is employed as classifier. The predicted output is true if a lightpath BER is lower than the system threshold. Authors test several architectures of random forests and choose the classifier with 100 estimators, which provides the best trade-off between model accuracy and computation complexity. The results of whether the lightpath is feasible are used when establishing a new lightpath.

A case-based reasoning (CBR)-based method is proposed for lightpath QoT estimation which classifies the lightpaths into two classed including high- or low-quality in impairment-aware resource allocation in optical networks [77]. In this study, CBR method stores a knowledge database with each sample consisting of a set of features that are related to lightpath, and the corresponding Q-factor value. When estimating the QoT of a new sample, the features of the the new lightpath will be compared with the samples in CBR database, and the weighted Euclidean distance is computed to evaluate similarity between two lightpaths. The corresponding Q-factor of the lightpath in the knowledge base with the largest similarity is assigned to the new lightpath as its Q-factor. The lightpath Q-factor is compared to a Q-factor threshold (Q-threshold) for lightpath performance classification. The authors also discussed a CBR with a learning and forgetting techniques to optimize the knowledge base to decrease its complexity.

Neural networks are exploited for estimating the blocking probability of bufferless OBS/OPS networks in [78]. The input features are information about the traffic and lightpath. The training set is the combination of features and corresponding blocking probability. Sartzetakis et al. [79] proposed two ML-based methods for QoT regression. Firstly, the ML-based model learns the relationship among dispersion, fiber attenuation, nonlinearity, and corresponding QoT value. ML is used to learn the input parameters of the physical layer model to improve its accuracy. The second approach adopts supervised learning for QoT estimation. In the method, the choice of the features greatly determines the accuracy of the estimator. Thus, appropriate features are selected for the estimators for the heterogeneous networks.

Mo et al. [80] proposed a transfer learning-based method for QoT prediction in real-time mixed line-rate systems without retraining ANN models from scratch. The transfer learning-based method is used to predict the Q-factor of different optical systems with only a few additional training samples. The transfer learning-based method not only helps to enhance the capability of system upgrade but also reduces the computational complexity in model retraining and data collection [80].

A comprehensive comparison is given among several classification algorithms under different network characteristics and a full-size synthetic data in [23]. Besides, both regression and classification algorithms are proposed and are evaluated with an extended and concise set of features collected by the controllers.

4.3 Enabling technologies in network aspect

The enabling technologies in network aspects in AI-driven autonomous optical networks include traffic prediction, resource allocation, and failure management.

4.3.1 *AI based optical network traffic prediction*

In the current optical networks, the network traffic is exponentially increasing. Besides, the types of services are also increasing, which result in strong dynamic of the traffic and the need to dynamic adjustment of resource allocation. To deal with the dynamic traffic with flexible resource allocation, traffic prediction is needed. There are two major reasons for the network traffic prediction in optical networks. On the one hand, traffic prediction can assist in elaborate resource allocation and reduce network operating costs. In current networks, the resources, such as bandwidth, are often allocated according to peak conditions to ensure network performance and reliability. However, this method will generate high resource redundancy and cause huge resource waste. Future transport network resource allocation should be able to dynamically adjust with the service to provide more refined network resources. Accurate prediction of network traffic, and timely expansion and reduction of network resources are of great significance to improve network stability, enhance user experience and save operational expenditure (OPEX) [81, 82]. On the other hand, traffic prediction can discover and predict traffic anomalies to ensure stable network operation. Through traffic prediction, traffic anomalies existing in the network can be perceived or even predicted in advance, and network operation and maintenance personnel can be reminded and assisted to make corresponding decisions to ensure the safe and stable operation of the network.

From the perspective of industry data, it is feasible to use AI algorithm for traffic prediction. Firstly, the behavior of users and the bandwidth changes of the services are not completely random, the network traffic carried by the optical network often presents a certain regularity and periodicity. These features make it possible to predict the future data according to the historical data. Additionally, in the field of transmission network, a large amount of traffic historical data are accumulated in network operation and maintenance. And the Internet service providers (ISPs) usually have the ownership of these data, so that they can use these massive data to build accurate traffic prediction model. From the perspective of AI algorithm, many studies have shown that most machine learning algorithms, such as random forest, neural networks, have a strong ability to learn nonlinear relations, and a good tolerance to data noise. With appropriate AI algorithm combined with mass data, more accurate traffic prediction can be achieved.

AI based traffic prediction is usually solved with supervised learning, which is divided into the following steps.

(a) Collect historical flow data for data sorting work, and set the input time window.

(b) Use historical data as model input, future traffic volume as model output, and train a supervised learning model.

(c) Verify the trained model, confirm the model performance, determine the hyperparameters and input dimensions existing in the supervised learning, and put them into use.

(d) When using the model, there is no future traffic as supervisory data, and historical data is used as input to predict future traffic data.

There are several studies that deal with traffic prediction with machine learning algorithms. DNNs have been used to predict bandwidth resource demand of the optical networks between data centers [83]. In a virtual optical network (VON), the input of model training is traffic characteristics (such as source node, destination node, historical traffic information), and this information is used to predict the bandwidth requirement of the next time slot. The infrastructure provider (InP) uses the predicted value of the business resource requirements to determine whether network resource allocation should be reconfigured. When InP monitors a significant mismatch between the future traffic and the currently allocated resources, InP reconfigures an appropriate VON to handle future traffic.

DNNs are also used inside the datacenter optical networks for traffic prediction. The predicted traffic information is used for resource allocation to improve bandwidth resource utilization and reduce blocking probability [84]. The datacenter network of hybrid electro-optical structure uses both optical circuit switching (OCS) and electrical packet switching (EPS). OCS is used for transporting large-capacity services and EPS is used for transmitting short-lived and bursty data streams. This hybrid structure can transport traffic of different granularities at low congestion rates. Traffic prediction is critical for early decision on whether traffic should pass OCS or EPS transmission. The nonlinear autoregressive neural network (NARNN) is used for traffic prediction in a hybrid electro-optical DCN scenario in a busy service scenario. The predicted traffic information allows administrators to prioritize the heaviest traffic flows in the future for optical switching and electrical switching.

LSTM is utilized to predict the time remaining of traffic transmission for traffic aggregation in an optical data center network [85]. LSTM is specially designed for the tasks whose inputs are sequential data. Each hidden unit not only receives the input data, but also takes the output of hidden unit in previous time. The average remaining life (MRL) of traffic is a function of time and hold time information (HTI) that has been spent, and the average remaining lifetime must be known when resources are allocated or reallocated in the data center. Owing to the heterogeneity and diversity of data center applications, the HTI of traffic is not available. Although the traditional method assumes that the HTI has an exponential distribution, it is ineffective for data center traffic owing to the heavier tail characteristics. Therefore, LSTM can be used to learn the complex relationship between historical traffic data and HTI.

4.3.2 *AI based resource allocation in optical networks*

The optical transport network needs to allocate multi-dimensional physical resources owing to its special network location. The resources that need to be allocated usually include fiber links, fiber cores, wavelengths, spectrums, and modulation format.

The traditional way of exchanging redundancy for network reliability will cause a huge waste of resources. In the scenario of exponential traffic growth and increasingly scarce network resources, it is necessary to use AI algorithm to make accurate resource allocation. The AI based optimal resource allocation can consider different requirements of users (such as, delay) and cost of operators (such as bandwidth utilization, and load balancing). It can provide an accurate allocation to save costs and improve resource utilization efficiency. Besides, the traditional studies mostly use rule-based policy which are usually built on domain knowledge. These methods often model the resource allocation problem with the data plane operation and mathematical optimization theories, which engages significant efforts of networking experts and operators and lacks the scalability [86]. The AI based resource allocation can reduce the computation time in the online processing stage. There are mainly two paradigms of using AI methods for resource allocations.

Resource allocation strategy fitting with supervised learning. In this way, a large number of instances, which are obtained by solving traditional optimization models, are used for supervised learning. Then use the supervised learning algorithm to learn the inherent law of the traditional model resource allocation strategy. The training process for supervised learning requires computing resources, but this process can be performed offline, and can be performed in a data center with rich computing resources. When used online, the trained model can quickly calculate the results.

Iterative learning optimal strategy with reinforcement learning. Reinforcement learning learns the optimal strategy through interacting with the environment. In the resource allocation task, the network state is used as the input of the reinforcement learning model, and the resource allocation scheme is used as the output of the reinforcement learning model.

(1) Routing assignment in optical networks. In optical network, the optical links are allocated to the optical path to transmit the traffic. The traditional shortest path first (SPF) algorithm will lead to low utilization rate of network resources as well as a high blocking rate. Heuristic routing assignment will face high computational complexity which is impractical in large scale network.

In supervised learning-based routing, the route assignment is solved with classification or regression method. The training dataset consists of traffic information and is the pre-computed route. Troia et al. [87] proposed a classification-based routing decision to assign the optimal route for current traffic demands in software defined optical network. The traffic demands are collected with REST APIs for machine learning based routing computation. Then the traffic matrices are classified to select optimal route assignment. The classification result corresponds to a pre-computed optimal routing solution. The machine learning algorithm, logistic regression, is trained with input of several traffic metrices and output of the optimal routing sets. The proposed method can obtain a real-time network reconfiguration. A short processing time can be obtained with only 80 ms.

In multi-domain network scenarios, it is difficult for the controllers to obtain all intra-domain network information because the information is presented from exterior access for security. To generate a route without using intra-domain network information, LSTM is adopted to learn the rules inside the routes from historical route set. The LSTM-based model can output a feasible route for a traffic without the intra-domain information [88]. The training input of LSTM includes traffic volume, historical routing schemes, and link capabilities in each domain. The supervised output of the LSTM is the route set pre-computed with backward recursive PCE-based computation (BRPC). There is no need to know the intra-domain information when computing the routing among domains.

Routing problems can be also model as decision-making tasks. In such scenario, the learning models learn the optimal policies under a specific network states through interacting with network and obtain the reward. Reinforcement learning is usually used for decision-making problems and can be used to decide optimal route in optical networks. A reinforcement learning-based model is proposed in OBS networks [89]. In this approach, all nodes are equipped with reinforcement learning agents. Each learning agent contains a Q-table, which is a table storing the pairs (destination, neighbor) and Q-value of this pair. The Q-table is used for the selection of the next hop of the traffic with a reinforcement learning manner. The RL based method out-performs the traditional shortest path-based methods.

(2) RWA and RSA. Generally, in a WDM network, a resource allocation task is called a routing and wavelength assignment (RWA) problem, and in an elastic optical network (EON), the resource allocation task is called a routing and spectrum assignment (RSA) problem. The RWA problem refers to the allocation of routing and transmission wavelengths for each traffic flow, while the RSA aims to establish an optical path with multiple spectrum time slots for traffic transmission [90]. Spectrum allocation refers to the allocation of appropriate spectrum time slots for the requested optical path. In addition, the resource allocation in EON usually involves the selection of a modulation format based on transmission distance and signal quality perception, and the joint resource allocation is also called RMSA. The difference between RSA and RWA is that the EON architecture provides flexible spectrum allocation to meet the required data rate. The RSA and RWA are also used for network slicing and virtual network embedding [91–93]. Both RWA and RSA are NP-complete issues [94].

The RWA is modeled as a classification task with the optimal RWA scheme as the output, which is solved by DNNs and logistic regression [95]. Integer linear programming (ILP) is used for the pre-

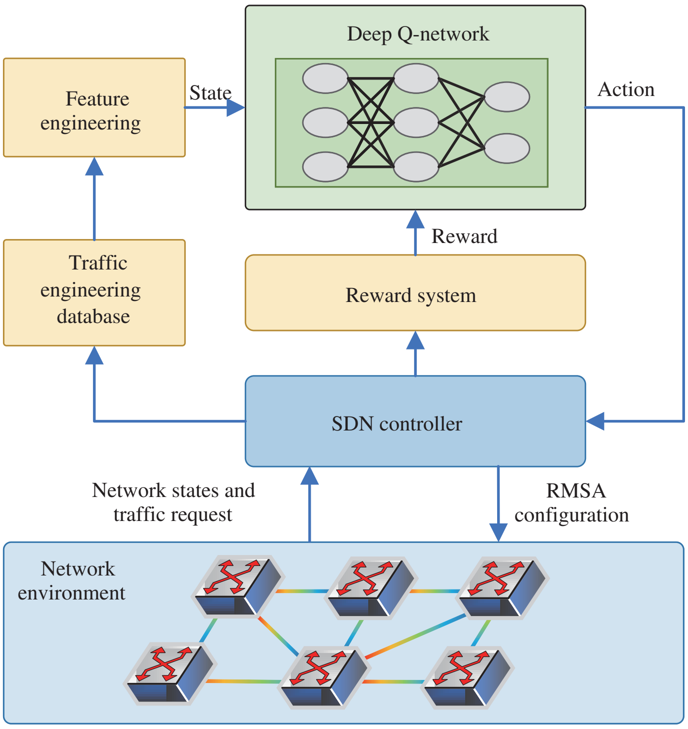

Figure 7 (Color online) Operation principle of DeepRMSA [97].

computation of optimal RWA scheme. The input features are network status including topology, the capacity of links, wavelengths usage and traffic matrix. The expected output is the optimal RWA configuration. The network status and corresponding optimal RWA are used to train the logistic regression and DNN models.

The machine learning based RWA that considers the physical impairments was proposed in [96]. In this method, the wavelength continuity constraint and QoT constraint should be satisfied for a traffic not being discarded. The wavelength of a traffic should stay the same along the route, and the lightpath QoT should reach the performance requirement to be used. The QoT of a lightpath is firstly estimated under several impairments and examined. If the QoT reaches the threshold, the lightpath can be added into the candidate list for future usage.

A DRL-based routing, modulation, and spectrum assignment framework (DeepRMSA) is used to learn the optimal online RMSA scheme in EONs in [97]. As shown in Figure 7, the DeepRMSA model deals with each lightpath request with the optical RMSA with network status including traffic requirement and state of each frequency slot. Two training mechanisms for DeepRMSA are proposed, which take the characteristics of the RMSA problem into considerations, to train the deep Q-learning. The numerical results demonstrate the superiority of DeepRMSA in blocking rate over the heuristic algorithms.

(3) Orchestration in optical networks. Facing the real-time and bursty traffic in the future optical networks, the deployment of dedicated middleboxes will extremely increase the CAPEX and OPEX. Network function virtualization (NFV) is adopted to replace the dedicated middleboxs with vNFs in datacenters. These vNFs can dynamically and adaptively response to bursty traffic [42]. Deep reinforcement learning is used for virtual network functions (vNFs) service chaining provisioning in EON of inter datacenters (Deep-NFVOrch) [98]. The traffic is perdicted before the vNFs assignment, and the DRL module is adopted as an observer for adaptive interval time generation in Deep-NFVOrch. The DRL is trained with asynchronous advantage actor critic (A3C). When a service cycle ends, the DRL agent receives the instant performance metrics and updates the DL-based request predictor. The DRL-based observer uses an asynchronous training scheme to ensure high learning accuracy for online operations. Simulation results show that Deep-NFVOrch can obtain adaptive vNF-SC provisioning and balance the system performance on resource utilization, network reconfiguration cost, and blocking rate, under the

scenario of highly dynamic vNF-SC requests.

4.3.3 *AI based optical network failure management*

With the extension of network scale and increasing of network devices, the failure detection tasks and analysis of large number of alarms should be processed. When facing large number of alarms and different kinds of failures, traditional methods may fail in accuracy and time efficiency. The AI techniques can be used to learn the complex and nonlinear relationship between the failure features and failure classes and localization information. The failure information can be used for failure recovery [99].

(1) Alarm analysis. With the expanding of optical networks, the number of alarms in optical networks may reach over one million within one week [32]. The alarms from optical networks are complicated to process. The complexity of dealing with large number of alarms is from two aspects: on the one hand, a real fault will cause large number of alarms which may cause many redundant alarms, on the other hand, there may exist lots of false alarms which do not belong to a specific fault. Especially, the alarms in OTNs may rise from the optical transport plane, the service plane and the control plane, so that a large number of alarms from different planes will interact with each other. So that the large amount of alarms should be pre-processed with efficient tools. Wang et al. [32] pre-processed alarms from OTNs with K-means and neural networks. Firstly, the alarm attributes are quantized, and then the alarms are classified with K-means algorithm. Then, the neural network (NN) algorithm is used to infer the importance of alarm attributes (IAAs). The proposed method can give an importance score to evaluate each alarm and compress the alarms to a certain rate.

(2) Failure localization. Because of the large network topology and the network components connectivity, several alarms may be triggered by the same failure [100]. A deep neural evolution networks (DNEN) based method for massive failure localization in WDM networks was proposed in [100]. The DENE-based method can extract the deep hidden failure features and localize the real failures. DNEN generates a series of neural networks, and creates new networks by crossover and mutation until the model meets the accuracy requirements. The experimental results with real optical network data show that the DNEN-based method can achieve the highest accuracy in localizing failures with low computation complexity.

Yang et al. [101] presented a hybrid multiple failure location method with Hopfield neural network (HNN) in radio and optical wireless networks. Through processing the alarms, network topology and service information, the actual failure nodes and links can be localized. Then, the correspondence between detected failures and alarms is modeled to establish a bipartite graph. The bipartite graph is computed using the fast processing of HNN to solve combinatorial optimization problems. The HNN-based method can be benefited from the parallel computing training process to reduce computing time. Simulation results demonstrate the time-efficiency of the proposed method.

Data visualization method is adopted in failure localization to leverage the human operation with the aid of K-means [102]. The max BER and the trend of BER are adopted as features. The paths are clusters with K-means method according to the features. The different centroids of clusters are plotted with different colors for visualization. After the visualization, it is convenient for the operator to inspect each of these optical links to find whether it causes the degradation.

5 Conclusion

The development trend of future optical communications needs to improve the intelligence performance to meet the exponentially increasing traffic and complex network environment. Artificial intelligence techniques are guaranteed techniques to leverage autonomous capability for optical networks. In this study, we first review the evolution of intelligent optical communications from WDM to ASON, SDON, and intelligent optical networks incorporating with AI. Then we propose a 3S architecture of AI-driven autonomous optical network, which includes the functions of self-awareness, self-adaptiveness, and self-management. The AI powered technologies, including adaptive EDFA controlling, fiber nonlinearities compensation, optical performance monitoring, optical network traffic prediction, optical networks resource allocations, quality of transmission estimation, and optical network failure management will enable autonomous features of optical network. In the future, the dataset openness, model explainability and system reliability could be improved, to make the optical network more efficient, more flexible, more reconfigurable according to the service requirements and network status in an autonomous approach.

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