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Overview on routing and resource allocation based machine learning in optical networks

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ABSTRACT

For optical networks, routing and resource allocation which considerably determines the resource efficiency and network capacity is one of the most important works. It has been widely studied and many excellent algorithms have been developed. However, theoretical analysis shows that routing and resource allocation belongs to the Nondeterministic Polynomial Complete (NP-C) problem no matter in wavelength division multiplexing (WDM) optical networks, elastic optical networks (EONs), or space division multiplexing (SDM) optical networks. At presents, there doesn't exist a polynomial-time algorithm for routing and resource allocation. In recent years, machine learning which shows great advantages in solving complex problems has been widely concerned and researched. Using machine learning to conduct routing and resource allocation has aroused a great interest of researchers. This paper provides an overview on routing and resource allocation based on machine learning in optical networks. At first, we briefly introduce the routing and wavelength allocation (RWA) problem in WDM optical networks, the routing and spectrum allocation (RSA) problem in EONs, and the routing, core, spectrum allocation (RCSA) problem in SDM optical networks respectively. Commonly used machine learning techniques in optical networks are briefly elaborated. Then, the problems of quality of transmission (QoT) estimation, traffic estimation, and crosstalk prediction which can help to routing and resource allocation are also elaborated. The machine learning enabled RWA algorithms, RSA algorithms, and RCSA algorithms are elaborated, analyzed and compared in detail. In addition, the applications of machine learning in the QoT estimation, traffic estimation, and crosstalk prediction, etc., are also elaborated. Based on the existing research results, we present future research directions about how to use machine learning techniques to conduct routing and resource allocation in multidimensional time–space-frequency optical networks and satellite optical networks.

Glossary: ANN, Artificial Neural Network; BBP, Bandwidth Blocking Probability; BER, Bit Error Rate; BLP, Burst Loss Probability; BPM, Beam Propagation Method; BV-OXC, Bandwidth Variable Optical Cross Connector; BV-SSS, Bandwidth Variable Spectrum Selective Switch; BVT, Bandwidth Variable Transponder; DBSCAN, Density-Based Spatial Clustering of Applications with Noise; DC, Direct Clustering; DLE, Dynamic Light-path Establishment; DNN, Deep Neural Network; DRL, Deep Reinforcement Learning; DT, Decision Tree; EDFA, Erbium Doped Fiber Amplifier; ENN, Elman Neural Network; EONs, Elastic Optical Networks; FCM, Fuzzy C-means Clustering; FM-MCF, Few-Mode Multiple-Core Fiber; FSs, Frequency Slots; ILP, Integer Linear Programming; ISI, Inter-Symbol Interference; ISPs, Internet Service Providers; kNN, k-Nearest Neighbors; LR, Logistic Regression; LSTM, Long Short-Term Memory; MCF, Multiple-Core Fiber; MDL, Modulation format Distance Limit; MDP, Markov decision processes; MLES, Machine Learning-assisted loading Energy consumption Selecting; MMF, Multiple-Mode Fiber; MSP, Multiprocessor Scheduling Problem; NN, Neural Network; NP problems, Nondeterministic Polynomial problems; NP-C, Nondeterministic Polynomial Complete; NP-Hard, Nondeterministic Polynomial Hard; OBS, Optical burst switching; OFDM, Orthogonal Frequency Division Multiplexing; OS-ELM, Online Sequence Extreme Learning Machine; OSNR, Optical Signal to Noise Ratio; OXC, Optical Cross Connection; P problems, Polynomial problems; QoE, Quality of Experience; QoS, Quality of Service; QoT, Quality of Transmission; RCSA, Routing, Core and Spectrum Allocation; RF, Random Forest; RL, Reinforcement Learning; RMSA, Routing, Modulation and Spectrum Allocation; ROADM, Reconfigurable Optical Add-Drop Multiplexer; RSA, Routing and Spectrum Allocation; RWA, Routing and Wavelength Allocation; SDM-EONs, Space Division Multiplexing Elastic Optical Networks; SDN, Software Defined Network; SDON, Software Defined Optical Network; SLE, Static Light-path Establishment; S-RMLSA, Survivability-Routing, Modulation Level and Spectrum Allocation; SSS, Spectrum Selection Switches; SVM, Support Vector Machine; TDM, Time Division Multiplexing; WCES, Whole network Cost-Effectiveness value with Survivability; WDM, Wavelength Division Multiplexing

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1. Introduction

In the information age, people have put forward high-level and diversified demands for communication services that poses huge challenges to the capacity of communication networks. The optical network which shows great advantages of large transmission capacity, small transmission loss, good anti-interference, strong confidentiality, and so on, has brought vigorous development opportunities to the communication field. It effectively supports the increasing demand for data transmission and communication, and is expected to be the main body of the network in the communication market in the future.

Initially, optical networks mainly adopted an architecture based on the wavelength division multiplexing (WDM) technique, which couplings multiple optical carriers with different wavelengths to a single fiber to improve the capacity of optical fibers. Assuming that the transmission rate of one wavelength is 100Gbit/s, if 10 wavelengths are used for dense wavelength division multiplexing (DWDM), the transmission capacity of one optical fiber is expanded by 10 times to 1Tbit/s. The WDM optical network has many excellent performances, such as large capacity, transparency, re-configurability, and easy capacity expansion [1]. However, due to its wavelength allocation based on the fixed channel interval, it is difficult to adapt to services with different rate requirements, resulting in low spectrum utilization [2]. If the bandwidth of a service is less than the capacity of one wavelength, the whole wavelength must be allocated. When the bandwidth of a service is greater than the capacity of one wavelength, multiple wavelengths must be allocated to carry this service, resulting in unnecessary spectrum waste. In addition, the guard band is required between any adjacent wavelengths. In order to solve these problems, the orthogonal frequency division multiplexing (OFDM) technique is applied to optical communication. The OFDM is a multi-carrier digital modulation technique that encodes the high-speed data and then modulates it to orthogonal low-speed subcarriers for transmission. Its typical application is elastic optical networks (EONs) [3–7]. In EONs, by using the OFDM technique, each optical node can modulate services to an appropriate number of adjacent optical carriers according to the required transmission rate of arriving services. Meanwhile, the OFDM technique allows the partial overlap of carriers. When the interval of subcarriers is slightly greater than or equal to the Nyquist bandwidth, the same frequency crosstalk in the channel can be effectively suppressed and the maximum bandwidth efficiency can be guaranteed. Therefore, with immense flexibility and scalability in spectrum allocation and service accommodation, EONs have opened up a new prospect to build highly-efficient optical networks in the future. In [7], authors presented a comprehensive survey on OFDM technique and OFDM-based EONs. They not only introduced basic principles of OFDM including mathematical formulation, the main building blocks, and related key functions, but also detailed the architecture of the OFDM-based EON and the key enabling techniques including node-level techniques and network-level techniques.

With the rapid emergence of 5G high-speed mobile media services and Internet of Things applications, the traffic in the backbone network has increased dramatically and is expected to continue to increase substantially [8]. In addition, since digital signal processing (DSP) algorithms cannot completely alleviate the random nonlinear impairments of fiber channels, the transmission capacity of single core fiber has almost reached the limit of Shannon theory, even if the OFDM technique with extremely high spectrum efficiency is adopted. Therefore, the SDM technique is introduced into optical communication. It utilizes the multi-mode fiber (MMF), the few-mode fiber or the multi-core fiber (MCF) to multiplex multiple channels to break the capacity bottleneck of traditional optical fibers [9]. For the SDM technique based on the MMF, it expands the transmission capacity by using different modes to transmit signals in a fiber core. The SDM technique based on the MCF introduces multiple independent fiber cores into traditional single fiber, and expands the transmission capacity by increasing the number of channels transmitted in a single fiber [10]. Current researches on the SDM technique are mainly focused on the latter. The EON with the MCF, which is referred as the space division multiplexing elastic optical network (SDM-EON), greatly increases the network transmission capacity [11]. On February 13, 2019, researchers of China Academy of Information and Communication Technology (CAICT) realized the experiment of ultra-large capacity WDM and SDM optical transmission systems. The experimental capacity can reach 1.06 Pbit/s that nearly 30 billion people can realize simultaneous communication on a single optical fiber [12].

No matter how multiplexing techniques change, routing and resource allocation that considerably determines the resource efficiency and capacity is one of the most important works in optical networks. In WDM optical networks, by establishing a light-path between a source–destination pair, then assigning a free wavelength to all links along this light-path, data can be transmitted [13]. In the absence of wavelength converters, a light-path must occupy the same wavelength over all fiber links it passes. This property is named the wavelength continuity constraint [14]. The problem of setting up light-paths by routing and assigning a wavelength to each source–destination pair for each request is named the RWA problem [15]. In EONs, spectrum is divided into many frequency slots (FSs), the routing and resource allocation problem is to allocate FSs flexibly and effectively according to the required transmission rate of arriving services, so it is named the RSA problem. There are three important constraints related to the FS allocation which must be guaranteed in the RSA algorithm, i.e., spectrum contiguity constraint, spectrum continuity constraint, and uniqueness constraint. Spectrum contiguity means that these allocated FSs must be placed near to each other for one service. Spectrum continuity means that the same contiguous FSs must be allocated on each link along the route of a service, and it is similar to the wavelength continuity constraint in WDM optical networks. Uniqueness constraint means that FS blocks allocated for different services cannot overlap. Furthermore, in actual transmission, a light-path may be impaired, so that a transponder should make the modulation level of its subcarrier slots adaptive to the quality of transmission (QoT) of a light-path [16]. Modulation format adaptive routing and resource allocation is named the routing, modulation level, spectrum allocation (RMSA) problem [17]. For routing and resource allocation problem in SDM-EONs, not only the spectrum resources of EONs, but also effective and reasonable utilization of fiber cores resources in the MCF must be considered, this problem is referred as the routing, core, spectrum allocation (RCSA) problem. Along with the massive increase in capacity, a new problem has emerged, i.e., crosstalk. Inter-crosstalk occurs when transmitting signals among fiber cores which are close to each other. And more serious crosstalk occurs when adjacent cores transmit signals of the same frequency at the same time. Since crosstalk would affect signal transmission quality and network transmission performance, crosstalk becomes a major technical challenge in the MCF transmission [18]. More detailed discussion on optimization problem in optical networks can refer to [19].

Theoretical analysis shows that routing and resource allocation belongs to NP-C problem no matter in WDM optical networks, EONs, or SDM-EONs. At presents, there doesn't exist a polynomial-time algorithm for routing and resource allocation. Lately, machine learning which presents great advantage in solving complex problems has been widely concerned and researched as a new innovation mode. Machine learning can extract meaningful information from historical network data, and take decisions pertaining to the proper functioning of networks from network-generated data. In optical networks, routing and resource allocation, fault management, optical performance monitoring, non-linearity mitigation are all important tasks, and using machine learning to solve these complex problems has aroused a great interest of researchers. In [20], authors gave an overview on applications of machine learning in optical networks, including physical layer and network layer. Although there are a large number of research papers about how to apply machine learning techniques to routing and resource allocation, research in this area is still in its infancy. This literature review aims to provide an introductory reference for researchers and practitioners willing to get acquainted with existing machine-learning enabled routing and resource allocation algorithms as well as to explore new research directions. The contribution of this paper can be summarized in four parts:

- Routing and resource allocation problems in WDM optical networks, EONs, and SDM-EONs are elaborated. We elaborate that why routing and resource allocation belongs to NP-C problem.
- The routing and resource allocation problem, the QoT estimation problem, the traffic estimation problem, and the crosstalk prediction problem belong to which application scenarios of machine learning are elaborated respectively.
- The machine learning enabled RWA algorithms, RSA algorithms, and RCSA algorithms are elaborated, analyzed and compared in detail. Besides, the applications of machine learning in the areas of the QoT estimation, traffic estimation, crosstalk prediction, and etc., which can help to improve the resource efficiency of routing and resource allocation, are also elaborated.
- Time-space-frequency multidimensional optical networks and satellite optical networks are the research focus in recent years, so that we present some future research directions about how to use machine learning techniques to route and allocate resources in these two types of networks respectively.

The remainder of this paper is structured as follows. In Section 2, the RWA problem, the RSA/RMSA problem, and the RCSA problem are introduced in detail respectively. Section 3 elaborates the application scenarios of machine learning techniques in optical networks, i.e., routing and resource allocation, the QoT estimation, traffic estimation, and crosstalk prediction. The commonly used machine learning techniques and machine learning frameworks in optical networks are also introduced. Then in Section 4, the machine learning enabled RWA algorithms, RSA algorithms, and RCSA algorithms are elaborated, analyzed and compared in detail. Moreover, the machine learning enabled algorithms that are used for the QoT estimation, traffic estimation, crosstalk prediction and etc., are also elaborated. Thereafter, in Section 5 we present future research directions about how to route and allocate resources for multidimensional optical networks and satellite optical networks by using machine learning techniques. Finally, we conclude this paper in Section 6.

2. Problem description

Considering different traffic pattern, i.e., static or dynamic, in this section, we first briefly introduce the objectives of routing and resource allocation under different traffic patterns. Then we elaborate the tasks to be accomplished and the constraints to be met in routing and resource allocation, from the RWA problem in WDM optical networks to the RSA/RMSA problem in EONs, and then to the RCSA problem in SDM-EONs. At last, taking the RMSA problem as an example, we explain why routing and resource allocation belongs to NP-C problem.

2.1. Traffic pattern

For the static traffic pattern, connection requests between any source–destination pairs are generally given in advance. The objective is to minimize total resource consumption while accommodating all connections. The static RWA problem is referred as the static light-path establishment (SLE) problem. Its typical objective is to use minimal number of wavelengths to set up light-paths for all connection requests, or to set up as many light-paths as possible for a given number of wavelengths. The SLE problem can be formulated as an ILP model with the wavelength-continuity constraint. In particular, it was proven to be NP-C by showing the equivalence to the graph-coloring problem in [21]. The objective function of the SLE problem is to minimize the traffic in each link [22]. A review of approaches to the SLE problem can be found in [23]. For the static RSA/RMSA problem and RCSA problem, traffic matrix is also provided in advance, and the objective is to accommodate all connection requests with the minimal number of spectrum resources.

For the dynamic traffic pattern, connection requests arrive sequentially and randomly, and then are dismantled after being held for a certain period of time. Namely, light-paths are dynamically established and taken down. Therefore, routing and resource allocation decisions must be made when connection requests reach the network. If there are not sufficient network resources to set up a light-path for a given request, this request is blocked. Since it is difficult to consider routing and resource allocating simultaneously for dynamic traffic pattern, this problem can be divided into two sub-problems, i.e., routing sub-problem and resource allocation sub-problem. The dynamic RWA problem is known as the dynamic light-path establishment (DLE) problem, and its general objective is to minimize blocking probability, or to establish as many light-paths as possible over a given period of time. For the dynamic RSA/RMSA problem, due to frequent establishment and demolition of light-paths in the network, there are a lot of spectrum fragments which can block future connection requests [24]. Therefore, the blocking probability caused by spectrum fragments should be considered, and how to solve spectrum fragmentation problem effectively is one of the most important work while designing dynamic RSA/RMSA algorithms in EONs. For the dynamic RCSA problem, in addition to reducing the impact of spectrum fragmentation, how to effectively suppress crosstalk is one of the main objectives.

2.2. The RWA problem in WDM optical networks

WDM optical networks are consisted of wavelength routing nodes interconnected by optical fibers, and networks transmit data between access nodes in the optical domain without any intermediate optical to/from electronic conversion. Given a set of connections, it is necessary to determine both the routes over which these light-paths should be established and the wavelengths that should be allocated for these light-paths [25]. In a wavelength-routed WDM optical network, wavelength continuity constraint limits the effective utilization of link resources. If adding a wavelength converter on the intermediate device, data arriving at a certain wavelength on one link can be converted to another wavelength, and then transmitted on the next link. The effect of wavelength continuity constraint is effectively alleviated. As shown in Fig. 1, assuming that two wavelengths are multiplexed on each link, i.e., λ_1 and λ_2, and node 8 is capable of wavelength conversion. There are four connections, i.e., node 1 to node 9, node 3 to node 2, node 4 to node 5, and node 10 to node 8. For the connection from node 1 to node 9, data is transmitted from node 1 to node 8 using λ_1. Even if λ_1 on the link between node 8 and node 9 is occupied by the connection from node 10 to node 8, the connection can be successfully established by using available λ_2 between node 8 and node 9 through wavelength conversion. For other three connections, since all occupied links have available free wavelengths that meet the wavelength continuity constraint, those can all be established successfully.

At present, there are many researches and literatures about how to solve the RWA problem. The work in [26] studied the blocking probability of both fixed routing and least-congested routing combined with random wavelength allocation. In [27], authors gave an analytical model for the fixed routing and alternate routing with the First-Fit wavelength allocation. In [28], authors analyzed the performance of least-congested routing with random wavelength allocation. In [29], authors elaborated three basic routing approaches including fixed routing, fixed-alternate routing, adaptive routing, and several heuristic resource allocation approaches, i.e., random wavelength allocation, First-Fit and etc. They compared those approaches from the perspectives of complexity and performance. In [30], authors presented

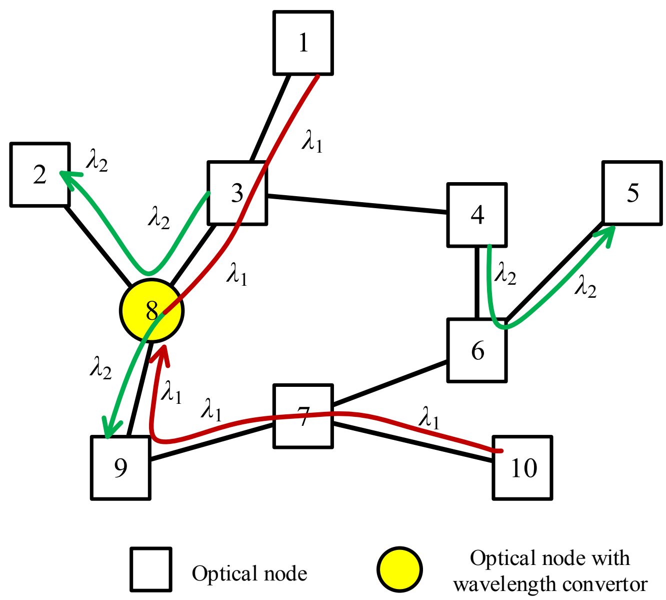

Fig. 1. The RWA problem in WDM optical networks with wavelength converter.

algorithms and methodologies related to routing, regeneration, wavelength assignment, subrate-traffic grooming, and protection.

2.3. The RSA/RMSA problem in EONs

EON is consisted of two types of nodes, respectively the network boundary node formed by bandwidth variable transponder (BVT) and the network core node formed by bandwidth variable optical cross connector (BV-OXC) [31]. At the network boundary node, according to the service demand, a BVT can generate a series of continuous orthogonal subcarriers to configure transmission bandwidth, and can select an appropriate modulation level to modulate the signal at the same time, so as to achieve high frequency utilization. The BV-OXC on the network core node can complete the multiplexing and demultiplexing of signals, and serve the input signal to realize its selection, separation and switching. An important component of BV-OXC is the bandwidth variable spectrum selective switch (BV-SSS), which can flexibly schedule resources according to different bandwidth demands.

EONs effectively improve the flexibility of spectrum utilization and spectrum allocation. However, the more flexible resource allocation method also makes the allocation and management of spectrum resources more difficult. The RSA problem is to establish corresponding end-to-end light-paths and allocate appropriate FSs according to the data-rate requirements of different requests. As shown in Fig. 2, four FSs and three FSs are respectively used for supporting the first request and the second request. The guard band between the two requests is *G* Hz to ensure that they do not interfere with each other. In addition, spectrum contiguity constraint and spectrum continuity constraint must be satisfied when developing RSA/RMSA algorithms. As shown in Fig. 3, assuming that a request requires three slots from source node 1 to destination node 5. This request cannot be accommodated through two shortest paths, i.e., 1 → 2 → 3 → 5 and 1 → 2 → 4 → 5. For the shortest path 1 → 2 → 3 → 5, *Link_1, Link_2* and *Link_6* all have three contiguous FSs, but three FSs are not continuous in those three links. For the shortest path 1 → 2 → 4 → 5, there does not exsit three contiguous FSs in *Link_3*. For the path 1 → 2 → 3 → 4 → 5, this request can be accepted while satisfying contiguity and continuity since FSs 6, 7, 8 are contiguous and free in *Link_1*, *Link_2*, *Link_4,* and *Link_5*.

At present, there also exist a large number of literatures about how to solve the RSA/RMSA problem in EONs. In [32], authors not only presented the architecture of the EON and its operation principles, but also compared the pros and cons of different routing approaches and spectrum allocation approaches. In addition, they summarized the literatures on issues related to RSA, such as fragmentation, modulation, the QoT, traffic grooming, survivability, energy saving, and networking cost. In [16], authors reviewed all existing RSA and RMSA algorithms, and compared them through their both efficiency in resource management and computational complexity. In [33], authors developed two approaches to realize on-demand RMSA for the light-tree based multicast service aggregation scheme, i.e., an integer linear program (ILP) model for small-scale EONs and a heuristic approach for large-scale EONs. The on-demand RMSA strategy can effectively eliminate spectrum redundancy and reduce spectrum consumption. In [34], they proposed a novel distributed sub-tree-based optical multicasting scheme with low blocking probability and high spectrum efficiency to serve multicast demands.

2.4. The RCSA problem in SDM-EONs

SDM-EONs and their advanced transmission techniques, i.e., advanced modulation, polarization multiplexing, OFDM, high resolution spectrum selection switches (SSS), coherence detection, digital equalization, are considered to be effective solutions for future transmission capacity expansion [35–37].

The RCSA problem can be divided into three processes, i.e., routing, fiber core allocation, and spectrum allocation. First a route is selected for a connection, then a fiber core is assigned to it, and finally the appropriate FSs are allocated. With an additional fiber core selection process, the RCSA problem becomes more complex and more challenging. On the one hand, the increase of transmission capacity is bound to be accompanied by more frequent establishment and demolition of light-paths, which can lead to a sharp increase in spectrum fragmentation. On the other hand, physical constraints introduced by inter-core crosstalk must be considered. A simplified model of fiber core crosstalk is shown in Fig. 4. This model assumes that crosstalk only occurs when FSs in the same position of the core are used. Since core 2 and core 3 are adjacent, crosstalk occurs when both core 2 and core 3 use f_1 and f_2 to transmit data. Since core 2 and core 4 are not adjacent, even if both cores transmit data using f_4 and f_5 simultaneously, there is no crosstalk.

Lately, there also exist some literatures about how to solve the RCSA problem. In [38], authors gave an overview on resource allocation schemes and algorithms that aim at efficient and optimized using transmission resources in spectrally-spatially flexible optical networking. In [39], authors used crosstalk-aware spectrum compactness as parameter to measure the network status. Based on this, they proposed two RCSA schemes, which both reduce blocking probability and effectively increase spectrum utilization. In [40], authors proposed an on-demand core and spectrum allocation method to reduce blocking probability and inter-core crosstalk for SDM-EONs. In order to reduce spectrum fragmentation, authors in [41] proposed a crosstalk-aware spectrum defragmentation algorithm based on spectrum status. In [42], for the static RCSA problem, authors proposed novel ILP and mixed integer linear program (MILP) methods to determine the optimal route, and allocate FSs and cores to all connections simultaneously. In [43], authors introduced a prioritized area concept to solve the spectrum and core/mode allocation problem.

2.5. Why routing and resource allocation belongs to the NP-C problem?

In the field of computers, problems can be classified into two categories, i.e., unsolvable problem and solvable problem. Unsolvable problem can be divided into two types, one type is just like halting problem, and the other type is with high time complexity. Solvable problem can also be divided into two types, polynomial problem (the P problem) which is solvable in polynomial time and nondeterministic polynomial problem (the NP problem) which can be verified in polynomial time [33].

If there is such a NP problem, all NP problems can be reduced to it.

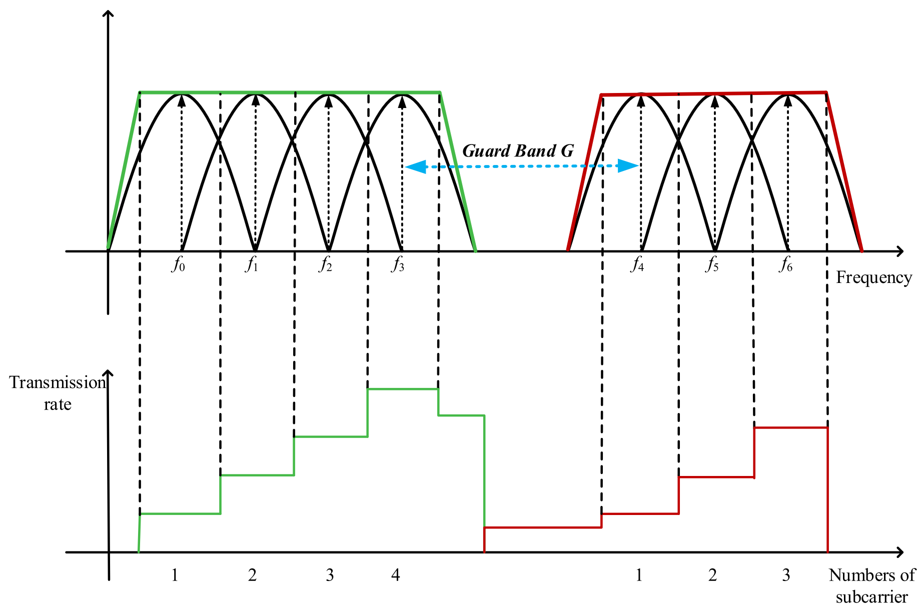

Fig. 2. Data-rate/bandwidth variation through subcarrier number adjustment.

This NP problem is a NP-C problem. The NP-C problem is one of the seven major mathematical problems in the world. If a polynomial algorithm for a NP-C problem can be found, then all NP problems can be solved. Nondeterministic polynomial hard (NP-Hard) problem is more difficult to solve than the NP-C problem. Specifically, any NP problem can be reduced to this problem in polynomial time, but this problem is not necessarily a NP problem. Namely, even if one day a polynomial algorithm for the NP-C problem is proposed, the NP-Hard problem still cannot be solved by polynomial algorithms since it is not necessarily a NP problem. In Fig. 5, we use sets to represent the relationships of those four problems. Based on [44], we take the RMSA problem as an example to elaborate why routing and resource allocation belongs to the NP-C problem. The multiprocessor scheduling problem (MSP) is known as a NP-C problem, and there is no effective solution so far. Authors in [36] reduced the MSP into a related RMSA problem to prove that the RMSA problem belongs to the NP-C problem. The problem of the MSP is defined as: there are series of independent and indivisible tasks $t_i \in T$, $i = 1, 2, \ldots n$, series of identical processors $m_j \in M$, $j = 1, 2, \ldots k$, the time spent on each task t_i using m_j is $w(t_i, m_j) \in Z^+$. The question is to search the minimum time that these processors need to complete those tasks. The solution of the MSP is a function that maps the tasks to processors. The objective is to minimize the make-span, i.e., the time between the start and the finish of the execution of all the tasks. In Fig. 6, they define the following structure to solve the RMSA problem as MSP. Assuming given a set of connections T, each connection t_i has source node s_i and destination node d, required capacity Λ_{t_i} of each connection is translated into requiring $w(t_i, m_j)$ subcarriers over path $p_{ij}(s_i \to m_j \to d)$, assuming that the modulation level of connection t_i over path p_{ij} is represented by the capacity $\Lambda_{t_i}/w(t_i, m_j)$ of each subcarrier. The objective is to minimize the resources used. The MSP is a NP-C problem. Therefore, RMSA belongs to the NP-C problem and routing and resource allocation also belongs to the NP-C problem.

3. Machine learning

Machine learning has five typical application scenarios, classification, regression, anomaly detection, clustering and dimensionality reduction [20]. Classification algorithms, aiming at which already know category does the new input data belong, and regression algorithms deal with modeling between variables. Clustering algorithms target at finding the cluster with similar characteristics for input data, which are similar to classification, but the difference lies in that the number of categories in classification algorithms is known, while it is unknown in clustering. Anomaly detection algorithms are to find abnormal data in input data, the purpose of dimensionality reduction algorithms is using a lower dimension subspace to represent original high-dimensional feature space to eliminate the redundancy of features. This section first introduces commonly used machine techniques in optical networks, i.e., logistic regression (LR), random forest (RF), clustering, Q-learning and deep neural networks (DNN). Then the application of machine learning in optical networks including routing and resource allocation, the QoT estimation, traffic estimation, and the crosstalk prediction is elaborated respectively.

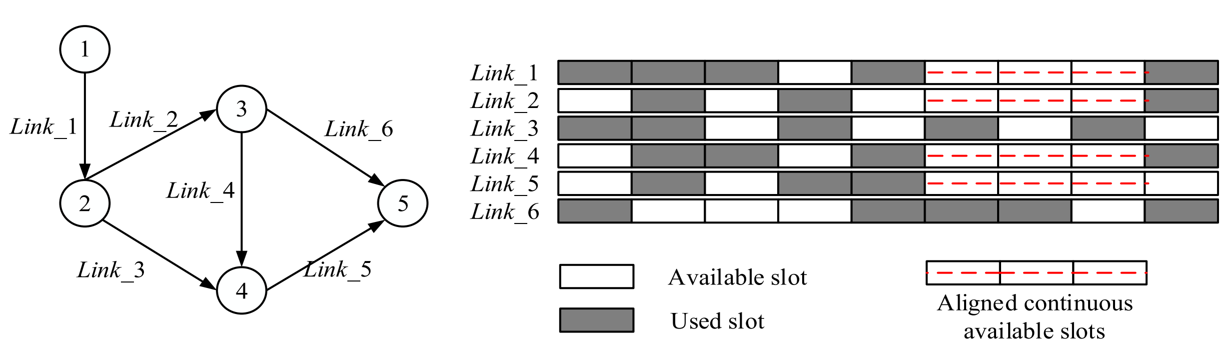

Fig. 3. The continuity constraint and the contiguity constraint in EONs.

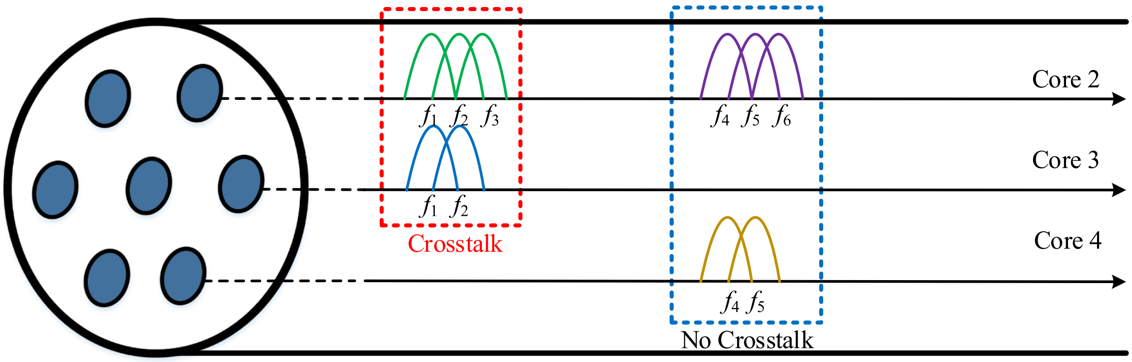

Fig. 4. Crosstalk between adjacent cores in SDM-EONs.

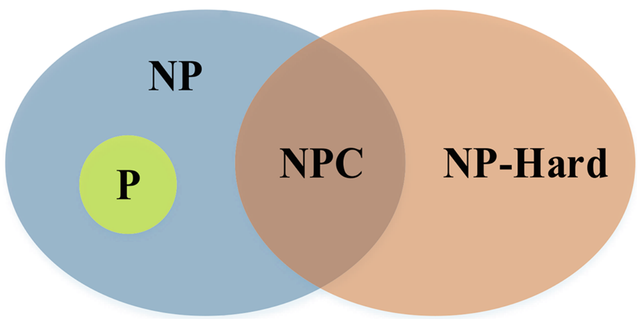

Fig. 5. The relationships of the four problems.

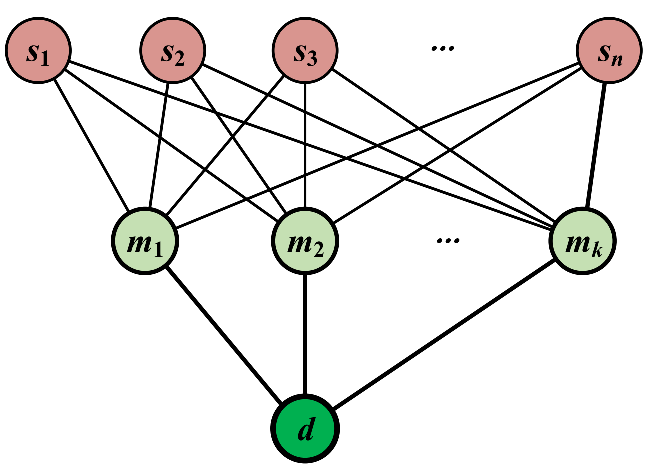

Fig. 6. Solving the RMSA problem as MSP [44].

3.1. Commonly used machine learning techniques in optical networks

In this subsection, we focus on introducing the implementation process for each commonly used machine technique in optical networks and the problems they are suited to solve.

3.1.1. The LR technique

LR is a generalized linear regression analysis model, which belongs to classification techniques [45] and is often used to solve binary classification or binomial distribution problems, such as spam detection, text emotion analysis, and the QoT estimation. The implementation process of the LR algorithm is as follows. Firstly, any input data is transformed into the predicted value through linear regression [46], and then the predicted value is mapped to the sigmoid function to complete the conversion from value to probability. Assuming the threshold value of classification is 0.5, and then output over 0.5 would be classified into class 1, while the output below 0.5 would be classified into class 0. The output of the classifier will be compared with the known label and the model parameters are adjusted until the desired accuracy is achieved. From training perspective, LR is simple to implement, efficient to calculate, and easy to regularize [45]. However, it cannot solve the nonlinear problem well and easy to overfit.

3.1.2. The RF technique

RF is a technique that integrates multiple decision trees (DTs) by means of ensemble learning. It is mainly used for classification and regression problems [20]. The implementation of DT can be summarized as follows. Supposing each sample have k features, the corresponding quantitative evaluation criteria (i.e., information gain, Gini coefficient) is adopted to select the one with the best classification ability as the classification standard. And then according to different values of this feature, training sample set is divided into several subsets, each subset represents a class. Then previous steps are repeated for each class and recursion stops when all samples belong to the same class or no remaining features can be used as classification standard. For the RF technique, supposing there are N samples and M features, bootstrap sampling is adopted to sample n times from N samples to form n subsample set. For a subsample set, m features are randomly extracted from M features in each classification, and finally n DTs are formed. Final classification results can be obtained according to the statistical analysis of the judgment results of these DTs. For the RF technique, not only training samples of each DT are random, but features in each classification are random [47]. These two kinds of randomness make RF not easy to fall into overfitting, and have a good anti-noise ability.

3.1.3. The clustering technique

Clustering means to divide a sample set into different classes or clusters according to a specific standard (i.e., distance), so that the similarity of samples within a cluster is as great as possible, and the difference of samples not in same cluster is also as great as possible. Four main clustering techniques are location-based k-means clustering technique, sliding window-based mean-shift clustering technique, density-based spatial clustering of applications with noise (DBSCAN), and gaussian mixture model (GMM). The more detailed description of each clustering technique can be found in [48]. Clustering technique performs better when used for the small-scale and low-dimensional data. With the data scale and dimensions increase, its performance drops dramatically. In addition, traditional clustering techniques are generally suitable for a certain situation. For example, k-medoids technique is not affected by outliers, but its computational cost is very high. If different clustering techniques can be fused to form a new clustering technique, this problem can be effectively alleviated by the comprehensive use of multiple clustering techniques in a clustering process.

3.1.4. The Q-learning technique

Q-learning is a value-based technique in reinforcement learning

Table 1
Q-table.

	a_1	a_2	a_3	…	a_m
s_1	$Q(s_1, a_1)$	$Q(s_1, a_2)$	$Q(s_1, a_3)$	…	$Q(s_1, a_m)$
s_2	$Q(s_2, a_1)$	$Q(s_2, a_2)$	$Q(s_2, a_3)$	…	$Q(s_2, a_m)$
…	…	…	…	…	…
s_n	$Q(s_n, a_1)$	$Q(s_n, a_2)$	$Q(s_n, a_3)$	…	$Q(s_n, a_m)$

(RL) [49]. RL usually involves two entities, i.e., agent and environment. By interacting with environment to obtain current state, the agent selects an action to act on environment. After environment receives this action, state changes and the reinforcement signal (reward or punishment) is generated to feed back to the agent. The reinforcement signal is a kind of evaluation of this action produced by the agent. If the selected action results in a positive reward for environment, then the tendency of the agent to generate this action would be strengthened. The goal of the agent is to find the optimal strategy in each discrete state to maximize expected cumulative discount rewards. The core of Q-learning is Q-table, as shown in Table 1, the first row of the table is different actions, and the first column is different states, and $Q(s_n, a_m)$ refers to the expected reward that the agent can obtain when taking an action a_m in a state s_n at time t. The main idea of Q-learning is to build states and actions into a Q-table to store each Q-value, and then selecting an action that can obtain the maximum reward according to Q-values [50]. Specifically, each learning process of an agent can be viewed as starting from a random state, and using Boltzmann or ε-greedy strategy to randomly select an action. After executing the selected action, the agent observes new state and reward, and then updates the Q-value of the previous state and action according to the obtained reward and the maximum Q-value of new state. The agent would continue to select actions based on new states until reaching a termination state. Since Q-learning does not require a training set, it can receive a wider range of data. It can be applied to classification, regression, clustering, and dimensionality reduction. However, as the number of states increases, the expansion of Q-table makes it more time-consuming to search and store Q-values.

3.1.5. The DNN technique

DNN, which is also known as a multi-layer perceptron, can be understood as a neural network (NN) with multiple hidden layers. Since the output layer has multiple neurons, this model can be flexibly applied to classification, regression, clustering, and dimensionality reduction. In DNN, each layer is fully connected, namely any neuron in layer k must be connected to any neuron in layer $k + 1$, and neurons are connected to each other by variable link weights, which represent the importance of each neuron in the previous layer to this neuron. In addition, in order to make the model more differentiated, activation function (e. g. sigmoid, tanh, Relu) is used for nonlinear calculation on each neuron in each hidden layer [51]. Each neuron in a hidden layer learns to recognize a specific set of features based on the output of the previous layer. As the depth increases, features that the neuron can recognize become more and more complex. Most importantly, DNN can discover potential structures in unlabeled and unstructured data. Therefore, one class of problem that DNN is best at is to process and cluster various kinds of unlabeled raw data in reality [52].

3.1.6. The applications of machine learning techniques in optical networks

As shown in Table 2, the corresponding applications of LR, RF, clustering, Q-learning and DNN in optical networks are summarized. The LR technique and the RF technique both belong to supervised learning, mainly are used for the QoT estimation and traffic prediction, where the labeled data can be easily obtained from networks. Clustering is mainly used for non-linearity mitigation. Due to the flexibility of Q-learning and DNN, these are used not only for the QoT estimation,

Table 2
Different applicable scenarios and characteristics of machine learning techniques in optical networks.

Machine Learning Technique	Type	Applications	Solved problems in optical networks	Advantages	Disadvantage
LR	Supervised learning	Classification	The QoT estimation [53] RWA [54]	Simple to implement, extensible, model clearly.	Unsuitable for nonlinear problems, easy underfitting.
RF	Supervised learning	Regression & classification	QoT estimation [55,56,57] Failure management [58]	Strong resistance to overfitting, fast training.	Long training time, high cost of calculation.
Clustering	Unsupervised learning	Classification	Non-linearity mitigation [59,60] Traffic prediction and virtual topology (re)design [61] Resource allocation [62]	Suitable for small and low dimensional data, low computational complexity.	Unsuitable for large scale, high dimensional data, noise sensitivity.
Q-learning	RL	Classification & regression & clustering & dimensionality reduction	Routing [63–67] Service differentiation [63,64] Path selection and wavelength selection [68] RMSA [69]	No training set is required and a wider data set can be received.	Difficult to training.
DNN	Semi-supervised learning	Classification & regression & clustering & dimensionality reduction	Traffic prediction [70,71] QoT estimation [70,72,73] Routing and resource allocation [70,71,74–79]	Better at depicting reality, strong approximation ability and nonlinear degree.	Easier to fall into local optimality and overfit, parametric quantitative expansion.

traffic prediction, but also to solve more complex problems in optical networks, such as routing and resource allocation and service differentiation.

3.2. Application scenarios of machine learning in optical networks

Machine learning has five typical application scenarios, i.e., classification, regression, anomaly detection, clustering, and dimensionality reduction. The classification algorithm is to judge which category the new input data belongs to when all categories are known. Regression algorithms deal with modeling between variables. Clustering algorithms target at finding the cluster with similar characteristics for input data, which are similar to classification, but the difference lies in that the number of categories in classification algorithms is known, while it is unknown in clustering. Anomaly detection algorithms are to find abnormal data in input data. The purpose of dimensionality reduction algorithms is using a low-dimension subspace to represent original high-dimensional feature space to eliminate the redundancy of features. In this subsection, we briefly introduce the main application scenarios of machine learning in optical networks including routing and resource allocation, the QoT estimation, traffic estimation, and crosstalk prediction.

3.2.1. Routing and resource allocation

When a service arrives, a light-path should be routed and resource should be allocated in real time based on the current resource status in the network. In other words, each traffic demand has corresponding routing and resource allocation solution. By fitting the mathematical relationship between network states and routing and resource allocation solutions, the appropriate solution for a new request can be intelligently selected. Therefore, routing and resource allocation problem can be converted into a classification problem [74]. However, considering that there may be many available solutions for requests, if one solution corresponds to one class, this can lead to the so-called curse of dimensionality, preventing machine learning techniques from learning data patterns correctly. Therefore, one of the most important works when designing machine learning enabled routing and resource allocation algorithms is how to process data to reduce the number of classes.

3.2.2. The QoT estimation

When optical signal transmits in fiber links, it will be affected by various physical impairments, such as signal broadening caused by dispersion, noise introduced by Erbium-Doped Fiber Amplifier (EDFA), circuit noise, and etc. Signal distortion caused by these impairments accumulates continuously in the transmission process, and results in the decline of signal transmission quality so that the destination node cannot receive the optical signal correctly and effectively. If the QoT of a light-path / light-tree can be accurately predicted before a service is established, the success rate of service establishment can be effectively improved, and the use of network resources can be optimized. Generally, the received optical signal-to-noise ratio (OSNR) and the bit error rate (BER) are used to quantitatively determine if a predetermined value of QoT is guaranteed.

For the QoT estimation, its objective is to predict whether the candidate light-path of a new service meets the transmission requirement. Therefore, this problem is usually expressed as a binary classification problem [55], where the classifier outputs a yes/no answer based on the light-path characteristics (i.e., the total length, adopted modulation format, the number of links along this light-path).

3.2.3. Traffic estimation

The Internet traffic exhibits a similar pattern, the similar or periodic traffic pattern over a long period has been referred to as time-varying traffic. Therefore, traffic estimation is feasible. The study and estimation of network traffic distribution is an important tool to evaluate the performance of the communication network. By analyzing network traffic data and extracting network data characteristics, the rules and mechanisms of network operation can be explored. In optical networks, due to the change of the user's access location, there will be a tidal flow phenomenon in which the network load changes with time period. In the face of such dynamic traffic change, spectrum waste will be caused when network resources cannot be flexibly scheduled in real time. Therefore, how to quickly and accurately estimate the change of tidal flow and reasonably allocate resources according to estimated traffic are the key problems to be solved in optical networks.

Essentially, network traffic data is a kind of time series data [80]. Traffic estimation can be solved as a time series problem in mathematical statistics, historical traffic and time are used to predict the trend of traffic changes over a period of time in the future [70]. The key is to find the relationship between traffic and time series. Therefore, it can be regarded as a regression problem in machine learning.

3.2.4. Crosstalk prediction

According to the different coupling modes, the MCF can be divided into the strongly coupled MCF and the weakly coupled MCF. In the strongly coupled MCF, the inter-core crosstalk is introduced deliberately by reducing the distance between the cores to improve the density of cores, theoretically, super-mode can be formed by superposition of each core mode field in the strongly coupled MCF, so it can be thought of as a form of multimode fiber [81]. When using weakly coupled MCFs to transmit signals, part of the optical power emitted to one of the fiber cores will be coupled with adjacent fiber cores, resulting in inter-crosstalk, which would lead to serious physical impairments and degrade the QoT. At present, the research is mainly focused on using weakly coupled MCFs to achieve high speed and large capacity transmission.

There are mainly two methods to suppress inter-core crosstalk. The first method is to reduce the coupling coefficient between fiber cores. In recent years, researches have proposed the trench assisted MCF to reduce the coupling coefficient, through greatly suppressing the overlap of electromagnetic fields between fiber cores, the inter-core is effectively reduced [82]. The second method is to introduce refractive index difference between adjacent cores to cause phase mismatch [83]. This kind of fiber is called the heterogenous MCF, which is composed with several different fiber cores. Due to different propagation constants of fiber cores, the resonance between fiber cores is reduced, thus crosstalk is suppressed. In addition to the coupling coefficient and propagation constant, there are still many parameters that affect inter-crosstalk, such as core pitch, bend radius, etc., they cause high complexity of inter-crosstalk calculation for the network layer. Crosstalk prediction is to obtain the predicted crosstalk value by establishing the mapping relationship between multiple parameters and crosstalk value, thus reducing the computational complexity, which belongs to regression problem [84].

Table 3
Commonly used machine learning frameworks.

Name	TensorFlow	Theano	Keras	Scikit-learn	Caffe	MXNet
Supported programming languages	Python/C++	Python/C++	Python	Python	Python/C++/Matlab	Python/C++/Matlab
Supported hardware	CPU/GPU/mobile	CPU/GPU	CPU/GPU	CPU/GPU	CPU/GPU	CPU/GPU/mobile

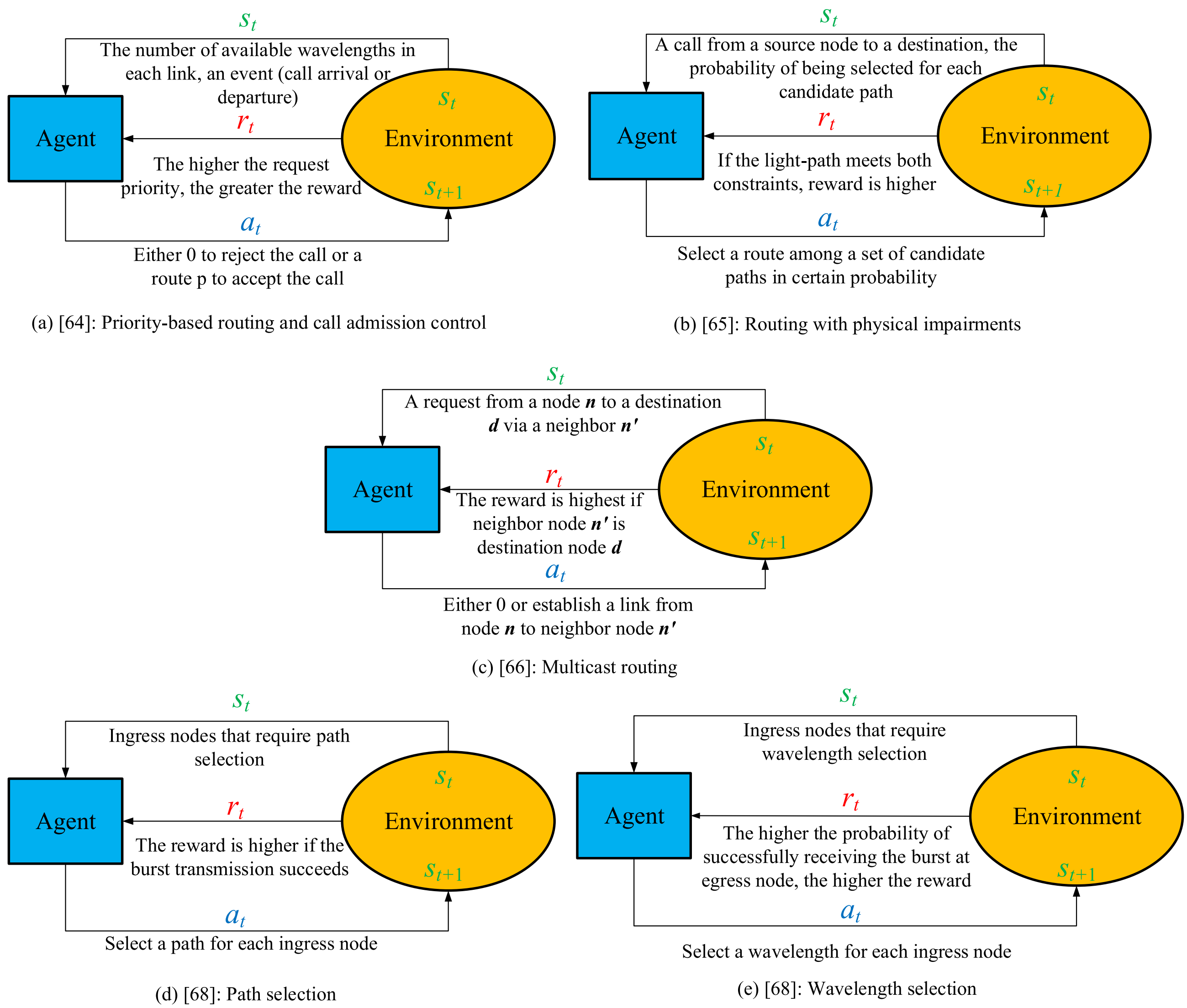

Fig. 7. The RL applications in RWA.

3.3. *Common machine learning libraries/frameworks*

In Table 3, we summarize commonly used machine learning libraries/frameworks in optical networks. TensorFlow is one of the best maintained and widely used frameworks in machine learning, it can compute on any CPU or GPU, but it lacks many pre-trained models [85]. It supports Python and C++. Theano can effectively solve the problem of multi-dimensional array calculation, and it is the first open source framework for deep learning. The original intention of the design is to perform the operation of large-scale neural network algorithm in deep learning [86]. Since Theano transparently uses the GPU to perform data-intensive computing, the efficiency is very high. The programming languages it supports include Python, C++, etc. Keras is an open source software library aimed to simplify the creation of deep learning models, it can be deployed on TensorFlow, Theano and other frameworks. No matter which framework it deploys on, the configuration of the neural network becomes easy. It can run seamlessly on the CPU and GPU [86]. Scikit-learn is an open source Python library for machine learning, which implements classification algorithms, regression algorithms, clustering algorithms and dimensionality reduction algorithms. Caffe is a powerful deep learning framework, and is much easier to extend the data format since its modularity, it supports Python, C++, Matlab [87]. MXNet is a deep learning library, and has data flow diagrams similar to Theano and TensorFlow [88]. It provides interfaces for C++, Python, Matlab, etc.

4. Routing and resource allocation based on machine learning in optical networks

Machine learning techniques aim at extracting knowledge from data, based on some characterizing inputs, often referred to as attributes or features [89]. In this section, the machine learning enabled RWA algorithms, RSA algorithms, and RCSA algorithms are elaborated, analyzed and compared in detail. Besides, the applications of machine learning in the QoT estimation, traffic estimation, crosstalk prediction, and etc., are also elaborated.

4.1. *Machine learning applications in RWA*

In this subsection, we respectively introduce machine learning enabled routing algorithms and RWA algorithms. At last, we detailed compare the performance of different algorithms.

4.1.1. *Machine learning enabled routing algorithms*

For WDM optical networks, the bandwidth of an optical fiber is divided into many individual wavelength channels to accommodate requests. In addition to rapidly increasing capacity demands, new multimedia services are driving the demands for high QoS (Quality of

Service). According to Internet Service Providers (ISPs), the differentiation of call blocking probability in core networks is crucial to meet different service level agreements and earn maximum system operation revenue [89,90]. In [91], authors proposed a Markov Decision Processes (MDP)-based method, which achieves service differentiation by setting different rewards for receiving different service classes. It effectively solves the problem that static method cannot effectively use idle wavelength. However, it is supposed that the arriving time of each service is subject to Poisson distribution, and the duration of each light-path is subject to exponential distribution. In real environments, assumptions mentioned above are not necessarily guaranteed. In order to adapt to real environment, authors in [63] proposed an RL-based light-path establishment method for all-optical WDM networks, which can perform service differentiation while not increasing overall blocking probability. Taking the number of light-paths established for each service class at time *t*, the result of light-path establishment at time *t-1*, and the priority of the service class defined in advance as parameters, they proposed a new method for calculating rewards. By combing this method with Q-learning, it is available even when the number of wavelengths is very large.

In [64], authors used R-learning realizing priority-based routing and call admission control. For each source–destination pair, *K* candidate paths are calculated in advance, authors decomposed routing process into single link processes, the Q-value of each candidate path is the sum of the Q-value of each link that constitutes each candidate path. By updating the Q-value of each used single link, the Q-value of this candidate path can also be updated. Its structure can be found in Fig. 7(a), the number of available wavelengths on each link at time *t* and an event (call arrival or departure) are taken as the state s_t. The actions fall into two categories, namely, rejecting this call or choosing a route for this call. The objective of their method is to choose a candidate path with maximum Q-value for different service classes to achieve higher revenue.

Physical impairments in actual transmission process are inevitable. When a light-path satisfies the wavelength continuity constraint but exceeds the acceptable threshold of QoT, it will also be rejected. Therefore, taking both requirements into account, authors proposed a RL-based routing algorithm for all-optical networks subject to physical impairments [65]. The involved physical impairments include inter-symbol interference (ISI), optical amplifier noise, inter-channel crosstalk, and node crosstalk (OXCs). The developed structure is shown in Fig. 7(b), first *K* candidate paths are calculated for each source–destination pair in advance. When a call arrives, the agent selects a path from the set of candidate paths and then constantly allocates wavelength for this path to check whether the wavelength continuity constraint and the QoT requirement are satisfied simultaneously. If the path meets both requirements, the reward is higher, namely, the selected probability of this scheme is increased, else is decreased. In their algorithm, each node decides to route calls based on past events, such as blocking or acceptance of previous calls, rather than based on network state, which is desirable because as network state floods every node at any time, the state-based routing imposes a high overhead on the network.

In order to send data from one source to several destinations, many different paths have to be created for each destination, which can be achieved by a multicast tree. Multicast communication is a generalization of unicast communication. In order to provide multicasting on WDM optical networks, the light-path concept has to be extended to a point-multipoint concept, named the light-tree [92]. In [66], authors used the Q-learning technique for multicast routing in WDM optical networks. Authors proposed using learning component to update the Q-value of sending a request from a source node *n* to a destination *d* via a neighbor *n'*, and using constraint satisfaction component to schedule all multicast requests of the node *n* according Q-table, so that the sum of Q-values to complete all requests of the node *n* is maximized. As shown in Fig. 7(c), by interacting with the environment, the agent either rejects the request or establishes a link from node *n* to neighbor *n'*. This method not only has lower block probability but also can adapt to topology and traffic change.

For optical burst switching (OBS) networks, multiple packets with different sources and the same destination are aggregated into a burst, then are transmitted along an optical path. Since requests among a burst arrive at a core node simultaneously, contention is indispensable and can lead to burst loss [91]. Therefore, the development of efficient algorithms for path selection and wavelength allocation is crucial to minimize the burst loss probability (BLP). In [68], authors formulated path selection and wavelength allocation as a multi-armed bandit problem, and proposed two Q-learning based algorithms for these two problems respectively to reduce the BLP. For path selection, before training, *n* mutually disjoint candidate paths for each ingress-edge node pair that will be used for transmission are calculated in advance, using the shortest path routing algorithm to initialize the Q-table, the shorter the path is, the greater the Q value is. The structure of this model is presented in Fig. 7(d), according to the ingress nodes that require path selection, the agent selects a path for each ingress node, and the reward is higher if the burst transmission succeeds. For wavelength allocation, they used random wavelength allocation to initialize Q-table, as shown in Fig. 7(e), according to the ingress nodes that require wavelength selection, the agent selects a wavelength for each ingress node, and the higher the probability of successfully receives the burst at the egress node, the higher the reward is. As a result of continuous learning, the proposed methods can adapt to the dynamic network conditions, thereby avoiding the performance degradation common in fixed policy schemes.

4.1.2. Machine learning enabled RWA algorithms

Performing RWA corresponds to assigning physical resources to each of the demands in a given traffic matrix, in [54], authors transformed the RWA problem into a multi-class classification problem, which can be addressed by the LR with Lasso and Ridge regularization. Specifically, a training sample includes features of the given network and the corresponding target label. Network features include network topology, capacity, available wavelengths, and the traffic demand matrix. The target label is the associated RWA configuration for this traffic matrix, which is obtained by the ILP. Their method presents a new framework to solve RWA problems. Based on [54], in [79], authors proposed an improved DNN enabled RWA algorithm, which effectively reduce computational time compared with the method in [54]. When a new traffic matrix arrives, the trained model can output optimal or near-optimal RWA configurations much faster than ILPs and Heuristics. More, importantly, the applicability of their method is demonstrated in an ONOS-based software defined optical network (SDN) scenarios.

As traffic increases, faster service provisioning and capacity management in the optical layer are necessary, these functionalities require increased capacity along with rapid reconfiguration of network resources, when reconfiguring network resources, the QoS of existing users must not be affected, therefore, a key challenge is the optical power dynamics, which arise and cascade in a reconfigurable optical add-drop multiplexer (ROADM) system in the presence of optical circuit switching [93]. To solve the problem of providing wavelengths with minimum power dynamics is the key to the development of optical dynamic networks, wavelength defragmentation and realize real-time RWA algorithms [94]. Power excursions is one of the main types of power dynamics in optical networks, resulting from the use of EDFAs between two terminal nodes. Power excursions occur on active channels, and grow over multiple EDFAs along the propagation path, the cumulative effect of these power dynamics can increase nonlinear impairments at high power, and lead to OSNR degradation at low power, both resulting in increased BER [95]. In [96], authors developed a scalable neural network to predict channel power excursions resulting from optical circuit switching and allocate wavelengths. Due to the different effects of active channels and new channels, they are separate

Table 4
Summary of machine learning applications in RWA.

Reference	Problems	Approaches	Communication	Description	Training data	Output data	Advantages
[54]	RWA	LR	Unicast	NP-C	Network features and corresponding RWA solution.	An RWA solution for new coming input traffic matrix.	Reduce computational time.
[63]	Light-path establishment& Service differentiation	RL	Unicast	NP-Hard	/	/	Do not increase overall blocking probability.
[64]	Routing& service differentiation	R-learning	Unicast	/	/	/	Obtain maximized system revenue.
[65]	Routing	Linear Reward-ε Penalty	Unicast	/	/	/	Reduce blocking probability.
[66]	Multicast Routing	Q-learning	Multicast	/	/	/	Reduce blocking probability.
[68]	Path selection & wavelength selection	Q-learning	Unicast	/	/	/	Simpler to implement, reduce BLP.
[79]	RWA	DNN	Unicast	NP-C	Different input traffic matrices, corresponding optimal RWA solution.	An RWA solution for new coming input traffic matrix.	Reduce computational time.
[96]	Wavelength allocation	NN	Unicast	/	Active channels and new channels.	The predicted maximum power excursion among all active channels.	Have high wavelength assignment precision.

input features for the neural networks, and the output is the predicted maximum power excursion among all active channels. Then according to the predicted power excursion, recommending a wavelength channel under optical circuit switching operations that does not generate a large excursion on active channels as to keep power fluctuations within allocated margins. Their method performs efficiently for the large data set of a full C-band multi-hop ROADM system with a high wavelength assignment precision, and can be implemented in dynamic optical networks to allow for quick wavelength assignment.

4.1.3. Performance comparison

We summarized all mentioned algorithms in detail in Table 4. All algorithms are used for dynamic traffic pattern. There are four RL-based routing algorithms, respectively in [64–66,68]. For [64,65] and [68], they are all used for unicast communication. *K* candidate paths for each request are calculated at first, then the corresponding Q-value is updated according to the transmission result, i.e., success or failure. Differences among their algorithms lie in the update mode of Q-value and the calculation method of reward. In [64], authors achieved priority-based routing by setting different rewards when serving different level requests. And they updated the Q-value of a candidate path by updating the Q-value of each link constituting this candidate path. However, in [65] and [68], the Q-value of a corresponding candidate path is directly updated based on whether the request was successfully transmitted. Therefore, due to the refinement of the updating mode of the Q-value, [64] can achieve higher accuracy. However, as the network structure continues to expand and the number of links increases, computational complexity in [64] will become higher and higher, which is a practical problem that must be considered. Unlike above three algorithms, the developed algorithm in [66] is used for multicast communication, and they updated the Q-value of each node that can reach the destination nodes through neighbor nodes. The greater Q-value is, the better it is to send through the given neighbor node. Thus, when the number of fibers and the number of wavelengths per fiber are sufficient, the method can give good solution. However, it is important to note that the algorithm has a high time complexity. Different supervised learning enabled RWA algorithms were proposed in [54] and [79]. As long as the training data are sufficient, the method in [79] can effectively reduce more computational time than [54]. In addition, the optimal solutions they used for training are all derived from the ILP solution. Therefore. the trained DNN model can offer ILP-like routing and resource allocation solutions within less time.

4.2. Machine learning applications in RSA

In this section, we respectively introduce machine learning enabled RSA algorithms, RMSA algorithms, QoT estimation algorithms, traffic prediction algorithms, and modulation level selection algorithms. At last, we detailed compare the performance of different algorithms.

4.2.1. Machine learning enabled RSA algorithms

By setting up variable-sized channels with series of spectrally continuous fine-grained FSs, EONs offer unprecedented flexibility for spectrum management in the optical layer. The traditional RSA strategy is to select a path according to the routing algorithm and then to allocate spectrum according to specific rules. Differently, in [74], authors proposed a new method of sample labelling, and transferred the RSA problem into a classification problem. They used four-layers NN to fit the mathematical relationships between network states and RSA strategies. The sample labeling method is as follows. For each sample, all appropriate candidate paths are calculated using the *K*-shortest path algorithm at first. Then, an optimal path is selected by traversing spectrum fragmentation degree of all candidate paths, and next spectrum resource is allocated. The matrix consisting of *K* candidate paths and the location of spectrum allocation is the label of this sample. The structure of this method is presented in Fig. 8. For each sample, its

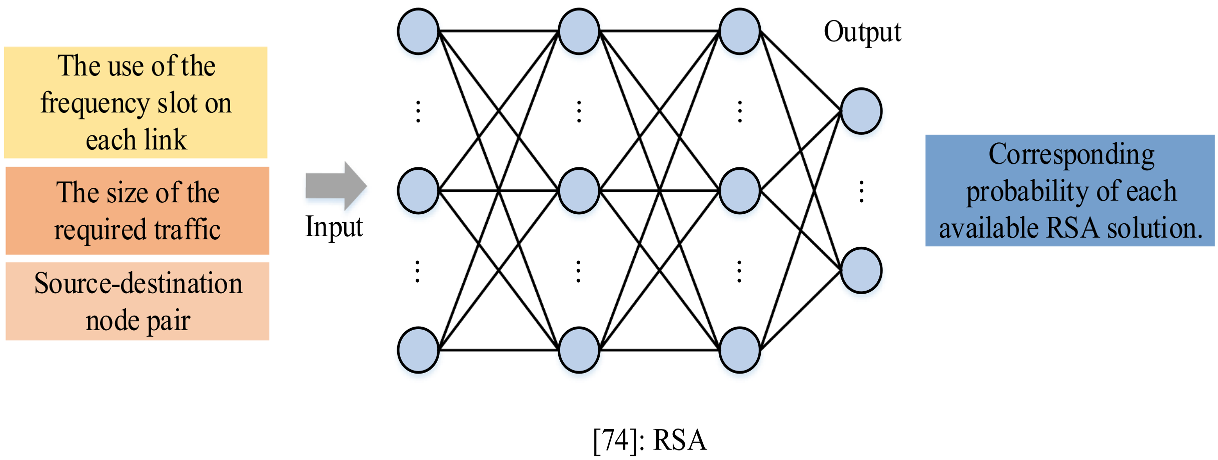

Fig. 8. DNN enabled RSA algorithm.

corresponding network state are input features of DNN, including the usage of each FS on each link, the required traffic, and its source–destination node pair. The DNN model outputs the corresponding probability of each available RSA solution. By using a large number of labelled samples to train the DNN model, the bandwidth blocking probability is obviously reduced and the degree of spectrum fragmentation is superior to traditional RSA strategies.

Recently, deep reinforcement learning (DRL) shows good performance while solving large-scale online control tasks [97,98]. Using DRL to conduct routing and resource allocation has aroused extensive research interests. In [69], authors proposed using DRL to search the optimal RMSA solution by precepting network states and rewards from environment. They first calculated K shortest paths and allocated resources for each request to form the set of RMSA solutions. Different with traditional Q-learning, they used DNN to parameterize the Q-network. As shown in Fig. 9, for each request, the Q-network takes source node, destination node, demanded data and the spectrum utilization on all fiber links as the input (state s_t) and outputs the corresponding Q-value of each RMSA solution. Then a Q-value for this request is selected and the corresponding RMSA solution (action a_t) is executed. Next, adjusting the parameters of the Q-network according to obtained immediate reward and calculating future reward so that the output Q-value is close to the real Q-value, namely future reward. Their method is able to capture successful features from network states and learn correct RMSA policies. However, it has to predict future requests, which induces additional complexity and oscillations of the cumulative rewards. Therefore, authors in [75] proposed two new DRL solutions to solve mentioned problems by setting the scope of a DRL task. As shown in Fig. 10, they proposed that using feature engineering to calculate K candidate paths for a request, and combining spectrum usage of each candidate path for this request as the state s_t at time t. Then they respectively used policy DNN and value DNN to calculate RMSA policy for this request and the value of the state s_t. SDN controller selects an RMSA solution to execute based on the RMSA policy and gets reward. They used this set of state, action and reward as a new sample to train DNNs to achieve the goal of online learning RMSA strategy. Comparing with the baseline algorithms, i.e., the K-shortest path routing and first-fit, their method effectively reduces blocking probability while reducing computational complexity.

In the actual transmission process, network failures are inevitable, which can lead to a large number of data loss. Therefore, the survivability of the network must be maintained so that the network can continue to operate under failures. Survivable routing, modulation level and spectrum assignment (S-RMLSA), which is used to find the appropriate working and protection routes for a source–destination node pair, and allocate adaptive modulation level and suitable frequency resource to the established working and protection light-paths, is one of fundamental problems in EONs [99]. In [76], authors proposed a new criterion to evaluate the overall performance of the network under failures, i.e., the whole network cost-effectiveness value with

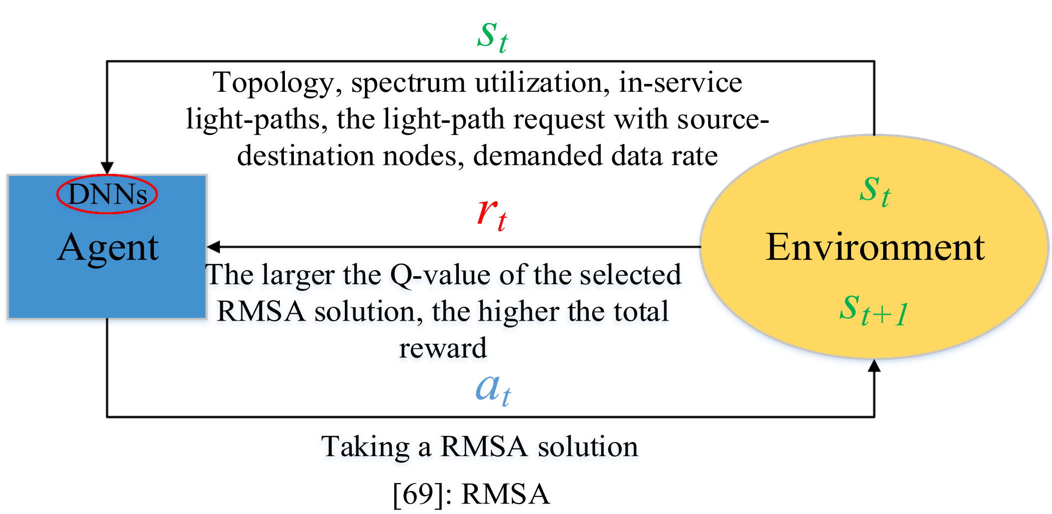

Fig. 9. DRL enabled RSA algorithms and RMSA algorithms.

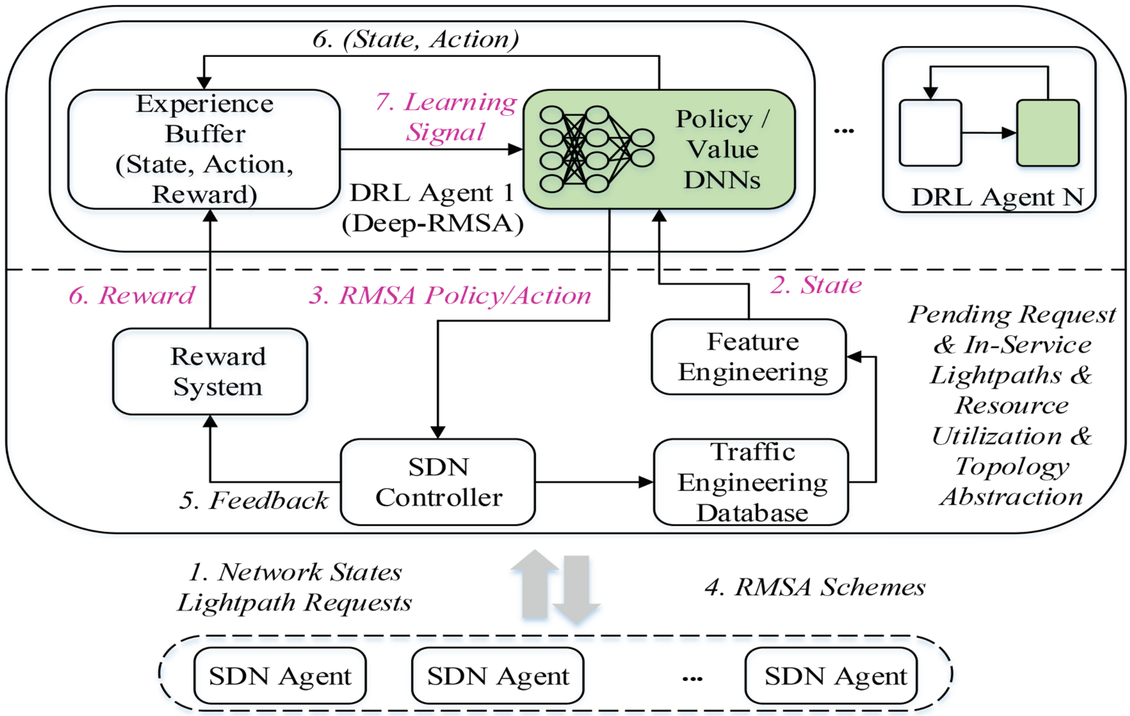

Fig. 10. Schematic of RMSA [75].

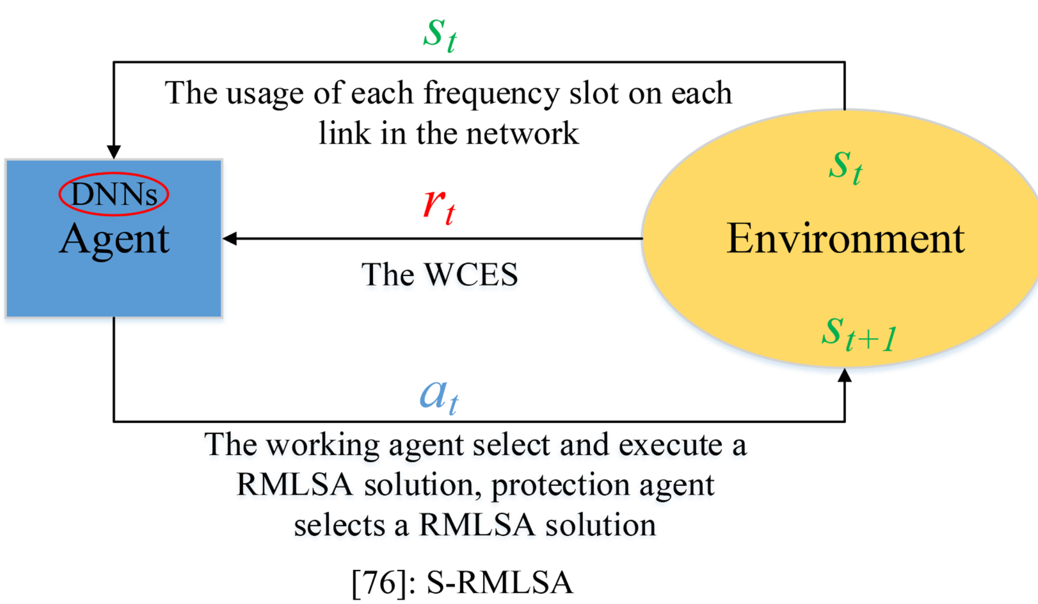

Fig.11. DRL enabled S-RMLSA algorithm.

survivability (WCES), which includes the information of all served and blocked incoming requests before current time slot. In order to maximize the WCES, authors proposed using the double-agent-DRL algorithm to solve S-RMLSA problem. In their method, working agent and protection agent explore feasible working RMLSA solution and protection RMLSA solution respectively, and two agents are combined by reward controller with the objective of maximizing WCES. Specifically, first all available working RMLSA solutions and protection RMLSA solutions for each request are calculated, where the same link cannot be used between each working RMLSA solution and protection RMLSA solution pair. As shown in Fig. 11, according to current network state s_t (the usage of each FS on each link in the network at time t), the working agent selects and executes a corresponding RMLSA solution according to the Q-network. Then the protection agent executes a protection RMLSA solution according to the new network status and gets reward, which is the WCES value at current time, then the Q-network is updated. Through numerical results, they demonstrated the proposed algorithm can effectively optimize overall performance of the network while ensuring survivability of EONs against the single-link failure.

4.2.2. Machine learning enabled QoT estimation algorithms and traffic prediction algorithms

Considering that physical impairments can affect signal propagation, in order to obtain feasible RSA/RMSA solutions, the QoT of a lightpath must be estimated before deployment. In [70], authors integrated a DNN-based QoT estimator and a DNN-based traffic estimator in the

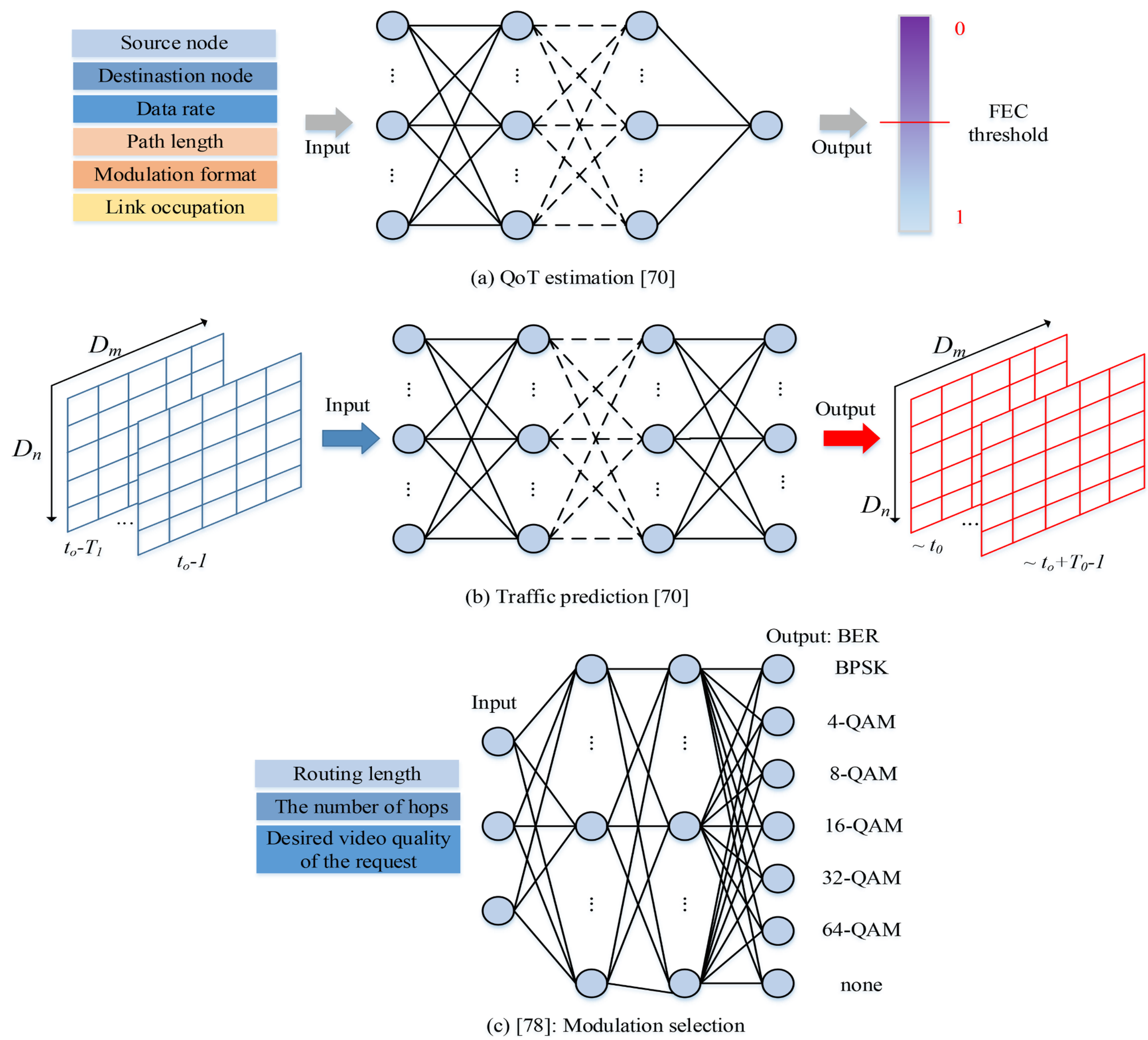

Fig. 12. Different DNN enabled algorithms in RSA and RMSA.

RMSA algorithm. For the QoT estimator, its structure is presented in Fig. 12(a). For each request, the authors used source node, destination node, data rate, path length, modulation format, and link occupation as input features of the DNN model, and the DNN model outputs whether the BER of a light-path meets the QoT requirement. For traffic estimator, its structure is shown in Fig. 12(b). The pairs of light-path requests and corresponding traffic matrices are taken as input features of the DNN model to predict future demand matrixes for new requests. Through combining well-trained DNN models with the RMSA algorithm, the most cost-effective light-path can be selected. However, one disadvantage of the DNN enabled estimators is that they are error-prone. For example, although the actual received BER does not exceed threshold, the light-path may be misclassified as unfeasible. In order to solve this problem, in [77], authors proposed using two RF-based models to judge and check the probability of a RMSA solution acceptance at the receiver. Given a traffic request, the first RF model takes alternative configurations of routes and modulation formats as input, and for each of them, the classifier outputs a probability that the light-path configuration will satisfy a given threshold on the BER measured at the receiver. On the basis of the first model, for each light-path in the solution, issues a query to the second RF classifier containing the exact features of that light-path and of its neighboring channels. Specifically, if the classifier returns a negative outcome (i.e., the light-path QoT is not acceptable), an additional constraint is added that excludes from the RMSA solution the unacceptable deployment of the light-path and its neighbors. The proposed method has more accuracy than [70] and effectively saves spectrum resource. However, as computing complexity increases, it does not work well on large-scale networks.

4.2.3. *Machine learning enabled modulation level selection algorithms*

The QoT estimation methods discussed above are all in the case that modulation level is known. In [78], for video communication, authors proposed to integrate an artificial neural network (ANN)-based modulation level selector in the RSA algorithm to maximize spectrum efficiency while guaranteeing user quality of experience (QoE) with minimum bandwidth utilization. The key of their method is the generation of ground-truth data, for each possible source–destination pair, some candidate shortest paths are selected using the Dijkstra routing algorithm. Then the OSNR of each source–destination pair is calculated and BERs are estimated for candidate modulation levels, i.e., BPSK, 2^m-QAM, m = 2, 3, 4, 5, 6. According to the multiple BERs obtained, estimating corresponding video quality, a modulation level which

Table 5
Summary of machine learning applications in RSA and RMSA.

Reference	Problems	Approaches	Traffic pattern	Description	Trained data	Output data	Advantages
[69]	RMSA	Deep Q-network	Dynamic	NP-C	/	/	Save spectrum.
[70]	Traffic estimation & QoT estimation	DNN	Dynamic	NP-C	/	/	Improve the throughput of the multi-domain EON, achieve higher spectrum efficiency.
[74]	RSA	DNN	Dynamic	NP-C	/	/	Reduce the degree of spectrum fragmentation and blocking probability.
[75]	RMSA	DRL	Dynamic	NP-C	/	/	Reduce blocking probability.
[76]	S-RMSA	Deep Q-network	Dynamic	NP-C	/	/	Improve the performance of network.
[77]	The QoT estimation	RF	Static	NP-C	Routing and modulation format of each RMSA solution, corresponding threshold BER.	The probability that predicted BER does not exceed the threshold BER.	Save spectrum.
[78]	Modulation selection	DNN(ANN)	Dynamic	NP-C	/	/	Increase spectral efficiency.

satisfies the minimum user requested QoE and has the maximum efficiency of spectrum utilization is selected as the label. The structure of this model is shown in Fig. 12(c), for each request, the routing length, the number of hops, and desired video quality are regarded as input features of the ANN model, and the model outputs the corresponding BER value in combination with each modulation level. This method saves more spectrum compared with the distance-adaptive modulation scheme, and the blocking probability of EONs is significantly reduced.

4.2.4. Performance comparison

Summary of all mentioned machine learning enabled algorithms is presented in Table 5. Except for [77], other algorithms are all used for dynamic traffic pattern. There are three DRL enabled RMSA algorithms, respectively in [69,75,76], all of them are used for unicast communication. The similarity of three algorithms lies in that all available RMSA solutions are calculated according to current network state for a new request at first, and the Q-value of the corresponding solution is updated according to the transmission result (i.e., success or failure) after executing the selected RMSA solution. Their difference lies in that authors in [69] and [75] considered how to choose the RMSA solution to reduce blocking probability, while authors in [76] considered how to maintain the survivability of EONs when failures happen. In addition, since [75] does not need to predict future requests, its complexity is much lower than [69]. In [74], authors transferred the RSA problem into a classification problem, which can be solved by DNN. Although this method has better performance of spectrum fragmentation and the bandwidth blocking probability, one of the drawbacks of DNN is that it requires a lot of data for training. For the QoT estimation, there are two methods, respectively in [70,77]. In [70], authors only used one DNN model to estimate whether the solution allocated for a request meets the threshold QoT. Although their method has high accuracy, errors are inevitable. In [77], authors used two RF-based models for prediction and verification respectively. The second model adds the information of adjacent channels as input features to confirm whether the solution really meets the threshold QoT. Compare with [70], due to the addition of adjacent channel information, their method can achieve higher accuracy. But as network size increases, the number of available solutions and adjacent channels of each solution also increases, which makes computational complexity increase nonlinearly with network size. Therefore, this algorithm may not be applicable to large-scale networks.

4.3. Machine learning applications in RCSA

In this section, for SDM-EONs, we respectively introduce existing machine learning enabled resource allocation algorithms, traffic prediction algorithms, crosstalk estimation algorithms, and modulation format selection algorithms. At last, we summarize mentioned algorithms in detail.

4.3.1. Machine learning enabled resource allocation algorithms

Considering the effects of crosstalk and physical impairments, in [62], authors proposed two resource allocation algorithms based on fuzzy clustering. They first calculated all feasible RCSA solutions for each request, which satisfy the requirements of crosstalk and physical impairments simultaneously. Then, the corresponding resource allocation algorithm based on fuzzy clustering is selected according to the number of feasible RCSA solutions, fuzzy C-means clustering (FCM) for large sample scale and direct clustering (DC) for small sample scale. Whether it is FCM or DC, according to crosstalk value, it divides all available RCSA solutions into two classes to serve two different levels of requests. For a high-level request, a resource allocation scheme in the class with low crosstalk value is selected. For a low-level request, a resource allocation scheme in the class with high crosstalk value is chosen. Simulation results indicated that their method not only improves spectrum utilization but also effectively reduces the blocking probability.

Table 6
Summary of machine learning applications in RCSA.

Reference	Objective	Approach	Description	Structure	Traffic pattern	Trained data	Output data	Advantage
[62]	Resource allocation	FCM& DC	/	Single mode 7-core	Dynamic	All available resource schemes for each request.	Two classes serving two different levels of services.	Improve the spectrum resources utilization and reduce blocking probability.
[71]	Traffic estimation & RCSA	ENN	NP-Hard	Single mode 7-core	Dynamic	The size, arrival time, holding time, actual traffic of each history request.	Predicted traffic of future requests.	Reduce crosstalk and blocking probability.
[84]	Crosstalk prediction & resource allocation	Bayesian Regularization LevenbergMarquardt Scaled Conjugate Gradient	NP-Hard	2-mode 7-core	Dynamic	The core index, the mode index, wavelength, the path length and the crosstalk value for each available resource allocation solution of each request (sample).	Predicted crosstalk values for future requests.	Improve the quality of services.
[100]	Traffic estimation	LSTM	/	2-mode 7-core	Dynamic	The source node, destination node, size, arrival time and holding time of the request.	Predicted traffic of future requests.	Has higher prediction accuracy and a fairly good generalization ability.
[102]	Traffic estimation	OS-ELM	/	Single mode 7-core	Dynamic	The size of historical traffic demand in each sample.	Predicted future demands.	Reduces the network energy consumption while maintaining the blocking probability at suitable levels.
[103]	Modulation formats selection	kNN	/	Single mode 7-core	Dynamic	A number of samples MDL_i with different MDLs, corresponding *BBPi*.	Predicted BBP.	Improve the spectrum resources utilization.

4.3.2. Machine learning enabled traffic prediction algorithms

In order to avoid crosstalk and spectrum fragmentation, in [71], authors integrated an Elman neural network (ENN)-based traffic estimator in a novel RCSA algorithm. They proposed that the size, arrival time and holding time of each traffic request are regarded as the input of ENN, and ENN outputs the predicted traffic demands. Then, the prediction error between the predicted value and the actual value for each request is calculated. When prediction error is greater than the threshold, updating the weight value of each layer of ENN until the error is lower than the threshold. Taking the predicted traffic as parameters, they introduced a spectrum partition scheme for adjacent cores of a link to reduce inter-core crosstalk. Specifically, they converted resource allocation problem into a rectangular packing problem. Their method effectively improves the performance of network by considering spectrum fragmentation and crosstalk. In [100], they further proposed combining historical traffic data and deep learning techniques to more accurately predict future traffic requests. Especially, they designed the DL model based on the long short-term memory (LSTM) to predict five attributes of the requests at time t, i.e., the source node, destination node, size, arrival time and holding time of the request. The LSTM has long running time, but because the predictions happen before the request arrives, these calculations are worth it so as to achieve higher accuracy.

With the introduction of spatial domain, the accelerated growth of network traffic leads to the increase of energy consumption. Energy is becoming an increasingly important part of operational or even capital costs [101]. Therefore, the study of energy saving from the perspective of network is of great significance for establishing green networks. In [102], authors proposed a machine learning-assisted loading energy consumption selecting (MLES) algorithm to search for the idle light-path with the least loading energy consumption. Specifically, they used the online sequence extreme learning machine (OS-ELM) to obtain an accurate forecast of future traffic load based on historical data, namely, using the OS-ELM to predict idle light-path (i.e. when the traffic load of a certain light-path is zero). Then the set of idle light-paths with inter-core crosstalk lower than the crosstalk threshold is selected out. In this set, the idle light-path with the lowest loading energy consumption is selected to transmit new traffic demand. When the crosstalk limitation is satisfied, their proposed algorithm greatly reduces the network energy consumption while maintaining the blocking probability at suitable levels.

4.3.3. Machine learning enabled crosstalk estimation algorithms

The inter-core crosstalk in [71] is calculated by the specific parameters of a request and the network, calculation complexity is high in the network layer. In order to solve this problem, authors in [84] proposed an accurate machine learning-based crosstalk estimation model, which can be directly applied to resource allocation design in few-mode multiple-core fiber (FM-MCF). Specifically, they first used the beam propagation method (BPM) to obtain training data, which contain the core index, the mode index, wavelength, the path length and the crosstalk value for each available resource allocation solution of each request (namely, each sample). Then these data are fed as input into the NN model which can be used to predict the practical crosstalk values for incoming services. This method simplifies crosstalk calculation, and shows good performance from the respect on training regression and time-consuming.

4.3.4. Machine learning enabled modulation format selection algorithms

Modulation format offers a different tradeoff between spectrum efficiency (the number of occupied FSs) and transmission reach. However, it is difficult to quantify the impact of the modulation formats used in a network on the deterioration in QoT due to the crosstalk effect and on overall network performance. Therefore, in order to adopt appropriate modulation format for a particular light-path, in [103], authors proposed using supervised learning regression methods to support the selection of modulation formats for incoming requests. Specifically, for each analyzed modulation format, they defined a modulation format distance limit (MDL) parameter to directly select the modulation format for a light-path by comparing the considered routing path length against the MDL parameter. In other words, the selection of the MDL of each modulation format is equivalent to the selection of the modulation format. Especially, a number of samples MDL_i with different MDLs (e.g. MDL^{BPSK}, MDL^{QPSK}, MDL^{8QAM}, MDL^{16QAM}) are generated at random. For each sample, a crosstalk-aware dynamic routing algorithm is run to obtain bandwidth blocking probability (BBP) resulting from using modulation formats selected according to MDL_i. Then a set of tuples [MDL_i, BBP_i] is obtained, which is next used as an input data of the k-nearest neighbors (kNN) model, MDL_i is considered as the analyzed feature space, BBP_i is a label. The trained regressor is used with the grid search procedure to find a combination of MDLs that provides the lowest value of BBP. Their method achieves intelligent selection of modulation formats and provides lower blocking in the network, so that leads to better utilization of available resource.

4.3.5. Performance comparison

In Table 6, we summarize above mentioned algorithms in detail, including objectives, approaches, model structures, and etc. Six algorithms are all used for dynamic traffic pattern. [84] and [103] are used for resource optimization. Specifically, [84] combines an accurate crosstalk evaluation model to address the issue on resource allocation scheme considering the crosstalk, which achieves better performance both on the connection set-up time and spectrum resource utilization. [103] is able to find a better tradeoff between spectrum efficiency and crosstalk penalty (QoT) of the applied modulation formats and in consequence the blocking can be reduced. There are three machine learning enabled traffic estimation algorithms, respectively in [71,100] and [102]. In [71], ENN is easy to fall into the local optimal solution during training, obviously, they cannot effectively extract inherent long-term traffic flow features, in [100], the LSTM can automatically decide to retain and forget part of the information from inherent long-term traffic flow features. Therefore, [100] can achieve higher prediction accuracy and have a fairly good generalization ability. However, in [102], the OS-ELM training time, the test time, the difference in root-mean-square error between the training set and the test set is less than the LSTM, which indicates that OS-ELM has the better prediction accuracy.

5. Future research directions

5.1. Time-space-frequency multidimensional optical networks

As shown in Fig. 13(a), by using time division multiplexing (TDM) technique, SDM technique, and OFDM technique, optical networks have evolved into high speed and large capacity networks for multi-dimensional resource fusion of time–space-frequency. The improvement of the resource dimension changes the structure of network resource model, and resource allocation in optical networks becomes more complicated. Specifically, in multidimensional resource aggregation optical networks, when switching capacity of a single node reaches the order of tens of T bit/s or even P bit/s, synchronization frequency and interactive information of entire network resource can increase dramatically, excessive control overhead and information clutter can lead to resource congestion and conflict problems, the independent allocation of resources of different dimensions makes it difficult to optimize and control. In addition, due to the complexity of end-to-end signaling interaction, it is difficult to find the optimal balance point between resource occupation and connection efficiency, which leads to the problems of long connection establishment time and high network resource occupancy. Therefore, before routing and allocating resources, we should focus on studying the unified scheduling method of time–-space-frequency multidimensional resources to reduce time delay and cost of light-path establishment, and to improve the efficiency of resource allocation of large-scale and large-capacity optical networks.

In order to further achieve intelligence, we present a simplified model in Fig. 13(b). As shown in Fig. 13(b), we plan to implement the machine learning module in the centralized controller, and add a deep learning unit in the existing Software Defined Optical Network (SDON). In the deep learning unit, there can be multiple machine learning modules to realize different functions respectively, such as traffic estimation, OSNR prediction, crosstalk prediction, modulation level selection and etc. SDON controller and the deep learning unit can transfer information to each other, for example, the routing results of the new request obtained by the routing calculation module in the SDON controller are transmitted to the deep learning unit, then using the deep learning unit for OSNR prediction, crosstalk prediction, optimal route selection and etc. The results processed by the deep learning unit are fed back to the SDON controller so as to realize intelligent routing and resource allocation. For traffic estimation, based on [71], we can consider how to design novel NN models to accurately predict the traffic of a request to optimize resource allocation. For OSNR prediction, based on methods in [70] and [77], through establishing quantifiable eigenvalues that characterize the QoT of a light-path / light-tree, we can consider to use support vector machine (SVM), NN and naive Bayes to predict the OSNR of a light-path / light-tree with high precision prediction, then to conduct a comparative analysis of accuracy to select one with the best performance. For modulation level selection, based on [84], for each available routing and resource allocation solution obtained by machine learning, we can also consider using NN models to predict corresponding crosstalk for feasibility determination by characterizing them.

In section 3, we have elaborated existing machine learning enabled routing and resource allocation algorithms, based on these analyses, we found that deep learning algorithms represented by NN are more suitable for solving such complex problems, so through unified scheduling method of time–space-frequency multidimensional resources, we further present a simplified model about how to use deep learning to design routing and resource allocation algorithms that satisfy multi-objective constraints simultaneously. As shown in Fig. 14, the state representation s_t should contain the information of a request and the spectrum utilization on each candidate path for this request. Then, according to s_t, using DNN to generate routing and resource allocation policy (i.e., the probability distribution over the action space). The agent selects a scheme a_t to execute according to the learned policy, the reward r_t is higher if this request is served successfully. This is only a simplified model, and we will keep its specific implementation as one of our future tasks.

5.2. Satellite optical networks

Optical communications include wired optical communication on the ground and wireless optical communication in space [104]. Wired optical communication takes laser signal as the carrier and optical fiber as the transmission medium, which has become a very mature communication means. Wireless optical communication takes laser signal as the carrier but space or atmosphere as the transmission medium [105]. With the vigorous development of big data applications and mobile internet services, it is necessary to establish a communication network system with high transmission rate, large amount of information and wide coverage, and space satellite communication with extremely short wavelength and wide bandwidth is the best scheme to realize high code rate communication [106]. Therefore, satellite optical networks have become an important part of future space information networks [107].

In satellite optical networks, as shown in Fig. 15, the WDM technique is used to establish multiple transparent transmission and high bandwidth wireless optical channels between two satellites to carry services [108]. Therefore, for the routing and resource allocation of satellite optical networks, the wavelength continuity constraint must be

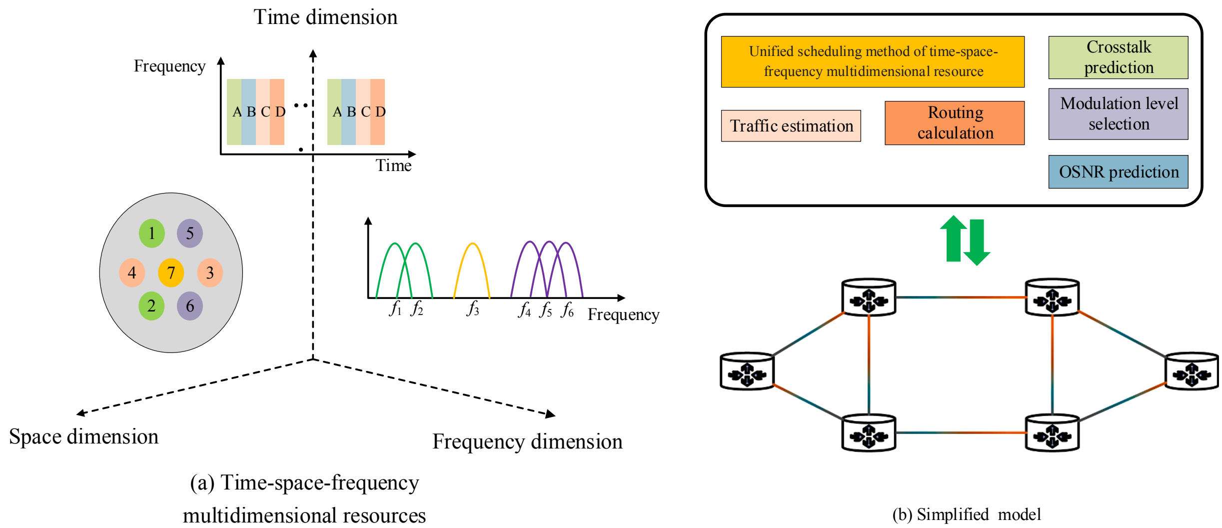

Fig. 13. Time-space-frequency multidimensional optical networks.

satisfied. However, in addition to this constraint, there are still many factors to be considered when designing routing and resource allocation algorithms for satellite optical networks. For example, satellites in non-geostationary orbit move rapidly relative to the earth's surface, the distance and angle of view between the two satellites change as the satellites move. Due to the mobility of the satellites, when the user terminal leaves the covered area of the satellite, the closure of the intersatellite link will lead to the handover, meanwhile, the small divergence angle of the received optical signal, the narrow field of view of the receiving antenna and the strong interference of the background light can lead the acquisition, tracking, and pointing process of the beam failed, the disconnection of the intersatellite link will also lead to the handover [109]. Most important, as shown in Fig. 15, the large-scale relative motion between satellites in different orbits would produce doppler effect, which can cause the shift of central wavelength, then lead to the decrease of signal power and the increase of noise power, so that affect communication quality and even can lead to communication failed [110].

Based on existing machine learning enabled RWA algorithms in wired optical communication, we further present a simplified model about how to design suitable RL-based RWA algorithms to avoid links with high Doppler shift as much as possible for satellite optical networks. As shown in Fig. 16, when a request arrives, all RWA solutions from the source satellite to the destination satellite can be calculated, then the agent can randomly choose one to execute according to the policy. When this solution succeeds, namely, wavelength continuity constraint and doppler shift threshold are met simultaneously, the reward is higher. Then the corresponding Q-value is updated. The main point is the calculation of the reward, it should include the corresponding doppler shift, transmission delay, and etc. After learning, the agent can choose an optimal optical path for each request. This algorithm can not only reduce the BP effectively, but also meet the transmission delay requirement of real-time service. Since this is only a simplified model, specific implementation and performance analysis will be presented in our future work.

6. Conclusion

Machine learning can make full use of the large quantity of data available from network monitoring elements, it is an irresistible trend to use advanced machine learning techniques to solve complex problems in optical networks. This paper provided an overview of machine learning applications for routing and resource allocation in optical networks. According to different multiplex techniques, routing and resource allocation problems can be divided into three categories, namely the RWA problem, the RSA problem and the RCSA problem. We started with respectively descripting three categories of problems in detail, and then turned to introduce why routing and resource allocation belongs to NP-C problem. Then commonly used machine learning techniques in optical networks were introduced, including LR, RF, clustering, Q-

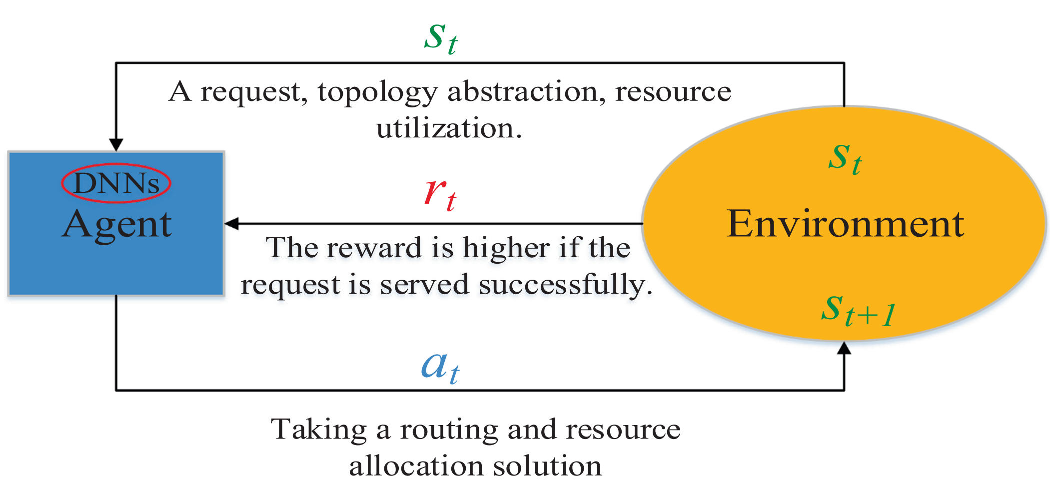

Fig. 14. A simplified DRL-based routing and resource allocation model.

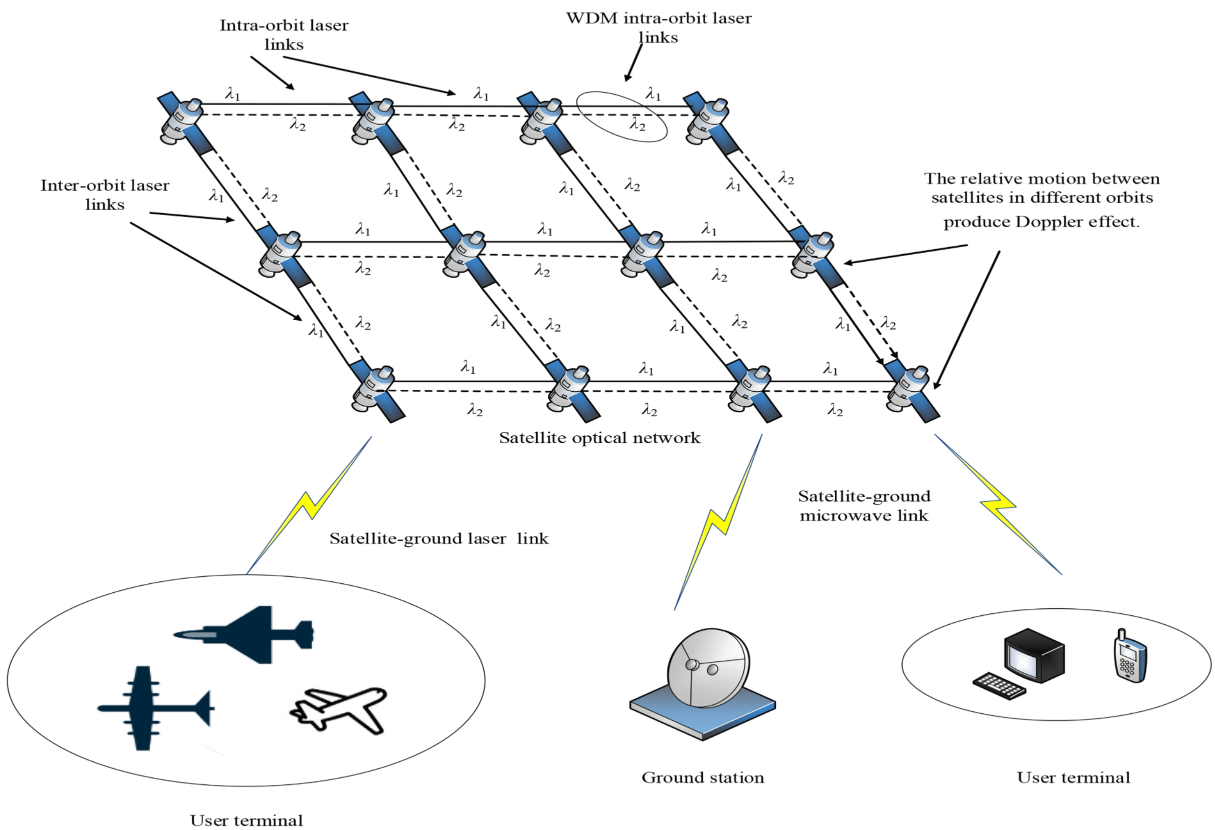

Fig. 15. A simplified satellite optical network model.

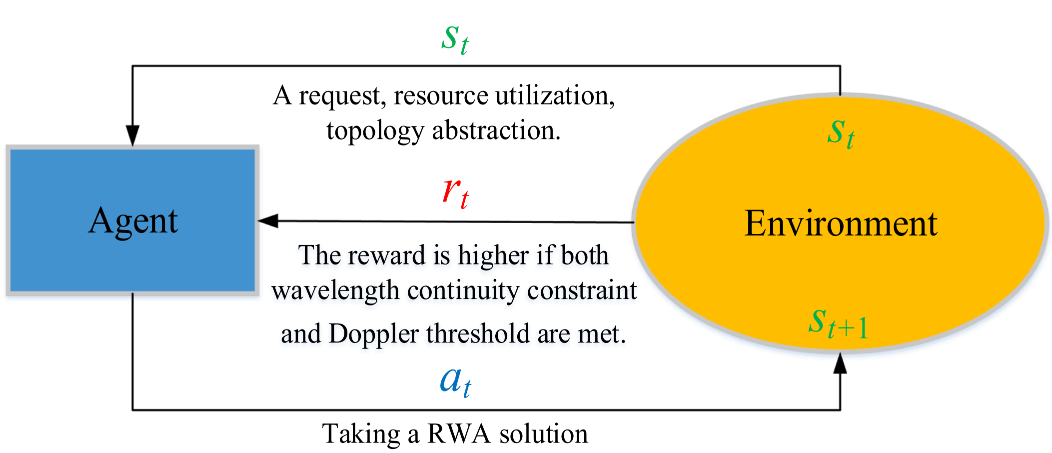

Fig. 16. A simplified RL-based RWA model for satellite optical networks.

learning and DNN, as well as their applications in optical networks. In addition, the commonly used machine learning libraries/frameworks were introduced. We also elaborated that routing and resource allocation problem, QoT estimation problem, traffic prediction problem, crosstalk estimation problem respectively belongs to which application scenario of machine learning. Next, the machine learning enabled RWA algorithms, RSA algorithms and RCSA algorithms were elaborated, analyzed and compared in detail. Besides, the applications of machine learning in QoT estimation, traffic estimation, crosstalk prediction, and etc., which can help to improve the success rate and resource efficiency of routing and resource allocation, were also elaborated. For each algorithm, we covered its objective, approach, model structure, advantages and etc. At last, since time–space-frequency multidimensional optical networks and satellite optical networks are the focus of research in recent years, we presented some future research directions about how to use suitable machine learning techniques to solve their routing and resource allocation problems respectively.

Authors contributions

Yongjun Zhang, Jingjie Xin and Xin Li were jointly responsible for the concepts and methods design, Jingjie Xin was responsible for the completion of the first draft of the manuscript. Yongjun Zhang, Xin Li and Shanguo Huang were responsible for the review, modification and editing of the manuscript. All authors read and contributed to the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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