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• REVIEW •
Special Focus on Artificial Intelligence for Optical Communications

An overview of ML-based applications for next generation optical networks

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Abstract Over the past few decades, the demand for the capacity and reliability of optical networks has continued to grow. In the meantime, optical networks with larger knowledge scales have become sources of numerous heterogeneous data. In order to handle these new challenges, many issues need to be resolved, among which the low-margin optical networks design, power optimization, routing and wavelength assignment (RWA), failure management are quite important. However, the use of traditional algorithms in the above four applications shows some shortcomings. Fortunately, artificial intelligence (AI), especially machine learning (ML), is regarded as one of the most promising methods to overcome these shortcomings. In this study, we review the applications of ML methods in solving these four issues. Although many ML-based researches have emerged, the applications of ML techniques in optical networks still face challenges. Therefore, we also discuss some possible future directions of investigating ML-based approaches in optical networks.

Keywords optical networks, artificial intelligence, machine learning, system margin, power optimization, routing and wavelength assignment, failure management

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1 Introduction

With the rapid progress of Internet services, 5G technologies [1], Internet of Things and so on, the traffic demand of optical networks has been ever-increasing. Such demand puts forward higher requirements for the capacity and reliability of the next generation optical network. In the past few decades, the capacity of fiber transmission systems has been remarkably increased and is now approaching the theoretical limit. Fortunately, with the development of elastic optical network (EON), network resources, e.g., spectrum, route, optical power, etc., can be utilized more efficiently to extract more capacity [2]. In addition, margins can be minimized so as to avoid resource underutilization [3]. On the other hand, reliability of optical networks is also of great importance. Since a massive amount of data is transmitted in optical networks, even a tiny disruption of a service may cause huge losses for customers.

As described above, the next generation optical network is expected to be more resource-efficient and more reliable, which requires intelligent and dynamic control of the system. The controller needs to be able to adapt the physical layer to the dynamic links and make proper strategies, among which the design of low-margin optical network, power optimization, routing and wavelength assignment (RWA) and failure

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management has drawn many attentions. Their functions are described as below. The design of low-margin optical network aims to extract capacity from spare margins. The power optimization applications can help obtain further capacity through adjusting the launch power of each lightpath [4]. The RWA applications allocate route and wavelength effectively, thus reducing blocking rate for a better resource utilization [5]. The failure management performs detection, identification and localization of anomaly that degrades performance of the system [6]. In many previous studies, traditional algorithms based on mathematical models have been widely studied. However, many of them show deficiencies in modern optical networks, because the optical networks are typically dynamic and heterogeneous, and analytical algorithms based on static models may be hard to fulfill the requirements [7]. Fortunately, the fast-growing artificial intelligence (AI) methods provide a promising alternative to build these applications [8]. The AI techniques are especially suitable for complex modeling and can adapt themselves to the dynamic system. In this study, we review the recent progress of applying AI to optical communication systems and networks, focusing on the design of low-margin optical networking, power optimization, RWA and failure management. In addition, the challenges of using AI in these scenarios are discussed, and the future of AI-enabled optical networks is outlooked.

The rest of the paper is organized as follows. In Section 2, we introduce the requirements for the next generation optical networks and motivations of applying machine learning (ML) to fulfill these requirements. In Section 3, the applications of ML in the aspects of designing low-margin network, power optimization, RWA and failure management are discussed, respectively. In Section 4, we review the recently reported experimental verifications of using ML in optical networks. Section 5 discusses the future directions and challenges of applying AI in optical networks. Finally, we give the conclusion in Section 6.

2 Background and motivations

In this section, we first describe the requirements of the next generation EON, and then provide a brief introduction of the ML, followed by the elaboration of the advantages of adopting ML, to help readers better understand these new technologies.

2.1 Requirements of management and control applications in optical networks

In order to improve the capacity and reliability of optical networks, the control of network needs to be fast-response, autonomous and intelligent. The detailed requirements are elaborated as below.

• Fast response. Since optical networks are changing dynamically, the control of the EON should be capable of tracking changes and making decisions accordingly. To adapt to the real-time status of optical networks and guarantee the transmission performance, many applications in the control layer need to respond in a short time. For example, failures in optical networks may result in network service interruptions, affecting tens of thousands of users and causing huge economic losses. Therefore, it is essential for the controller to recover links to the normal state as fast as possible [6].

• Automation and intelligence. The increase of network complexity requires the control of optical networks to be more intelligent and autonomous [9]. The increase of network complexity mainly comes from: (1) a great number of devices, protocols and applications are applied to optical networks, which greatly increases the heterogeneity of the network [10]; (2) the development of coherent transmission technologies including advanced coding, modulation and digital signal processing (DSP) introduces a large number of adjustable system parameters, e.g., modulation format, symbol rate, coding scheme, DSP configurations, etc. [11]. The increase of network complexity increases the difficulty of the network control, and it is preferable to build an autonomous and intelligent optical network.

2.2 Brief introduction of ML

As a branch of AI, ML can learn system patterns from a given dataset. Depending on the different types of the outputs, ML attempts to solve two categories of problems: classification (for discrete outputs) and regression (for continuous outputs). A typical workflow of ML consists of two phases: training and inference. At the training phase, ML methods are applied to learn the system characteristics using the training dataset. At the inference phase, the system obtains the estimated output for each new input.

The categories of ML can be divided into supervised learning (SL), unsupervised learning (USL) [12] and reinforcement learning (RL) [13]. SL utilizes a known output (labels) to establish a mapping between the input and output data. USL algorithms classify a set of data or discover the relationships among data without any label-driven feedback mechanisms [7]. In the area of optical networks, these two groups of algorithms are mainly investigated in the applications such as designing low-margin optical network, power optimization and failure management. RL refers to the mechanism that the agents interact with the environment periodically to obtain the feedback on the previous decision from the environment so as to make next decisions. RL is particularly useful in uncharted territories since it can learn from its own experience instead of getting trained with labeled datasets [12]. Most RL algorithms can be performed in the context of Markov decision process (MDP) and are often applied to solve RWA problems.

2.3 Advantages of ML-based methods

• Data-driven. For modern optical networks, there is a large amount of underutilized data which can be retrieved from network telemetry, quality indicators, network alarms, traffic traces, user profiling, etc. [11]. These data can be applied to monitor the networks but the underlying relationships among them are unclear. In this case, ML can show its advantages in discovering the hidden relationships between various types of information, thereby performing data-driven tasks with limited manual intervention [14]. For instance, the amplitude noise and phase noise correlations of the received symbols implicitly exhibit the same trend of the nonlinear noise [15], and the ML can make use of abundant data from experiments and simulations to learn such a relationship for nonlinear impairment monitoring.

• Self-adaptiveness. Many applications aim to optimize network performance and update network parameters through continuously monitoring the network environment. Analytical methods are often based on specific assumptions and constraints, which may not be compatible with such a target. On the contrary, ML shows its advantage in the ability of self-adaptiveness [7]. Compared with analytical models, ML can comprehensively analyze multi-domain data and adapt itself to the real-time conditions [16].

3 Review of the applications of ML-based methods in optical networks

3.1 Design of low-margin optical networks

In general, to ensure the quality of transmission (QoT) of an optical system, operators tend to set a high margin and prefer not to make any changes once the service is established. This kind of design strategy is the well-known "set and forget". However, with the physical layer approaching the theoretical limit, this traditional design method seems a waste of spectrum, and needs to be changed to fulfill the ever-increasing demand of the capacity. Therefore, the design of low margin optical networks has been drawing increasing attentions and many studies have been reported. In this subsection, we first explain the concept of the link margin and then review the previous studies on applying ML techniques to the design of low margin optical networks.

As described in [17], link margin can be classified into three types. Unallocated margins are caused by the mismatch between the required capacity demand and that of the equipment actually deployed. It can be addressed by using the bandwidth variable transponder (BVT). System margins are caused by the time-varying effects of a system, such as the aging or the increasing loading. Design margins are caused by the inaccuracy of planning tools. To reduce these margins, many investigations have been conducted, most of which focus on reducing design margins and system margins. The details are discussed as below.

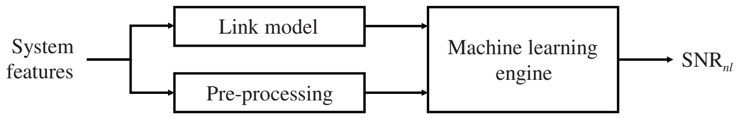

Figure 1 Block diagram of ML-aided fiber nonlinearity modeling [29].

3.1.1 *The reduction of design margins*

The current QoT tool mainly consists of approximate mathematical models such as the Gaussian noise (GN) model [18]. These mathematical models are based on some ideal assumptions (e.g., the transmitted signal is assumed to behave as stationary Gaussian noise [18]), which may not be compatible with practical situations. Besides, the parameters input to the model exacerbates the inaccuracy owing to the imperfect knowledge of the physical layer [19]. To overcome these two disadvantages of traditional QoT tools, many ML techniques have been investigated recently.

In [20], the ML model is combined with the physical layer model (PLM) to estimate the QoT performance. In this study, the uncertainty of the input parameters can be effectively reduced, and the accuracy of the estimating model can also be improved if more data from the network topology can be obtained. In [21], Gaussian process regression is used to estimate the optical signal-noise-ration (OSNR) of the link, and the mean-square error (MSE) is only 0.7 dB. In [22], an artificial neural network (ANN) is utilized to predict the OSNR. As a novel planning framework, this ML-based prediction tool and the software-defined network (SDN) controller are cooperated to adapt the actual network states. In [23], ANN-based transfer learning is used to assist the ML techniques to be applied to different link conditions. The result proves that the ML technique is flexible and can be adjusted easily to adapt to different conditions. In [24], the k-nearest neighbor (KNN) and random forest are used to determine whether a candidate path can be established. The accuracy of the random forest can achieve up to 96%, while the KNN can achieve 91% accuracy. In [25], the deep graph convolutional neural network (DGCNN) is employed to perform the same task as [24], and the achieved accuracy can be up to 97%. In [26], ANN, support vector machine (SVM) and KNN are used to determine whether the residual margin is positive or not. The accuracy can reach up to 99%. Besides, the value of residual margin is also estimated by using ANN and the average error of the estimation is smaller than 0.4 dB. In [27], the Gaussian process is utilized to estimate whether the BER values of unestablished links exceed the threshold. Meanwhile, active learning and transfer learning are adopted to optimize the accuracy in the presence of small-sized training datasets. Similarly, in [28], an evolutionary transfer learning approach is proposed for Q-factor estimation. Results indicate that this approach can reach the accuracy over 90% with the reduction of the training data amounts. In [29], the ANN and GN model are combined to achieve an accurate QoT estimator as shown in Figure 1. Compared with the GN model, the absolute SNR deviation can be reduced from 5.41 to 1.76 dB with ANN involved in. In addition, the result proves that the method has a much better tolerance to the uncertainty of the input parameters. In [30], SVM is utilized to estimate the QoT of the unestablished lightpaths using a synthetic bit error ratio (BER) database. And long short time memory (LSTM), which is a recurrent neural network, is adopted to predict SNR of the established lightpaths using historical field performance data. Results indicate that SVM shows a good accuracy of 99.5% in area under the curve and LSTM increases root mean-square error (RMSE) with a maximum improvement of 0.05 dB. In [14], ANN is applied to extract the network parameters (e.g., fiber coefficients) for the purpose of implementing a near-zero margin network.

All these studies above mainly focus on obtaining an accurate QoT model exploiting ML techniques. As for the uncertainty of the input parameters, in [31], the monitor information is feedback to a gradient descent algorithm to decrease this kind of uncertainty. The design margin of future demands can then be reduced with more accurate input parameters. In [32], a re-configurable model based on physical abstraction is proposed. The extended Kalman filter is used for parameter learning. The result with a 0.6 dB Q-factor accuracy is verified experimentally. In [33], the impact of wavelength dependent Erbium doped fiber amplifier (EDFA) gain ripple on the QoT is investigated and ML involves in reducing the uncertainty of EDFA-related parameters. While the polynomial regressions are adopted to estimate the gain ripple penalty, the reduction of OSNR from 1.02 to 0.08 dB is observed. In [34], deep neural network (DNN) is utilized to reduce the uncertainty of the received signal power and the amplified spontaneous emission (ASE) noise, and results indicate that the reduction of the margin for optical networks can achieve up to 3.2 dB. In [35], the customized ANN with a three-stage training framework is utilized to estimate the SNR of specific links in optical networks. Additionally, an active acquisition approach is adopted in the stage of online training to acquire real values of impairments. Results show that the customized training scheme can improve the ANN's tolerance to link parameter uncertainties. The RMSE can be reduced by over 50% compared with the ML-based modelling method in [29].

3.1.2 *The reduction of system margins*

As described earlier, system margins come from the time-varying effects in the system. It is necessary to monitor the real-time system status to reduce this part of margin. In [36], instead of assuming all the wavelength-division multiplexing (WDM) channels in C-band are occupied (96 channels with 50 GHz grid), the actual loading is monitored. In fact, as described in [36], the loading of 84% links of the North American backbone network is less than 50%. Through obtaining the actual loading, the real-time nonlinear interference between channels is computed by available models. Then the actual margin is extracted to increase the system capacity. Although the capacity of the network increases a lot, the main flaw of this study is that a traditional model is used, which may be inaccurate in some complicated scenarios [29]. This problem can be easily resolved by using a more accurate and flexible model based on ML techniques. In [37], the BER of the link is continuously monitored. The relationship between the link configurations, such as baud rate, forward error correction (FEC) overhead, etc., and the BER is learned by the stochastic gradient descent polynomial regression, which can then be used to choose an optimal link setting according to the real status of the optical network. The proposed method is quite appropriate for a dynamic system. In [38], the aging effect is considered. The results show that the cost savings can reach 14%. However, as in [36], the used model is also the traditional GN model, which may lead to inaccuracy. Another drawback of the method is that the aging function of the instruments is assumed to be a linear function of time which may not be the real scene. This can be resolved using some advanced time series ML models, such as the recurrent neural network, LSTM and gated recurrent unit (GRU). In [39], the cost reduction is calculated when using the actual system margin instead of the worst case. The result proves a 36% cost reduction of elastic networks, and the reuse of equipment can provide an extra cost reduction up to 8%.

Overall, ML has been adopted as an effective and accurate tool to reduce margins of optical networks. With the increasing evolution of ML in building the low-margin optical networks, more complex and novel models, such as LSTM and active learning, are utilized to estimate the QoT of targeted links with a good generalization ability. To summarize this subsection, we list the algorithms mentioned above in Table 1.

3.2 Power optimization

To obtain gains in capacity, channel power optimization can help mitigate the degradation imposed by linear and nonlinear impairments. On one hand, to design the channel power allocation for capacity maximization, many methods based on the information theory have been proposed. The maximization procedure can be formulated as a convex optimization problem [40] and various aspects of the optimization problems in heterogenous optical networks have been addressed in [41–43]. However, the analytical pre-design methods are based on some ideal assumptions, which may not perform as expected in practical systems. Therefore, adjusting the launch power based on the monitoring information is preferable for achieving the optimal ratio between ASE noise and Kerr nonlinearity. In this case, ML shows its potential in extracting the noise ratio of the signals from the receivers [44]. On the other hand, the transmission performance may be constrained by power excursions owing to specific gain-tilt of the EDFAs, EDFA gain-control mechanisms, and the number of EDFAs [45]. Power excursions can increase the discrepancy of the EDFA's output, and the excursion caused by each EDFA can be further exacerbated during the

Table 1 Applications of ML techniques in low-margin optical networks design problems

Algorithm	Ref.	Description
Regression model, nonlinear regression	[20]	Extracting the actual QoT metrics, reducing the inaccuracy of input parameters
Gaussian process regression	[21]	Estimating OSNR
ANN	[22]	
ANN, transfer learning	[23]	Predicting Q-factor
KNN, random forest	[24]	Estimating the feasibility of the candidate path
DGCNN	[25]	
ANN, KNN, SVM, logistic regression	[26]	Estimating the feasibility of the candidate path and the value of residual margin
Gaussian process, active learning, transfer learning	[27]	Estimating BERs of unestablished links with small-sized training data
Evolutionary transfer learning	[28]]	Estimating Q-factor and reducing the amounts of required training data
ANN	[29]	Estimating the nonlinearities
SVM, LSTM	[30]	Estimating the QoT of unestablished and established lightpaths
ANN, Q-learning	[14]	Extracting the network parameters, varying traffic patterns and bandwidth
Gradient descent	[31]	Correcting the deviations of the input parameters (power and noise figure)
Extended Kalman filter	[32]	Reducing the inaccuracy of physical layer parameters
Polynomial regressions	[33]	
DNN	[34]	
ANN, transfer learning	[35]	Estimating nonlinear SNR of specific links and improving tolerance to link parameter uncertainties
Stochastic gradient descent polynomial regression	[37]	Predicting accurate BER, then adapting modulation format, or FEC and slot-size

transmission. In this case, ML is a reliable tool to solve this problem and make the methods transferrable among dynamically changing heterogeneous networks. Learning form the historical data can help each ML-based engine adapt to the specific scenarios and mitigate power excursions effectively.

In this subsection, ML-based methods for optimizing the channel power allocation and reducing the power excursions are discussed. The details of these proposed methods are elaborated as below.

3.2.1 *Designing the channel power allocation for capacity maximization*

The power optimization problem is formulated as a convex optimization problem in [36–39]. The SNR of the nth channel is given by

$$\mathrm{SNR}_n(P_n) = \frac{P_n}{P_{\mathrm{ASE},n} + \mathrm{NL}_n(P_n)}, \tag{1}$$

where $\mathrm{SNR}_n(P_n)$, P_n, $P_{\mathrm{ASE},n}$, $\mathrm{NL}_n(P_n)$ is the SNR, signal power, ASE noise power and nonlinear noise power of the nth channel. However, in many previous analytical methods, the noise figure and gain of each EDFA are assumed to be accurate and ideal. These assumptions are not suitable for practical systems, and the performance of these methods may not perform as good as expected. To better utilize the data monitored from the real scenes for the power optimization, a few methods based on ML have been proposed. In [44], ANN is adopted to monitor the power ratio between the ASE noise and nonlinear noise so as to adjust the launch power. The input of ANN is the all-optical power density spectrum (without DSP) of the central channel, and the output is the correction term of the launch power. Results indicate that this method can make SNR gain up to 1 dB. Meanwhile, this ANN-based monitor can be placed anywhere along the link without interrupting the transmission since it does not require a full coherent reception.

3.2.2 *Reducing the influence of EDFA power excursions*

In metro optical networks, power excursions occur during the transmission because the wavelength-dependent gain and noise figure spectrum of EDFAs can cause the uneven output after the amplification [46]. At the same time, the output power level can be controlled via automatic gain control (AGC). If a channel is added with an undesired high gain, AGC reduces the gain of all channels to maintain the global mean gain. This leads to the situation that high gain channels steal power from low gain channels [47]. Hence, the disparity among channel powers increases. It has been verified in [46] that power excursions can reach up to 2 dB through occasional channel additions after 3-cascade EDFAs. Many previous analytical methods are based on the prior knowledge of one specific network, which limits these methods being extended to other dynamically changing networks. However, ML-based methods have promising prospects in solving this problem for their flexibility. The applications of ML on this issue are introduced as below.

For fixed-grid channels, in [48], authors adopted a neural network to estimate the EDFA gain for an individual channel. The input of the neural network is all-channel power levels. Results indicate that the ML model can effectively reduce the RMSE to 0.08 dB under the input of $+/-$ 3 dB. Instead of creating a separate neural network for each output channel in [48], in [49], authors employed the neural network to predict all-channel gain spectrum. The input is a vector including channel input powers, total input power and gain settings while the output is the full-fill gain profile. The power excursion predicted by the EDFA gain model is utilized to pre-adjust the input power [49]. Results demonstrate that the maximum channel gain is 0.18 dB and the error standard deviation (STD) is 0.019 dB. In [45], kernelized Bayesian regression (KBR) was applied and the output was the power STD of all active channels. According to the results, accurate suggestions on adding or dropping a channel are given. Based on [45], the ridge regression (RR) model was proposed in [50], which is more efficient than KBR and the error is less than 1% [50]. In [51], ANN was adopted with the same input as in [45, 50], and the output is the power excursion of each channel and the accuracy can reach up to 90%. However, the experiment environments of [45, 50] did not consider the interaction of channels in WDM systems and the wavelength switching operations. To solve this problem, authors in [52] extended the application to multiple reconfigurable optical add-drop multiplexer (ROADM) hops and full C-band WDM channels. Under the same setup in [50], the employment of the neural network in [52] can obtain further improvement with a RMSE below 0.15 dB compared to the RR model. And the accuracy of wavelength assignment can achieve up to 99%. Similarly, the DNN was utilized in [53]. It illustrates that DNN obtains 0.1 dB RMSE for 8400 random test samples and has better performance than the regression method and random forest.

For the flex-grid network, more flexible utilization of spectrum resources may lead to a fragmented spectrum [54], so the defragmentation is necessary [55]. However, the defragmentation algorithms can exacerbate the post-EDFA power discrepancy. Therefore, power excursions in flex-grid scenarios need to be addressed with the defragmentation algorithms. In [55, 56], in order to reduce the post-EDFA power discrepancy in flex-grid networks, RR was adopted to pre-adjust the pre-EDFA sub-channel powers based on different algorithms of the defragmentation. Results show that the mitigation of post-EDFA power difference among channels can achieve over 62%.

Overall, ML methods can help to estimate the wavelength-dependent gain and noise figure of each EDFA in order to effectively reduce power excursions. Because ML is able to address complex situations efficiently without any ideal assumptions, it has broad application prospects to design the power optimization strategy in complex heterogenous optical networks. To summarize this subsection, we list the algorithms mentioned above in Table 2.

3.3 Routing and wavelength assignment

RWA problem can be described as allocating the lightpath and wavelength for each request from the source node to the destination node under a given network topology and a set of information, such as traffic demand and traffic distribution. For many previous studies, RWA problems are usually solved by integer linear programming (ILP) methods to obtain the optimal solution [57–59]. However, the ILP

Table 2 Applications of ML techniques in power optimization problems

Algorithm	Ref.	Description
ANN	[44]	Obtaining the correction term of the launch power
Neural network	[48]	Obtaining EDFA gain for an individual channel
	[49]	Estimating the full-fill gain profile
Kernelized Bayesian regression	[45]	Outputting power STD of all active channels and giving accurate suggestions of slots on adding or dropping a channel
ANN	[51]	Estimating the power excursion of each channel
Ridge regression	[50]	Estimating power excursions with the input of channel states
	[55, 56]	Pre-adjusting the pre-EDFA sub-channel powers in flex-grid networks
Neural network	[52]	Extending the application scenarios compared with [45, 50]
DNN	[53]	

algorithm consists of a set of equations and inequations that describes the constraints (i.e., continuity constraint and nonoverlapping constraint) and the measurement index of the network state, making it not feasible in the complex real network environment for its complicated computation process. To solve this problem, many researchers propose heuristic algorithms. Nevertheless, traditional heuristic algorithms may not approach the optimal solution [60]. This is because the heuristic designs often apply fixed policies based on artificially defined rules and some potential influence factors are not included in the algorithms, resulting in suboptimal performance [61]. Therefore, inspired by the applications of AI in many other fields of optical communication, many researches utilize AI techniques to address the RWA problem. The specific ML-based methods are described as below.

First, the applications based on SL are introduced. SL is directly used to solve the RWA problem for the first time in [5]. The input features are network topology, network capacity, available wavelength and traffic demands while the output is the RWA configuration. In [62], the traffic matrices are classified using a logistic regression classifier and the pre-trained model can output the optimal routing solutions.

However, SL still shows some deficiencies, such as a relatively poor generalization ability and the demand of large amounts of data [61]. Fortunately, RL paves a new promising way. RL refers to a learning procedure that the agents interact with the environment periodically, make policy decisions and observe results, i.e., rewards and new states. Unlike SL, RL trains DNN with online experiences (rewards) rather than mass of data, which helps to realize self-learning. In [60], the bandwidth allocation (BA) was formulated as MDP and the predictive BA (PBA) model is constructed. In order to solve the RWA problem, the output of the PBA model is taken as the input of an ILP algorithm or alternatively a heuristic algorithm. In [63], owing to the underutilization of network characteristics in traditional algorithms, the concept of multi-mode network was proposed to represent various characteristics in optical networks. These characteristics are then utilized as the input of the RL algorithm (actor-critic algorithm). Compared with the heuristic algorithm, this algorithm can make better use of network features. In [64], RL was used to maximize the available paths which build a bridge between the link capacity and traffic distribution. Learning efficiency is improved by the following methods: reducing the dimension of the state vector, introducing the pre-training process and the temporal-difference (TD) learning process. In [65], a new criterion, named the whole network cost-effectiveness value with survivability (WCES), was raised for network performance measurement. To improve the network survivability, they also proposed the survivable routing, modulation level and spectrum assignment (S-RMLSA) algorithm with the shared backup path protection (SBPP). In [66], a semi-flexible spectrum assignment scheme was proposed to suppress spectral fragmentation. The number of input vectors is reduced because each specific-bandwidth channel is aligned to an equally spaced virtual grid, which also reduces computation cost.

Although performing well in solving the RWA problem, RL still takes a long time to approach the optimum strategy in the learning process because it requires the exploration and acquisition of knowledge about the overall system. This shortage leads to its unfeasibility in large-scale networks. Deep reinforcement learning (DRL) overcomes this shortage by combining RL with deep learning, which improves the learning speed and performance. The utilization of deep learning can help the decision-making of the agents through automatically extracting important features from the data and conducting modeling with high-level abstraction. The schematic representation of the DRL operation and its applications were introduced in detail in [67]. Based on the study in [65], a double-agent DRL based survivable routing, modulation level and spectrum assignment (DA-DRL-RMLSA) algorithm was further proposed in [68]. This algorithm is based on the double-agent DRL, in which the two agents refer to the working agent and the protection agent. Both algorithms in [65, 68] are measured by the new criterion and show improvement of overall network performance compared with the baseline algorithm. In [69], a multi-task-learning-aided knowledge transferring approach was proposed, which effectively reduce the training time of DRL through exploiting the similarities between tasks and reusing existing knowledge, i.e., the shared network state spaces. In [61], to avoid the low level of automation, which results from the demand of domain specific knowledge (e.g., working principle of data layer and mathematical optimization theory) to provide services in EONs, a new network framework, autonomic and cognitive networking framework, and a DeepRMSA agent based on DRL are proposed. Based on [61], the episode-based training mechanism (DeepRMSA-EP) was further raised [70]. It divides the dynamic provisioning process into multiple episodes, in which a certain number of lightpath requests are served. The training is performed at the end of each episode. A window-based flexible training mechanism (DeepRMSA-FLX) is proposed to overcome instability as well. This training mechanism significantly enhances the training stability and shows lower blocking rates compared to the benchmark. In order to further improve the scalability and universality, in [16], another inter-domain service framework named DeepCoop was proposed, in which DRL agents cooperate with each other. State parameters and rewards are shared and calculated collaboratively by the agents. Besides, in order to control the overhead, interactions among the agents are limited.

Although the algorithms mentioned above show great performance, the generalization ability of them is still limited. Firstly, traditional methods regard DRL as a black box and represent the observation space and the action space roughly. Secondly, the network topology is usually represented graphically while ordinary DRL cannot learn information about the graph structure. For the first problem, a representation of the network state named feature engineering was proposed [71–73]. This representation reduces the number of required data and can easily capture the singularities of network topology, such as the potential bottlenecks. In [72], in order to better understand the routing policy learned by the DRL agent, reverse engineering is conducted. Owing to the consideration of the overall network utilization and the dependency between links caused by the network topology, this method performs an easier and faster DRL procedure and can be applicated in many scenes. To solve the second problem, in [74], DRL was combined with graph neural network (GNN) that can learn the network environment by capturing the relations between the paths and links in the network topology. The algorithm behaves strong generalization ability when facing the unseen topologies during training.

Overall, ML has been applied to choose an optimal routing scheme, make fully utilization of spectrum and suppress the spectral fragmentation in a faster and less complex way. In this way, overall performance of optical network and convergence speed may be improved and the blocking rate may be reduced at the same time. With the development of flexible-grid optical network, the ML-based RWA algorithm may attract more attentions in the future. To summarize this subsection, we list the algorithms mentioned above in Table 3.

3.4 Failure management

The failure management is quite important for a reliable optical network. According to the news report, 70% of connections of Egypt to outside world are lost owing to the fiber cut in Mediterranean Sea in 2008. Therefore, an intelligent failure management system is of great significance. In general, soft failure management involves the following three problems as shown in Figure 2. (1) Failure detection that is responsible for detecting whether a failure occurs or not. (2) Failure identification that is responsible for identifying the cause of it. (3) Failure localization that is responsible for finding the failure location. Based on the results obtained, proper actions can be taken to restore the optical link to the normal state. The details of recent studies on this problem are discussed as below.

Table 3 Applications of AI techniques in RWA problems

Algorithm	Ref.	Description
Supervised learning	[5]	Directly solving the RWA problems with ML for the first time
	[62]	Classifying the traffic matrices with the optimal routing schemes
Reinforcement learning	[60]	Proposing the PBA model
	[63]	Proposing the concept of multi-modal and the actor-critic algorithm using convolutional neural network (CNN)
	[64]	Evaluating the network status values
	[65]	Presenting a criterion to measure the comprehensive network performance and a network resource assignment strategy
	[66]	Proposing a semi-flexible spectrum assignment algorithm for flexible-grid network
Deep reinforcement learning	[68]	Using WCES to measure the overall network performance
	[69]	Proposing a multi-task-learning-aided knowledge transferring approach by reusing network state spaces
	[61]	Proposing a new framework and a multi-agent DRL algorithm
	[70]	Proposing the DeepRMSA training mechanism and the flexible training mechanism
	[16]	Proposing an inter-domain service framework named DeepCoop in which DRL agents cooperate with each other
	[71–73]	Proposing a new representation of state and action
Deep reinforcement learning, graph neural network	[74]	Combing DRL with GNN that can capture the relations between the paths and links

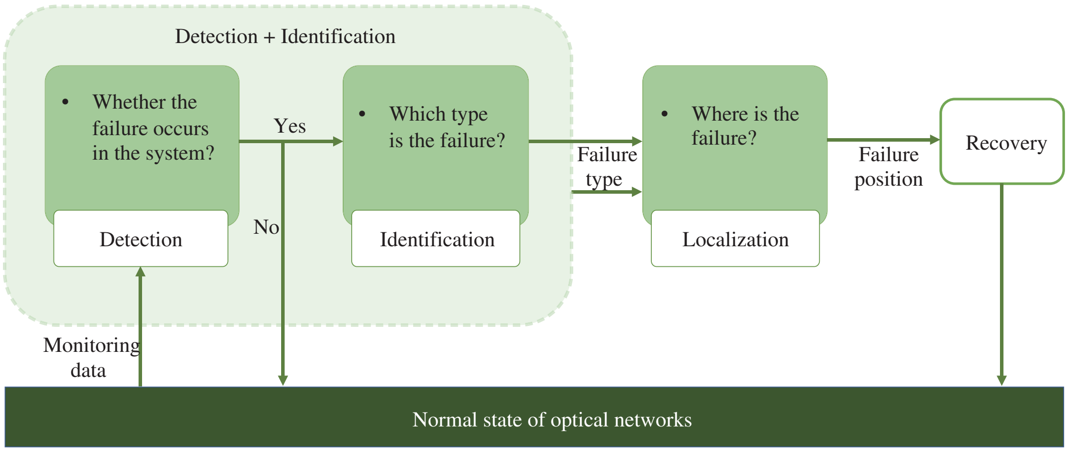

Figure 2 (Color online) The work flow of failure management.

3.4.1 *Detection and identification*

The accuracy of traditional failure detection methods is highly dependent on a pre-defined threshold. If the threshold is set too loose, failures may be neglected and lead to service disruption. If it is set too tight, many error detections will occur. Besides, the threshold is usually static that cannot adapt to a dynamic optical link. To overcome the shortcomings of the traditional method, recent research pays attentions to the ML techniques. After solving the detection task, failure identification is implemented to provide the type of failures to controller. In general, failure identification can be regarded as a classification task, for which ML has a promising potential to solve it.

In [75], a one-class SVM was used to analyze the tap value of the adaptive equalizer to detect the soft failure. Results indicate that the detection error is less than 4%. In [76], the digital spectrum of the signal from a coherent receiver was analyzed to perform the soft failure detection and the false positive rate was just 0.14%. In [77], a hybrid of SL and USL was proposed, the density-based clustering algorithm and DNN were used, the former was responsible for analyzing the patterns of monitoring data, and then the

Table 4 Applications of ML techniques in failure management problems

Algorithm	Ref.	Description
SVM	[75]	Analyzing the tap value of the adaptive equalizer
	[76]	Analyzing the digital spectrum of the signal
Density-based clustering, DNN	[77]	Analyzing the patterns of monitoring data, and detecting failures
Design tree, linear regression, SVM	[78]	Identifying the cause of soft failure between laser drift and filter failure
SVM, ANN, random forest, neural network	[79]	Detecting BER abnormality
CNN	[80]	Identifying the failure causes between the filter tightening (FT) and the shift of center frequency (FS), nonlinear Kerr effect and ASE noise of EDFA
Feedforward neural network	[81]	Detecting and identifying multiple impairments in optical networks
Bayesian network	[82]	Identifying the failure causes between inter-channel interference and filter tightening
XGboost	[83]	Detecting failures of equipment in optical networks
Gaussian process	[84]	Locating the link failures
Network Kriging	[85]	
Gated GNN	[86]	Locating the fault entities in optical networks
ANN	[87]	Locating the WSS anomaly

latter was responsible for detecting failures. The results show that up to 99% detection accuracy can be achieved in [78]. The optical spectrum of the signal is obtained using an optical spectrum analyzer, and a decision tree is used to detect the soft failure caused by the wavelength-selective switch (WSS) and the laser. Then SVM is used to identify the cause of failure. In [79], the BER is monitored continuously. An ANN is used to identify whether the failure is caused by WSS or EDFA. Results demonstrate the identification accuracy can reach 98%. In [80], a convolutional neural network was used to identify the cause between filter shift, filter tightening, nonlinear Kerr effect and ASE noise of EDFA. The accuracy can reach up to 100%. In [81], readily available adaptive filter coefficients (AFCs) were input to a feedforward neural network to detect and identify multiple impairments in optical networks. According to the experiments, both detection and identification can achieve an accuracy over 99%. In [82], a Bayesian network was used to identify the cause of soft failure between inter-channel interference and filter tightening, and the accuracy can reach up to 95%. In [83], an interpretable extreme gradient boosting (XGboost) method was utilized to detect the failure of equipment in optical networks. This proposed method achieves a high accuracy of 99.72%, and a low positive rate of 0.18%.

3.4.2 *Localization*

After the failure is detected and identified, we then need to locate it. In [84], the suspect links are first found through the graph-based correlation heuristic algorithms. Then, the failure probabilities are estimated for each suspect link by adopting the binary Gaussian process. Results indicate that this method achieves a high accuracy. In [85], the link failures were localized by the network kriging. Results indicate that this method can achieve unambiguous failure localization with fast response. In [86], a gated GNN, which is a variant of GNN, was proposed to locate the fault entities in optical networks. Results indicate that the accuracy of this reasoning model can reach up to 99%. In [87], WSS failure in an optical link was located based on receiver DSP and ANN method. Results show that the proposed algorithm can achieve an accuracy over 90% for most of the cases.

Overall, with numerous data collected from optical networks, it is difficult to obtain the knowledge related to failure conditions with traditional methods. ML has played an increasingly important role in failure management with its powerful data processing ability. It is foreseeable that in the trend of future research, ML is still a major solution of failure management. To summarize this subsection, we list the algorithms mentioned above in Table 4.

4 Field trial

In this section, we review the field trial and experiment verification from three aspects: (1) the optical performance monitoring (OPM), (2) the SDN, and (3) the failure management.

(1) Optical performance monitoring. The OPM is quite essential to a reliable operation and an efficient management of the optical network. Through OPM, the management system can be aware of the real-time state of the physical layer, and the parameters of the physical layer can be adjusted to achieve an optimum state [37]. In [88], an OSNR monitoring algorithm based on ANN was verified on the testbed based on the national dark fiber facilities (NDFIS) in UK. The inputs of the ANN are launch power, the gain of EDFA and the noise figure of it, etc. After training, the relationship between OSNR and the inputs of the ANN is learned, and it can predict the performance of the unestablished lightpaths accurately. According to the results, the BVT can be configured properly to maximize the spectrum efficiency of the link.

(2) SDN. With the advance of the optical network, its architecture is becoming more and more complex. To control the optical network more intelligently, researchers have been paying attentions to the SDN paradigm. By decoupling the data plane and control plane, the intelligent algorithms can be implemented in the center controller. In [89], an SDN architecture called ORCHESTRA was elaborated and validated through experiments. The QoT is continuously monitored, and then the cross-layer optimization is performed. The results are feedback to the controller. As a result, a closed loop is implemented, through which a self-adaption network is achieved.

(3) Failure management. It is widely regarded that the failure management is a key module to ensure the QoT of the optical links, and many experiment verifications have been performed on this topic. In [90], a double exponential smoothing (DES) algorithm was constructed to predict the future value of some network parameters, such as the laser bias current, optical power and so on. The predicted values of these parameters are input to an SVM classifier, which is pre-trained using historical data. The SVM will then output the future state of the network, i.e., normal or failed. One thing to be noticed is that the dataset used for training the two ML models is from the practical operation data of China Mobile Communication Corporation (CMCC). The results show the excellent performance of the DES and SVM. In [91], the rotation speed of the signal's state of polarization in coherent receiver was monitored continuously. Once the speed exceeds the pre-defined threshold, an alarm will be output that the fiber stress is detected. Subsequently, the Stokes vector is extracted to train a naïve Bayes classifier to identify the stress kind of the fiber, i.e., bending, shaking, etc. The accuracy of the classifier exceeds 95%. In [92], a convolutional neural network was used to detect the fiber bending through the constellation of the received data, and the experiment results show the detection accuracy is quite high.

5 Challenges and future work

The modern optical networks with enormous data have provided unprecedented opportunities to employ ML-based applications to further improve the capacity and reliability. However, it may be difficult to deploy many ML-based methods to practical systems. This is especially a big challenge considering the generalization ability and robustness of the ML models trained with data from simulations or lab experiments offline. Therefore, to achieve the successful deployment of AI techniques, many challenges still remain. In this section, we discuss the future directions for the ML-related investigations in optical networks.

- **Interpretability.** For many applications, ML-based methods are responsible for capturing some of the intrinsic regularities or patterns in the data. Because ML is data-driven, the performance of the ML methods highly depends on the training scheme. If the training dataset is extracted from or similar to the reality, the performance may be satisfactory. If the patterns or characteristics of testing data are different from the training data, the ML algorithms cannot work as expected. In this case, if the interpretable explanations for what kind of pattern or knowledge has been derived by ML algorithms are unavailable to users, the performance of the ML-based methods cannot be guaranteed, which is an obstacle for deployment. Therefore, interpretability is a paramount quality if ML-based applications are to be applied in practice [93].

• **Few-shot training scheme.** In the training phase, the training datasets need to be large enough so that the whole feature space is explored, thus ensuring the accuracy of the ML-based model [94]. However, the datasets, especially these from real systems, are not always easy to obtain. Probe lightpaths can be applied but the additional cost cannot be avoided. Therefore, the smaller-sized dataset is more preferable to help model accommodate new situations different from training environment. However, current ML methods are data-hungry and some naive approaches like retraining would overfit. Therefore, it is challenging to deploy ML engine to heterogenoues situations where fast adaptation with only few data is critical. To alleviate the overfitting, many training techniques like fine-tuning, transfer learning and data augmentation can be utilized to improve the performance.

• **Robustness.** In practical systems, many parameters such as the launch power, fiber length and noise figure of the EDFA are not ideally accurate. Since the ML-based applications are trained with accurate inputs and outputs, the generalization ability of them may show some deficiencies when parameter uncertainty exists. The uncertain inputs may limit these applications to be transferrable to other heterogeneous systems. Therefore, the robustness of these applications is of great significance for practical deployment. For future investigations, techniques such as data augmentation and ensemble learning may provide a promising way to enhance the robustness.

• **Implementation architecture.** A large traffic volume can be propagated through the existing infrastructure in a short time. Consequently, the burden of the center controller may be too high. Therefore, some functions such as the data pre-processing and data monitoring are moved out from the controller and implemented on a local chip [95]. Some distribution training algorithms have also been put forward to alleviate the burden of the center controller [96]. However, further researches are still needed for a scalable deployment of ML-algorithms. Unlike the situation mentioned above, the ML-based failure management are lack of real data. This is because the current design of optical link tends to adopt an ultraconservative way to ensure the QoT, which limits the number of datasets that can be obtained. The current research usually adopts a synthetic simulator to generate data to train the ML algorithms offline [24]. However, owing to the difference between simulation and practical system, the offline trained ML-based failure management system may give wrong alarms and an adaption or self-learning mechanism is necessary. In [24], an adaption method is proposed to address this problem. However, how to ensure the accuracy of the failure management system is still relatively unexplored.

6 Conclusion

To satisfy increasing requirements of capacity and reliability for next generation optical networks, we survey four typical applications aided by AI techniques in optical networks. They are low-margin design, power optimization, RWA, failure management. The adoption of ML techniques significantly improves the performance of these applications in increasing the capacity and reliability. Finally, based on the current related researches, we discuss the challenges and possible research directions of ML-based approaches in optical networks.

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