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Machine Learning for Broad-Sensed Internet Congestion Control and Avoidance: A Comprehensive Survey

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ABSTRACT It is challenging to deal with the Internet congestion problem because of several factors such as ever-growing traffic and distributed network architecture. The congestion problem can be solved or alleviated by various methods, including rate control, bandwidth-guarantee routing and bandwidth reservation. We use the term broad-sensed Internet congestion control and avoidance (BICC&A) to generally denote all of the above methods. Most BICC&A solutions depend on or benefit from the knowledge of network conditions, including traffic status (type and volume), available bandwidth and topology. In this paper, we present a comprehensive survey of the applications of machine learning to network condition acquirement methods for BICC&A and specific BICC&A methods. First, we provide an overview of the background knowledge of BICC&A and machine learning. Then, we provide detailed reviews on the applications of machine learning techniques to network condition acquirement methods for BICC&A and to specific BICC&A methods. Finally, we outline important research opportunities.

INDEX TERMS Machine learning, congestion control, congestion avoidance, traffic classification, traffic prediction, bandwidth, topology, rate control, routing.

I. INTRODUCTION

Congestion occurs on the Internet when the aggregated demands for network resources (e.g., link bandwidth and router buffer) exceed the available capacities of the resources [1]. Congestion can lead to long transmission delays, packet losses and even possible congestion collapse, in which all communication in the entire network ceases. Accordingly, the congestion problem has attracted much attention for a long time. In recent years, network traffic has increased rapidly. According to the report of the Visual Networking Index, network traffic is expected to grow to 396 EB per month by 2022, up from 122 EB per month in 2017. The ever-growing network traffic creates increasing stress on the Internet. Therefore, solving the congestion problem remains critical for maintaining good performance of the Internet.

To date, there are two main approaches for solving the Internet congestion problem, i.e., congestion control and congestion avoidance [2]. The former is reactive because congestion control typically comes into play after congestion is detected, while the latter is proactive because congestion avoidance comes into play before the network becomes congested [2]. Congestion control can be divided into rate-based congestion control and path-based congestion control. Rate-based congestion control is the most widely used method, and it solves congestion by reducing the end-to-end transmission rate. Path-based congestion control dynamically adjusts the transmission path using the available bandwidth as one of the major metrics, as shown in [3]. Generally, congestion avoidance can be achieved by reserving or planning bandwidth-guaranteed paths

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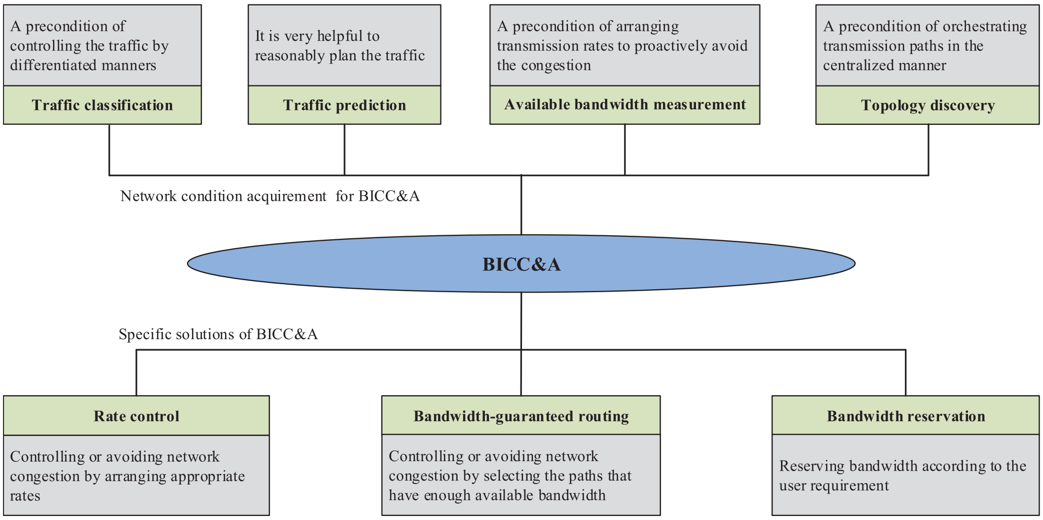

FIGURE 1. Scope of our survey in this paper.

(i.e., congestion-free paths) and determining the transmission rate in terms of available bandwidth. We use the term broad-sensed Internet congestion control and avoidance (BICC&A) to generally denote all kinds of congestion controls and avoidances.

BICC&A is a challenging research domain mainly because of resource limitations, considerable traffic requirements, distributed network architecture, isolated or local-optimized network protocols, and the dynamics of network traffic. The widely-used BICC&A solutions include rate control, congestion-avoidance routing and bandwidth reservation. Because the knowledge of network conditions (mainly including traffic types, traffic volume, available bandwidth and network topology) is very helpful to well solve the BICC&A problem, the network condition acquirement methods are also important for the BICC&A. Over the past few decades, machine learning (ML) has been exploited to solve the BICC&A problem from many aspects. Despite growing interest in ML applications for the BICC&A, a comprehensive survey of existing contributions is lacking. To fill the above gap, we provide a comprehensive survey on ML techniques applied to the BICC&A, as Fig. 1 describes. Additionally, we also discuss future research opportunities. We hope that our work can give readers an overall understanding of the BICC&A and inspire more studies on this area. In wireless networks, BICC&A has also attracted considerable attention. The BICC&A in wireless networks is independently studied in most cases. Therefore, it is not discussed in this paper. The readers can refer to some excellent surveys or tutorials (e.g., [4]) to understand how ML algorithms can be employed for solving various wireless networking problems including the BICC&A problem.

A. COMPARISON WITH EXISTING WORK

In 2003, Ryu *et al.* [2] presented a survey, published in IEEE COMST, on techniques in Internet congestion control and avoidance. Over the past nearly twenty years, both network traffic and network structure have experienced considerable changes, and a large number of related achievements have emerged during this period. Moreover, the survey [2] does not discuss ML techniques in Internet congestion control and avoidance. In contrast, our survey focuses on the ML applications for the BICC&A. In addition to the above difference, the scope of this survey is wider than [2]. The newly added topics in this survey include congestion-avoidance routing, bandwidth reservation, available bandwidth measurement and topology discovery.

In addition to [2], several existing survey papers involve a part of our survey scope, as Table 1 shows. Below, we further clarify the differences in the overlapping aspects of our paper and these papers.

Traffic classification: There have been several excellent surveys ([5]–[9]) on ML techniques in traffic classification. These surveys cover most ML-based traffic classification solutions. As a result, we do not conduct repeated investigations. For readers to conveniently understand traffic classification, we briefly introduce existing surveys in this paper.

Traffic prediction: Mohammed *et al.* [10] reviewed existing literatures related to ML-based traffic prediction. Usama *et al.* [11] provided a survey highlighting recent advancements in unsupervised machine learning (UML) techniques in networking. However, the above two surveys involve only a few related studies. In [12] (published in 2017), Fadlullah *et al.* investigated the literatures on deep learning (DL) applications for network traffic control, including traffic prediction. In recent years, especially in 2018 and 2019, many ML-based traffic prediction solutions have emerged. Thus, we investigate the literatures in the last 3 years to present a more comprehensive review of ML-based traffic prediction.

Rate control: Polese *et al.* [13] presented a survey on the advances in transport layer protocols, and Usama *et al.* [11] provided a survey on UML-based networking. The above two surveys involve ML-based rate control, but only a few related

TABLE 1. A comparison of the number of investigated papers between our paper and existing survey papers.

Ref.	Year	Beneficial supports for BICC&A				Specific BICC&A solutions			ML techniques
		Traffic classification	Traffic prediction	Available bandwidth measurement	Topology discovery	Rate control	Bandwidth constrained routing	Bandwidth reservation	
[5]	2019	√	×	×	×	×	Few	×	ML
[13]	2019	×	×	×	×	Few	×	×	ML
[14]	2019	×	×	×	×	×	Few	×	DRL
[11]	2019	×	Few	×	×	Few	Few	×	UML
[6]	2019	√	×	×	×	×	×	×	ML
[7]	2019	√	×	×	×	×	×	×	ML
[15]	2019	×	×	×	×	×	×	×	DL, RL
[10]	2019	×	Few	×	×	×	×	×	ML
[16]	2018	×	×	×	×	×	×	×	DRL
[12]	2017	×	Moderate	×	×	×	Few	×	DL
[17]	2016	×	√	×	×	×	×	×	DL
[8]	2015	√	×	×	×	×	×	×	ML
[18]	2015	×	√	×	×	×	×	×	ML
[9]	2008	√	×	×	×	×	×	×	ML
This paper	-	√*	√†	√	√	√	√	√	ML

×: The corresponding content is not investigated; √: The corresponding content is fully investigated.
∗: Introduce and cite excellent surveys; †: Introduce ML-based solutions in recent 3 years.

studies are discussed. In contrast, we conduct a comprehensive review of ML-based rate control.

Congestion-avoidance routing: Refs. [5], [11], [12], [14] discussed ML techniques applied to the routing. However, these papers mentioned few studies related to congestion-avoidance routing. Compared with these papers, our survey presents a full review of congestion-avoidance routing.

B. ORGANIZATION OF THE PAPER

The paper is organized as follows. First, the background knowledge is introduced in section II. Section III reviews how ML algorithms are applied in obtaining network conditions for the BICC&A, including traffic classification, traffic prediction, available bandwidth measurement and topology discovery. Section IV reviews ML algorithms in specific BICC&A solutions, including rate control, congestion-avoidance routing and bandwidth reservation. We discuss future research opportunities in section V, and present conclusions in section VI. Table 2 presents the list of abbreviations commonly used in this paper.

II. BACKGROUND KNOWLEDGE OF BICC&A AND ML

This section presents an overview of the background knowledge, including challenges in dealing with Internet congestion, the network condition obtainment solutions, ML algorithms and concerns on ML Algorithms in the BICC&A.

A. CHALLENGES IN DEALING WITH INTERNET CONGESTION

Although there has been a large amount of research effort, it is still challenging to deal with Internet congestion. Below, we introduce the main obstacles and difficulties in handling Internet congestion.

TABLE 2. List of commonly used abbreviations.

Abbreviation	Description
BICC&A	Broad Internet congestion control and avoidance
BS	Base stations
CNN	Convolutional neural network
C-RAN	Centralized radio access network
DBN	Deep belief network
DCN	Data center network
DCNN	Deep convolutional neural network
DCRNN	Diffusion convolutional recurrent neural network
DL	Deep learning
DNN	Deep neural network
DPI	Deep packet inspection
DQN	Deep Q-network
DRL	Deep reinforcement learning
HMM	Hidden Markov model
KNN	k-nearest neighbor
LSTM	Long short-term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
MLP	Multilayer perceptron
MPE	Mean percentage error
MPLS	Multiprotocol label switching
MPTCP	Multipath TCP
MSE	Mean square error
NDN	Named data networking
QoS	Quality of service
QoE	Quality of experience
RL	Reinforcement learning
RMSE	Root mean square error
RNN	Recurrent neural network
RRH	Remote radio head
SAE	Stacked autoencoder
SDN	Software-defined networking
SVM	Support vector machine
UML	Unsupervised machine learning
WAN	Wide area network
GNN	Graph neural network

1) HUGE TRAFFIC REQUIREMENT

In recent years, Internet traffic has maintained a rapidly increasing trend [19]. According to the Cisco Visual

Networking Index [20], IP traffic across the backbone network is expected to grow to 273 EB per month by 2022, up from 85 EB per month in 2017. Network bandwidths are crucial for handling network traffic. However, compared with the growth of IP traffic, the global average broadband speed will only double from 2017 to 2022, from 39.0 Mbps to 75.4 Mbps. As a result, the Internet will suffer heavier traffic stress in the near future. Moreover, the improvement of network bandwidth will cause more use of high-bandwidth applications, which makes the situation more serious.

2) DISTRIBUTED NETWORK ARCHITECTURE

In legacy networks, the status of global resource occupancy is difficult to obtain, and network resources are hard to manage. Additionally, the controlling and forwarding functions are implemented inside routing or switching devices, which reduces the flexibility of planning the resource use. For the above reasons, bandwidth resources cannot be fully used in legacy networks. For example, Uhlig *et al.* [21] noted that the maximum link utilization inside the GéANT network is approximately 90 percent, but the mean link utilization is only approximately 5 percent. Software-defined networking (SDN) can overcome the shortcomings mentioned above [22]. However, we also should note that software-defined WAN only accounts for a small part of all networks because of the deployment difficulties [23].

3) ISOLATED OR LOCAL-OPTIMIZED NETWORK PROTOCOLS

Most rate control protocols in legacy networks are designed for separate sessions, which is disadvantageous for globally optimizing the performance of congestion control. In addition, the unicast or multicast routes, corresponding to a designated session, are usually built in isolation in legacy networks. This may cause congestion on some links because the network simultaneously accommodates many sessions. Although SDN has its superiority on global traffic optimization, it is impossible to globally arrange all the transmission paths and rates mainly because of the scalability [24].

4) THE DYNAMICS AND DIVERSITY OF NETWORK TRAFFIC

Because of the dynamics and diversity of network traffic, traffic monitoring or traffic prediction is a significant condition for formulating effective congestion control or avoidance schemes. It is a simple but accurate method to monitor traffic. However, traffic monitoring with high timeliness produces a heavy load. An alternative method is traffic prediction. In recent years, sharing user-generated content (e.g., Tik Tok and Instagram) has become increasingly popular. It is difficult to rapidly predict the popularity of user-generated content, which complicates traffic prediction. In summary, traffic prediction is still an open issue, although it has been studied for a long time [25].

B. NETWORK CONDITION ACQUIREMENTS FOR BICC&A

In this section, we introduce the main network condition acquisition methods, including traffic classification, traffic prediction, available bandwidth measurement and network topology discovery.

1) TRAFFIC CLASSIFICATION

The objective of traffic classification is to classify Internet traffic into predefined categories, such as normal traffic, abnormal traffic, and types of applications. Traffic classification is helpful to reasonably use bandwidth resources and to ensure QoS requirements of some relatively important flows. In the early stage, traffic classification is implemented based the ports because each application was identified by its registered and known port. This approach becomes unreliable and inaccurate because of the new applications with unregistered or random ports. Deep packet inspection (DPI) is another important traffic classification solution, in which the contents of packets are observed by referring to the characteristic signatures of network applications in traffic. Compared with port-based techniques, DPI-based traffic classification tools (e.g., PACE and OpenDPI) provide accurate results. However, DPI-based techniques also have some disadvantages and weaknesses [26]. For example, they involve high computational costs and processing loads, they cannot deal with encrypted traffic because the contents of packets are inspected, and they suffer from privacy policy violations.

2) TRAFFIC PREDICTION

Traffic prediction is important to network providers and managers to offer better service by making appropriate decisions, including congestion-avoidance schemes [27]. To predict Internet traffic, historical and real-time traffic data should be collected [28]. In [18], the authors categorized traffic prediction techniques under four categories: the linear time series model, the nonlinear time series model, the hybrid model and the decomposed model. In network traffic prediction techniques, several metrics are used to estimating the prediction accuracy [18]. These metrics include mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), normalized root mean square error (NRMSE), mean percentage error (MPE) and mean absolute percentage error (MAPE).

3) AVAILABLE BANDWIDTH MEASUREMENT

Knowledge of the available bandwidth of a link or a path is very helpful for controlling or avoiding network congestion. A network administrator can simply access the information (e.g., configuration parameters, nominal bit rate of an associated link, average utilization, bytes or packets transmitted over some time period) associated with the router/switch using the SNMP network management protocol [29]. However, such access is typically available only to administrators and not to end users [30]. In addition, the available bandwidth status on a path is difficult to know based on SNMP because a path usually passes through different management areas. As an alternative, end users can estimate the available bandwidth of a path based on end-to-end measurements, without any information from routers. To date, there have been many various bandwidth measurement techniques for estimating available bandwidths of end-to-end paths, including pathload [31], pathChirp [32], etc.

4) TOPOLOGY DISCOVERY

Understanding the Internet topology and its main characteristics is beneficial for alleviating the congestion problem by fully using the network resources. Motamedi *et al.* [33] presented an excellent survey of the techniques for Internet topology discovery. In [33], Internet topology was viewed at four different granularity or resolution levels, including interface level, router level, point of presence (PoP) level and autonomous system (AS) level. Note that a PoP is a concentration of routers that belong to the same AS [34] and that an interface belongs to a host or a router, and there is a one-to-one mapping between nodes and IPs [35]. The topology that is the most relevant to the BICC&A is interface-level topology. The widely used interface-level topology discovery tools include TraceRoute [37], XNET [38], etc.

C. SPECIFIC BICC&A SOLUTIONS

In terms of the strategies for solving the BICC&A problem, existing BICC&A solutions can be divided into three categories, i.e., rate control, congestion-avoidance routing and bandwidth reservation, as shown in Fig. 1. Specifically, rate control uses the transmission rate adjustment strategy, congestion-avoidance routing employs the path planning strategy, and bandwidth reservation adopts the resource planning strategy.

Rate control solves the congestion problem by reducing transmission rates. According to the rate control scope, rate-based control solutions can also be divided into two types, i.e., independent and joint rate control. Independent rate control only adjusts the rate of a single session, while joint rate control simultaneously adjusts rates of multiple sessions. The congestion-avoidance routing is a particular form of the QoS routing. To improve the load balance performance and the maximum number of connections that the network can accommodate, various resource scheduling techniques are deployed to schedule the bandwidth reservation requests. One of the most commonly used techniques is the resource reservation protocol (RSVP) [39], which reserves the same bandwidth according to the service-level agreement (SLA) along the path calculated by the instant scheduling algorithm.

D. ML ALGORITHMS IN BICC&A

ML techniques have been widely applied to the BICC&A. These techniques include support vector machines (SVMs) [40], [41], Bayes' theory, k-nearest neighbor (KNN), the hidden Markov model (HMM), unsupervised learning (e.g., k-means [42], [43] and fuzzy C-means [44], [45]), semi-supervised learning, RL (e.g., Q-Learning and DRL), DL, transfer learning and ensemble learning (e.g., AdaBoost [46], bagging [47], and random forest [48]). Example algorithms of DL include DNNs, convolutional neural network (CNN), recurrent neural network (RNN) and deep belief network (DBN) [49]. Long short-term memory (LSTM) [50] is a commonly used type of RNN, and it is a popular ML algorithm applied in the BICC&A. In this paper, we introduce DL-based BICC&A solutions (not including DRL-based solutions) separately. A DL algorithm can use a supervised, unsupervised or semi-supervised learning manner. Thus, we use supervised, unsupervised and semi-supervised non-DL learning algorithms to denote supervised, unsupervised and semi-supervised learning algorithms that do not use the DL techniques.

E. CONCERNS ON ML ALGORITHMS FOR BICC&A

In this section, we introduce several key concerns when applying ML algorithms to the BICC&A from networking and communication perspectives.

1) THE DIFFICULTIES IN OBTAINING DATASETS

Because the Internet consists of a large number of heterogeneous networks that are managed by different operators, it is difficult to obtain desired data in many cases. Moreover, when the data are allowed to capture, handling the captured data is still challenging because the data on the Internet are generated by heterogeneous sources and exhibit nontrivial spatial/temporal patterns [51]. As a result, available data are a key factor of ML algorithm selection for the BICC&A.

2) PROCESSING LOAD

The processing load denotes the computation and memory load for training the model. In BICC&A, learning may be performed by different types of network entities, including user devices, routers, base stations (BS), and some special servers such as controllers. As a result, the processing load should be considered according to the specific application devices.

3) THE ADAPTABILITY TO TRAFFIC DYNAMICS

The traffic prediction technique can forecast traffic dynamics to some extent. However, the popularity of user-generated content sharing makes long-term traffic prediction inaccurate in some cases. In addition, disregarding the advantage of traffic prediction, it is difficult to practically deploy it to forecast the traffic passing through all or most network links.

4) CONSIDERATION OF DATA TRANSMISSION FEATURES

Today, there are a considerable variety of applications on the Internet, and ML algorithm selection should fully consider the data transmission features of associated applications. Some applications (e.g., file sharing) transfer data based on TCP or other protocols that can arbitrarily adjust the transmission rate according to network conditions. In other words, the traffic generated by these applications can avoid congestion when it occurs. For controlling the above traffic, the ML algorithms, with acceptable accuracy but low cost, may be a good choice.

III. ML IN CONDITION ACQUIREMENT FOR BICC&A

As mentioned previously, the BICC&A depends on or benefits from the network condition acquisition, including traffic classification, traffic prediction, available bandwidth measurement and network topology discovery. In this section, we review existing ML applications to these network condition acquirement methods. We summarize how ML techniques are applied in each field.

A. ML IN TRAFFIC CLASSIFICATION

1) ML-BASED TRAFFIC CLASSIFICATION SOLUTIONS

To date, there have been several excellent surveys on ML solutions applied to traffic classification. In 2008, Nguyen and Armitage [52] surveyed works in the field of ML-based traffic classification. In 2015, Namdev *et al.* [53] presented a review of the studies that consider encrypted traffic. In 2019, Pacheco *et al.* [54] presented a survey on ML in traffic classification. This survey attempted to gather different approaches, strategies and procedures regarding how and when to use ML techniques for traffic classification. The above surveys cover most ML solutions applied to traffic classification from 2004 to 2019. Accordingly, we do not conduct repeated investigations. In the following, we present a discussion on traffic classification.

2) DISCUSSION ON ML IN TRAFFIC CLASSIFICATION

So far a variety of ML techniques have been applied to traffic classification. These ML techniques include decision tree, SVM, k-means, Bayesian network, random forest, AdaBoost, LSTM, CNN, expectation-maximization [55], multilayer perceptrons [56] and genetic algorithm [57]. Namdev *et al.* [53] noted that k-means does not work well with clusters of different sizes and different densities. According to reports in the literatures, many ML-based traffic classification solutions can achieve a very high classification accuracy ($\geq$ 90%). The ML techniques for timely and continuous classification usually use a sliding window over which features are calculated [52]. The classification accuracy might be improved by increasing the length of this window. However, the increasement on the window length may decrease the timeliness of classification decisions and increase the required memory size. For the above reason, the real-time traffic classification is still an open problem.

B. ML IN TRAFFIC PREDICTION

Mohammed *et al.* [10] reviewed existing literatures related to ML-based traffic prediction. Usama *et al.* [11] provided a survey highlighting recent advancements in unsupervised machine learning (UML) techniques in networking. However, the above two surveys involve only a few related studies. In [12] (published in 2017), Fadlullah *et al.* investigated the literatures on DL applications for network traffic control including traffic prediction. In recent years, especially in 2018 and 2019, many ML-based traffic prediction solutions have emerged. For the above reasons, we investigate the literatures in the past 3 years to present a more comprehensive review of ML-based traffic prediction solutions, as Table 3 summarizes. Below, we introduce them according to the types of the used ML techniques.

1) DL-BASED TRAFFIC PREDICTION SOLUTIONS

In the past 3 years, different types of DL techniques have been applied to traffic prediction. In the following, we introduce these techniques in detail.

a: LSTM-BASED SOLUTIONS

In [71], Trinh *et al.* studied an LSTM-based architecture for BS traffic prediction in mobile networks, as depicted in Fig. 2. In the architecture, a stacked LSTM network consists of multiple layers of basic LSTM units, each of which extracts a fixed number of features. More layers of the LSTM network can better improve the prediction accuracy. In one step of the prediction, the mobile traffic is observed for a fixed number of timeslots until T and then attempts to predict the traffic in the next time slot $T+1$. The output of the LSTM network is passed to a fully connected neural network, which will finish the traffic prediction. Feng *et al.* [70] also introduced an LSTM-based model, namely, the deep traffic predictor (DeepTP), which forecasts BS traffic demands. In comparison to the solution proposed in [71], DeepTP adopts a features extractor module that employs the embedding and attention mechanism. The features extractor module is used to handle the complicated influential factors and comprehensive spatial-temporal correlations of the mobile traffic.

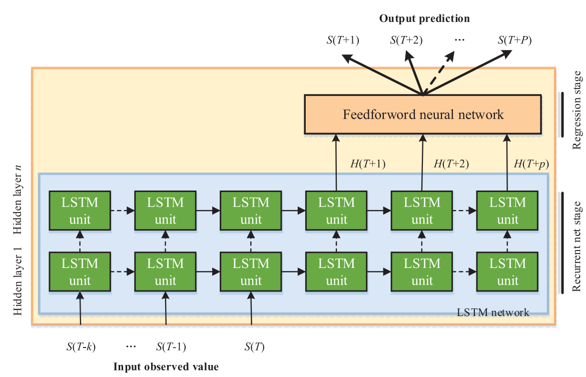

FIGURE 2. The architecture, proposed in [63], for mobile traffic prediction.

In addition to the LSTM-based traffic prediction solutions for mobile networks, there have been several studies that use the LSTM to predict the traffic of wired networks. In [66], the authors evaluated the performance of LSTM architectures for traffic matrix prediction. Note that a traffic matrix reflects the volume of traffic flows between all possible pairs of original and destination nodes. Lazaris and Prasanna [58] also presented an LSTM framework to effectively model the traffic of the backbone network. In comparison to [58], [66] employs several LSTM variations, including vanilla LSTM,

TABLE 3. Summary of recent ML-based traffic predication solutions. R-squared (R2) represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

Ref.	Published in	Network environment	Traffic type	Specific ML techniques	Metrics
DL-based prediction					
[58]	2019	Unspecified	Link traffic	LSTM	MAPE
[59]	2019	5G networks	Traffic of network slice	GRU	Mean utilization efficiency
[60]	2019	Cellular networks	BS traffic	CNN, LSTM	RMSE, MAE, R2
[61]	2019	DCNs	Intra-DCN traffic	Nonlinear autoregressive neural networks	MAE, MSE
[62]	2019	Unspecified	Link traffic	DCRNN	MAPE, MAE, RMSE, convergence epoch, convergence time
[63]	2018	MAN	Port-based traffic	Stack autoencoders	MAE, MRE, RMSE
[64]	2018	Unspecified	Link traffic	RNN	MSE
[65]	2018	Unspecified	Path traffic	Selecting among LSTM, RNN and GRU	MSE
[66]	2018	SDNs	Traffic Matrix	LSTM	MSE
[67]	2018	Optical networks	Provider-centric traffic	Monte Carlo tree search	Blocking percentage
[68]	2018	Mobile networks	Aggregated traffic	DNN	Traffic activity levels
[69]	2018	Backbone networks	Traffic matrix	GRU, RNN	MAE
[70]	2018	Cellular networks	BS traffic	LSTM	NRMSE
[71]	2018	Cellular network	BS traffic	LSTM	NRMSE
[72]	2017	Wireless networks	Not mentioned	DBN	Spatial and temporal relative errors
[73]	2017	Unspecified	Traffic matrix	Select among RNN, LSTM, GRU	MSE
[74]	2017	DCNs	Service-based traffic	CNN, GRU	RMSE
[75]	2017	5G networks	Aggregated traffic	Selecting among RNN, 3D CNN, CNN-RNN	MAE, MAPE, RMSE
[76]	2016	IP backbone networks	Traffic matrix	DBN	Prediction bias and standard deviation
[77]	2016	DCNs	Traffic matrix	DBN	Prediction bias, the standard deviation, error improvement ratio
Supervised learning-based prediction					
[78]	2019	C-RAN	RRH traffic	Gaussian process	RMSE, MAPE
[79]	2018	IP/Optical networks	Link traffic	Gaussian process	MAE
[80]	2018	4G networks	BS traffic	Bayesian network	The coefficient of determination, MAE, RMSE
[81]	2017	4G networks	Download BS traffic	Gaussian process	MAPE
Ensemble learning-based prediction					
[82]	2019	Mobile networks	Aggregate traffic	Bagging, LightGBM	MAPE, the coefficient of determination

delta-based LSTM (i.e. the model that predicts the consecutive flow-size deltas), and cluster-based LSTM.

b: GATED RECURRENT UNIT (GRU)-BASED SOLUTIONS

GRU [83] can enable each recurrent unit in RNN to adaptively capture dependencies on different time scales. In [69], the authors implemented a GRU RNN on real-world data from the Abilene1 network.[1] The authors proposed an evaluation automatic module, which automates the learning process and generalizes the prediction model. Guo *et al.* [59] proposed a GRU-based short-term traffic prediction framework for network slicing. In [62], Andreoletti *et al.* employed the GRU to forecast traffic load on the links of a real backbone network. Unlike [69] and [59], [62] uses a diffusion convolutional gated recurrent unit to capture important topology information of the network instead of directly predicting the traffic. Both [69] and [59] directly make use of the common GRU model. The main difference between [69] and [59] is that they focus on different scenarios.

[1] http://sndlib.zib.de/home.action

c: DBN-BASED SOLUTIONS

In [76], Nie *et al.* proposed a traffic matrix prediction and estimation solution based on DBN, designed for large-scale IP backbone networks. This method first trains the DBN from the achieved traffic matrix. Then, a predictor of network traffic is obtained via the trained DBN. Nie *et al.* took advantage of the contrastive divergence algorithm proposed by Hinton *et al.* [84] to approximately estimate the gradient instead of directly computing it. Nie *et al.* assessed the effectiveness of the proposed prediction and estimation methods by real network traffic datasets from the Abilene and Géant networks. The results show that the solution can more accurately deal with traffic matrix prediction and estimation problems than the PCA method proposed in [85].

Nie *et al.* also considered DBN-based traffic predictions in data center networks (DCNs) and wireless network environments [72], [77].

d: STACKED AUTOENCODER (SAE)-BASED SOLUTION

In [63], Wang *et al.* proposed a DL-based traffic prediction method named SDAPM. SDAPM uses a stacked denoising autoencoder (SDA) model to learn generic traffic features, and it was trained in a layerwise greedy fashion. In the SDAPM model, the first layer is an input layer, the last layer is an output layer to output predicted data, and other layers called hidden layers are SDAs, which are used for feature expression. The hidden layer of SDA is usually a logistic regression model. However, in SDAPM, the traffic prediction problem is actually a nonlinear regression problem.

e: LSTM AND CNN COMBINED SOLUTIONS

In [60], Zhang *et al.* proposed a cellular traffic prediction solution based on a combination of LSTM and CNN. This solution employs three kinds of cross-domain datasets, i.e., BS information, POI distribution and social activity level. The above dataset can fully characterize various factors that affect traffic generation. Based on these datasets, a DNN architecture, STCNet, was proposed to forecast cellular traffic. By combining CNN with LSTM, a two-layer ConvLSTM network is designed to simultaneously model the spatial-temporal dependencies and the sequence information.

f: GRU AND CNN COMBINED SOLUTIONS

In [74], Cao *et al.* constructed a GRU and CNN combined solution called the interactive temporal recurrent convolution network (ITRCN). ITRCN was designed for single-service traffic prediction and interactive network traffic prediction. In ITRCN model, the CNN is used to learn network traffic to capture the correlations between network-wide services, and the GRU learns the temporal features that can improve the interactive network traffic prediction. The interactive traffic matrices can be converted into one-channel images. To implement traffic-image conversion, the raw network traffic is transformed into interactive traffic matrices, each of whose elements represents the traffic value exchanged between certain services. Note that images are generated in terms of the matrices.

g: CASE STUDIES

In [61], the authors presented a solution for forecasting traffic in intra-DCN scenarios using nonlinear autoregressive (NAR) neural networks. Huang *et al.* [75] investigated mobile Internet traffic prediction based on different deep learning solutions, including RNN, three-dimensional CNN, and a combination of CNN and RNN. In [68], the authors investigated traffic prediction in telecom systems using DL. [67] focused on applying DL techniques for traffic prediction in elastic optical networks. In [65], Ramakrishnan and Soni employed several RNN architectures (the standard RNN, LSTM networks, and GRU) to solve the traffic prediction problem. Other similar case studies that investigate the application of existing solutions include [64], [73].

h: ANALYSIS

DL-based
traffic prediction solutions have the following advantages. First, they can handle high-dimensional traffic dataset. Second, they usually can obtain high accuracy for the long-term prediction. Third, the traffic prediction can be quickly executed once the prediction model is trained by these solutions. The main disadvantages of DL-based traffic prediction solutions include the high computation load and complex parameter configuration. For the short-term prediction, RNN (e.g., LSTM and GRU) work well because they can well capture the features on different time scales.

2) SUPERVISED NON-DL LEARNING BASED PREDICTION SOLUTIONS

In [78], Xu *et al.* proposed a C-RAN traffic prediction architecture, as shown in Fig. 3. The architecture inherits the two-layer structure, i.e., the remote radio heads (RRHs) deployed at remote sites, and the building baseband unit (BBUs) clustered centrally as the BBU pool. The RRHs monitor local traffic data and deliver them to the BBU pool that predicts traffic. To support large-scale and real-time executions, each BBU performs the traffic prediction model. Based on the above architecture, the authors proposed a scalable framework based on the distributed Gaussian process with significant innovations in both the training phase and the prediction phase. Xu *et al.* [81] proposed a prediction model over real 4G traffic data. In [81], a structured Gaussian process model was proposed to leverage the Toeplitz structure of covariance functions to significantly reduce the complexity of both hyperparameter learning and inference.

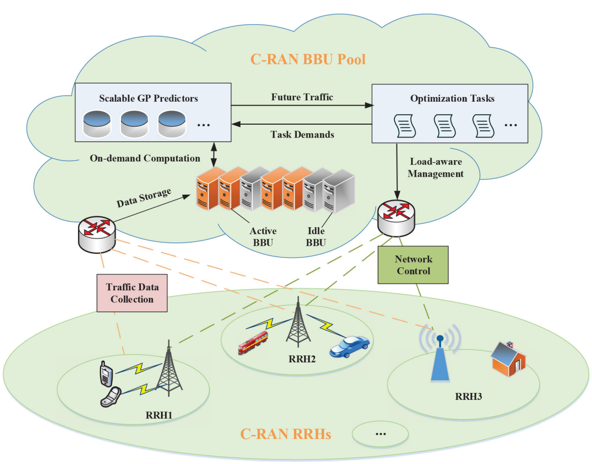

FIGURE 3. An architecture for wireless traffic prediction based on C-RANs [78].

Choudhury *et al.* [79] described two Gaussian process based applications for managing IP and optical networks. The first application allows significant cost saving based on the combination between long-term traffic prediction and global optimization of IP/optical layers. The second application enables the selection of improved reconfigurable optical add-drop multiplexers (ROADMs) [86] paths based on the latest optical performance data. Unlike [78] and [79], [81] uses the common Gaussian process model.

In [80], the authors introduced a comprehensive architecture for collecting and analyzing massive network data. This architecture uses the Bayesian network to study the relationship between the PKI (key performance indicators) and the traffic patterns. Based on this relationship, traffic can be forecasted by time series traffic forecasting or ML algorithms such as autoregressive and Gaussian processes. In [80], an application was proposed to avoid traffic congestion based on traffic forecasting.

a: ANALYSIS

The supervised non-DL learning based prediction solutions mentioned above have the following advantages. On one hand, they can be implemented easily because the Gaussian process and Bayesian network models are relatively simple to understand and produce relatively low computation load. On the other hand, they can work based on a small dataset. Despite the above advantages, these solutions cannot effectively handle high-dimensional dataset, and are hard to obtain high accuracy under the complex traffic environment.

3) ENSEMBLE LEARNING BASED PREDICTION

In [82], Xia *et al.* proposed a mobile network traffic prediction solution that uses random forest to filter redundant features and uses LightGBM [87] to train the prediction model. LightGBM is an implementation of the gradient boosting decision tree (GBDT) [88] with gradient-based one-side sampling (GOSS) and exclusive feature bundling. The framework proposed in [82] uses multiple LightGBM models as the base-learners, which are further integrated by bagging. Xia *et al.* evaluated the proposed solution with a real-life traffic dataset. The experimental results showed that the proposed model can effectively improve the prediction performance compared to single LightGBM given the same number of decision trees and some other popular algorithms, including multilayer perceptron (MLP) and linear regression.

a: ANALYSIS

The most important advantage of ensemble learning based prediction is that it can offer a prediction model for an objective environment without enough data generated in this environment. However, it is difficult to ensure the prediction accuracy of the ensemble learning based prediction solutions because of the lack of the training data generated in the objective environment.

4) DISCUSSION ON ML IN TRAFFIC PREDICTION

This section reviews ML applications for traffic prediction in the last 3 years. From our survey, we observe that DL-based prediction is the most popular solution. Other ML techniques applied to traffic prediction include supervised learning and ensemble learning. Several RNN techniques (e.g., LSTM and RNN) have a good capability of predicting short-term traffic, which is important for the current Internet because of the rapidly changing traffic pattern caused by the popularity of user-generated content sharing. RL can also adapt well to the network environment. However, to our surprise, we have not found RL-based traffic prediction solutions. One possible reason is that it is difficult for the reward function used in RL to provide an effective evaluation of the current state according to the realistic network.

Almost all the existing studies have shown that ML techniques are capable of improving traffic prediction accuracy. For example, in [58], the authors showed that their LSTM-based solution can achieve an average MAPE less than 30% even in the worst situation. Oliveira *et al.* [89] showed that MLP and RNN are better than SAE for traffic prediction; Nikravesh *et al.* [90] showed that SVM outperforms MLP and multilayer perceptron with weight delay (MLPWD) in predicting the multidimensionality of real-life network traffic data, while MLPWD has better accuracy in predicting unidimensional data. Although ML has successfully made some achievements in traffic prediction, the accuracy still needs to be further improved. To do this, more realistic traffic data for training are needed. In addition, RL, with the assistance of some carefully deployed devices that make feedback on real-time traffic static, is also worthy of consideration because of its adaptability.

C. ML IN AVAILABLE BANDWIDTH MEASUREMENT

End-to-end available bandwidth is important in many application domains, including congestion control [91]. Below, we introduce the studies on available bandwidth estimation using ML techniques.

1) SVM-BASED SOLUTIONS

In [92], Chen *et al.* proposed an SVM-based approach for estimating the available bandwidth of a path. This solution uses two probing models, i.e., the packet train model and the pathChirp-like model. In the packet train model, the sender sends 11 packets in one burst in each round, whereas in the pathChirp-like model, the sender sends a chirp of 15 packets such that the lowest sending rate is 5% of the bottleneck capacity. Chen *et al.* show that their solution obtains more accurate results than two widely used tools, pathChirp and Spruce. The solution proposed in [92] can work well on both linearly and non-linearly dataset. However, it sometimes fail to obtain high accuracy because SVM cannot handle the noisy dataset well due to overfitting problems [5].

2) RL-BASED SOLUTIONS

In [93], Khangura and Akın proposed a method to apply RL to available bandwidth estimation. This method defines a reward metric as a function of input and output rates, which reaches the maximum in the case where the input rate is equal to the available bandwidth. It runs the ε-greedy algorithm to find the available bandwidth by maximizing the designated reward function without a training phase. Khangura and Akın claimed that even though the additional links affect the convergence speed, the RL-based method results in accurate available bandwidth estimations with low variability. Malboubi *et al.* [94] studied a RL-based bandwidth measurement framework for SDNs. Unlike [93], [94] aims at inferring the traffic matrix. Note that the available bandwidth can be deduced according to the traffic matrix if the capacity of a link or path is known. [94] introduces an efficient algorithm to adaptively track and measure the most rewarding flows while achieving logarithmic regret over time, which is different from the work [93]. The RL-based available bandwidth measurement solutions can well adapt to the network dynamics and need no dataset prepared in advance. However, they usually spend some time to train a steady model.

3) DL-BASED SOLUTIONS

In [95], Maier *et al.* investigated two different approaches to reduce the consumed data volume in tests that determine the available download and upload data rate of an Internet connection. The first approach is simply a general shortening of the test duration. The second approach is a test with a dynamic test duration determined through a trained artificial neural network. In [96], the authors proposed a channel estimation approach, called ChanEstNet, to solve the problem that the downlink channel estimation performance is limited due to the fast time-varying and nonstationary characteristics in the high-speed mobile scenarios. ChanEstNet uses CNN to extract channel response feature vectors and RNN for channel estimation. We can note that the works [95] and [96] aim at solving the different problems. The DL-based available bandwidth measurement solutions can obtain high measurement accuracy. However, the computation load is a major concern because the available bandwidth measurement is usually performed by end hosts.

4) CASE STUDIES

In [97], Yin and Kaur designed a learning framework for available bandwidth measurement, in which the sender- and receiver-side interpacket gaps are used as input features, and an available bandwidth estimate is the output. The authors considered ElasticNet [98], RandomForest [99], AdaBoost [100], GradientBoost [101], and SVM. The authors applied ML techniques to estimate bandwidth in ultra-high-speed networks and evaluated our approach in a 10 Gbps testbed. The results showed that supervised learning helps to improve estimation accuracy for both single-rate and multirate probing frameworks. Sato *et al.* [102] proposed PathML, an ML-based available bandwidth estimation method. PathML considers using existing ML algorithms instead of proposing new algorithm.

5) DISCUSSION ON ML IN AVAILABLE BANDWIDTH MEASUREMENT

This section reviews ML applications for the available bandwidth measurement. We observe that ML-based available bandwidth measurements have not been widely studied compared to ML-based traffic classification and prediction. In the available bandwidth measurement, the measurement accuracy can be observed according to the packet arrival feature. As a result, RL is a feasible approach for measuring the available bandwidth. Supervised learning and DL-based solutions are also feasible because the training data can be easily obtained. A good available bandwidth measurement should obtain accurate results with a low test load. The above requirement should be fully considered in the ML applications for available bandwidth measurements. In the solutions proposed in [92] and [95], only a small number of probing packets are used to obtain acceptable accuracy; therefore, they are the desired approach. The further research direction in ML-based available bandwidth measurement is to obtain a better tradeoff between accuracy and load.

D. TOPOLOGY DISCOVERY

1) ML-BASED TOPOLOGY DISCOVERY SOLUTIONS

In [62], Andreoletti *et al.* employed the DCRNN to forecast traffic load on the links of a real backbone network. In contrast to legacy ML approaches, to the best of our knowledge, this is the first time that an ML algorithm is applied to capture the topological relations of the links of telecom networks. In the solution proposed in [62], the network traffic is represented as a directed graph $\mathcal{G}$ that can be described by the matrix $X(t) \in \mathbb{R}M_{\geq 0}^{X1}$ (which encodes the attributes of the M nodes, i.e., the load for each link of the telecommunication network) and by its adjacency matrix W, where $w_{ij} = 1$ iff l_i and l_j are connected, and 0 otherwise, which encodes the relation between the nodes. The forecasting problem is formulated as follows:

$$X^{(t+1)} = \mathcal{F}(W, X^{(t-T)}, \ldots, X(t)), \tag{1}$$

where $\mathcal{F}$ is the estimator learning-based DCGRU. The topology discovery solution proposed in [62] can work well in the case where the network nodes are known. However, the network node information is difficult to obtain in some cases.

In [103], the authors introduce a data-driven DL framework, Gumbel Graph Network (GGN), to accomplish the reconstruction of both network connections and the dynamics on it. The model consists of two jointly trained parts: a Graph Neural Network (GNN) based network generator that generates a discrete network with the Gumbel Softmax technique; a dynamics learner that utilizes the generated network and one-step trajectory value to predict the states in future steps. The solution proposed in [103] is designed to reconstruct the topology of a general network model in terms of the time series data of node states. Because it is difficult to observe node states of Internet, the solution proposed in [103] is not applicable to the network topology discovery considered in this paper.

In [104], the authors proposed a network model based on GNN. The proposed model can understand the complex relationship among network topology, routing and input traffic, thereby producing accurate estimates of the per-source/destination per-packet delay distribution and loss. The main objective of the work [104] is to reveal the relationship among network topology, routing and input traffic, which is different from the topology discovery concerned in this paper. There exist some literatures that model the dynamic network topology using dynamic graph neural networks [105]. However, these literatures focus on the dynamic features of a network such as social network, which is also different from the topology discovery concerned in this paper.

2) DISCUSSION ON ML IN TOPOLOGY DISCOVERY

This section reviews ML applications for network topology discovery. As introduced in section II-B, topology discovery is very important for the optimized utilization of network resources and has been widely studied for a long time. However, we have only found few studies that considered ML techniques in discovering topological relations. Since topology discovery is still an open issue, we believe that ML techniques can bring new power to discover topological features. To explore the relations between the test flow behaviors and underlying topology, some labeling data will be very useful. The labeling data of the topology can be obtained based on techniques such as TraceRoute, which can explicitly discover a part of the network topology. With labeled data, supervised learning or supervised DL is a desirable approach for ML-based topology discovery. Because an operation of topology discovery usually lasts for a short time, RL is not a good choice.

IV. ML IN SPECIFIC BICC&A SOLUTIONS

In this section, we summarize how ML techniques are applied in specific BICC&A solutions.

A. ML IN RATE CONTROL

In the field of rate control, ML has been applied in TCP and its variants, MPTCP and some other scenarios, as Table 4 shows. We introduce the above applications in this section. In addition, we introduce ML-based congestion detection solutions, which can be used for rate control.

1) ML IN TCP AND ITS VARIANTS

ML techniques have been widely applied to TCP and its variants. Below, we introduce the applications in detail.

a: UNSUPERVISED NON-DL LEARNING BASED SOLUTIONS

TCP Remy [116] is an ML-based congestion control approach. The objective of TCP Remy is to achieve high throughput and low queuing delay. The objective function with a parameter α can be used to set the aggressiveness of the protocol. For example, this parameter is set to 0 if the fairness on shared links is not considered and is set to ∞ if the fairness is maximized. TCP Remy uses state-to-action mapping to define the behavior of the congestion control mechanism. A more advanced version of Remy called a tractable attempt at optimal (TAO) [129], solves the problem of TCP awareness and performs well with heterogeneous competing flows but still requires extensive prior knowledge about the network to function [13].

b: RL-BASED SOLUTIONS

In [113], Li *et al.* proposed a Q-learning framework to improve TCP called QTCP. QTCP can automatically identify the optimal *cwnd* varying strategy, given the observation of the surrounding networking environment online. QTCP continuously updates the values of possible state-action pairs, and uses the Q-learning algorithm to search for the best action that adjust the *cwnd* in designated states so that the long-term reward of the sender is maximized. Note that the parameter *cwnd* denotes the size of the congestion window, which can adjust the rate. QTCP uses a function approximation, based on Kanerva coding [130] to solve the challenge of training the higher performance policy given the extremely large state space. QTCP elaborates on the effectiveness of a learning-based approach for TCP, but it is inaccurate for representing the network by a finite number of states and will cause performance degradation [120].

In [106], Nie *et al.* proposed a system called TCP-RL to dynamically configure a suitable initial window for short flows through group-based RL and to dynamically configure a suitable congestion control scheme for each long flow through DRL. TCP-RL is incrementally deployable at the server side without any client or router support, as shown in Fig. 4. The RL method used in TCP-RL is the discounted UCB algorithm [131], which was proposed to solve the nonstationary bandit problem. In [115], Kong *et al.* introduced two learning-based TCP congestion control schemes for wired networks with under-buffered bottleneck links, a loss predictor (LP)-based TCP CC (LP-TCP), and an RL-based TCP CC (RL-TCP). The experimental results in [115] show that LP-TCP and RL-TCP both achieve a better tradeoff between throughput and delay under various simulated network scenarios than the existing NewReno and Q-learning-based TCP [132]. Note that Q-learning-based TCP in [132] is designed for the IoT environment, and we do not discuss it.

c: DL-BASED SOLUTIONS

In [112], Kawakami *et al.* proposed an LSTM-based TCP throughput prediction method, TRUST, for mobile networks. TRUST has two stages: user movement pattern identification and throughput prediction. In the prediction stage, the LSTM model is employed for TCP throughput prediction. TRUST takes all the communication quality factors, sensor data and scenario information into consideration. Specially, it collects the throughput, received signal strength indicator (RSSI), cell ID, time, location, and other sensor data. In addition to [107], [112] presents a TCP for transmitting high-quality videos at low latency in disaster 5G mmWave networks.

TABLE 4. Summary of ML-based rate control solutions. In this table, extra assistance means that the rate control needs extra device support. Note that the differentiation between server and controller is that the former only provide some information but the latter can directly intervene the data transfer.

Ref.	Published in	Network environment	ML techniques	Main objectives	Extra assistance
			TCP and its variants		
[106]	2019	Unspecified	DRL	Improved initial window for short flows and control scheme for each long flow	Server-assisted
[107]	2019	5G networks	DNN	Deal with the blockage problem	-
[109]	2019	Unspecified	LSTM, Q-learning	Congestion detection and avoidance	Router-assisted
[110]	2019	Unspecified	LSTM, Q-learning	Control window congestion	-
[111]	2019	Mobile networks	LSTM, DCNN, DRL	Control window congestion	-
[112]	2018	Mobile networks	LSTM	Predict throughput with higher accuracy	Controller-assisted
[113]	2018	Unspecified	Q-learning	Learn optimal congestion control policy for different network scenarios	-
[114]	2018	Unspecified	Random forest	Identify transfer states of TCP clients	Intermediate-node assisted
[115]	2018	Unspecified	RL	Increased utility function in congestion control	-
[116]	2013	Unspecified	State-to-action mapping	High throughput, low queuing delay	-
			MPTCP		
[117]	2019	Unspecified	DRL, LSTM	Maximize the overall utility of all active MPTCP flows	-
[118]	2019	Heterogeneous networks	Q-Learning	Deal with diversities of multiple communication paths	-
[119]	2019	Heterogeneous networks	Deep Q network	Enhance the data scheduling to improve the throughput	-
			Other application		
[120]	2019	NDN	DRL	Congestion control according to user requirements and network conditions	Controller-assisted
[121]	2019	Unspecified	DRL	Congestion control according to user requirements and network conditions	-
[122]	2019	Unspecified	DRL	Maintain an optimum congestion window	-
[123]	2018	Unspecified	Gradient-ascent based online learning	Improved performance, convergence speed, friendliness, etc.	-
[124]	2018	NDNs	DBN	Adaptive congestion control	Router-assisted
[125]	2018	DTNss	Q-learning	Congestion detection and avoidance	-
[126]	2017	Unspecified	DL, RL	Selects bitrates for future video chunks	-
[127]	2005	ATM networks	RL	Adaptive congestion control	-
[128]	2008	Optical burst switching networks	HMM, expectation maximization	Differentiate between the congestion and contention losses	-

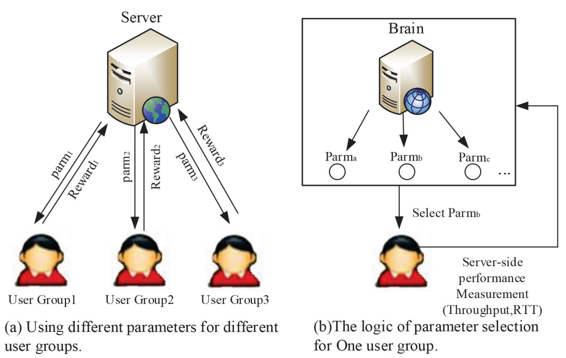

FIGURE 4. The framework of TCP-RL [106].

The proposed solution uses a learner engine for learning, a predictor, a mobility manager for managing velocity and location information, and a TCP agent for determining TCP behavior. [107] presents a multiclass deep-neural-network architecture, using the Xavier initializer [108], to predict the TCP throughput.

d: DL AND RL COMBINED SOLUTIONS

There are several studies on TCP congestion control solutions based on the combination of LSTM and RL. In [111], the authors presented a congestion control solution, namely, TCP-Drinc. TCP-Drinc uses a DRL-based agent that is executed at the sender side. The agent stores historical data in an experience buffer, and estimates features such as congestion window difference, RTT, and the interarrival time of ACKs. Then, it uses a deep CNN (DCNN) concatenated with an LSTM network to learn from historical data and select the next action to adjust the size of congestion window. In [109], Gomez *et al.* proposed exploiting explicit congestion notification (ECN) information to improve active queue management algorithms by applying LSTM to predict congestion and setting the AQM parameter on Q-learning. Note that AQM is a paradigm that aims to mitigate the congestion on the network layer through active buffer control to avoid overflow. Afonin *et al.* [110] studied the development of an adaptive TCP algorithm by integrating ML techniques such as RL, Q-learning and LSTM.

e: ENSEMBLE LEARNING BASED SOLUTION

In [114], Hagos *et al.* introduced how an intermediate node (e.g., a network operator) can identify the transmission state of the TCP client, which is associated with a TCP flow by passively monitoring the TCP traffic. The authors created an ensemble machine learning prediction model based on a random forest regressor algorithm to estimate the *cwnd* parameter. The experimental results indicate the effectiveness of the prediction model in [114].

f: ANALYSIS

We observe that the DL and RL are two widely-used learning methods for TCP and its variants. DL is mainly used to detect the congestion, while RL is mainly used to offer intelligent congestion control. The congestion control can be implemented based on the assistance of some extra entities, as Table 4 summarizes. Overall, the performance of the congestion detection and control can be obviously improved by the assistance of extra entities.

2) ML IN MPTCP

ML techniques have been applied to MPTCP. These ML techniques mainly include RL and LSTM.

In [117], Xu *et al.* introduced a DRL-based control framework, DRL-CC, for MPTCP congestion control. DRL-CC utilizes a single agent to dynamically and jointly perform congestion control for all active MPTCP flows on an end host, aiming at maximizing the overall utility. It utilizes LSTM to learn a representation for all active flows and deal with their dynamics. Moreover, DRL-CC integrates the above LSTM-based representation network into an actor-critic framework for congestion control, which leverages the deterministic policy gradient to train critic, actor, and LSTM networks in an end-to-end manner.

In [118], Li *et al.* proposed a learning-based multipath congestion control approach, namely SmartCC, to address the diversities of multiple communication paths in heterogeneous wireless networks. SmartCC adopts an asynchronous RL framework to learn congestion control rules, by which the sender observes the environment and takes actions to adjust the subflows' congestion windows. SmartCC uses a function estimation approach for Q-learning, which addresses the problem of infinite states in high-dimensional space.

In [119], the authors proposed a data scheduling algorithm based on the deep Q-network (DQN) framework to enhance the MPTCP data scheduling performance in the asymmetric path. The algorithm obtains the information of every path and adaptively chooses the most suitable path by artificial intelligence. Compared with common Q-learning, DQN can obtain better performance.

a: ANALYSIS

Compared with TCP, MPTCP is more complicated because it schedules the data transmission over multiple paths. For the above reason, the intelligent rate arrangement is more important in MPTCP. Unfortunately, there have been few studies on the ML-based MPTCP.

3) ML IN OTHER RATE CONTROL SCENARIOS

In addition to the rate control scenarios mentioned above, ML techniques have also been applied to other rate control scenarios. Below, we introduce them in detail.

a: RL-BASED SOLUTIONS

In [125], Aloizio presented a Q-learning-based congestion control framework, called Smart-DTN-CC, for delay and disruption tolerant networks (DTNs). Smart-DTN-CC nodes obtain input from the environment (e.g., its buffer occupancy and set of neighbors), and then choose an action to take from a set of possible actions. In, Smart-DTN-CC, a reward is given a reward in terms of an action's effectiveness in controlling congestion. The goal of Smart-DTN-CC is to maximize the overall reward, which translates to minimizing congestion. [127] is an early study that employed an RL scheme on congestion control in ATM networks. The scheme consisted of two subsystems: an expectation-return predictor, which is a long-term policy evaluator, and a short-term rate selector, which is composed of an action-value evaluator and stochastic action selector elements. Unlike [125], [127] controls source flow in consideration of high throughput and low cell loss rate.

In addition to the above RL-based solutions, there have been some DRL-based rate control solutions. Lan *et al.* [120] studied a DRL-based congestion control, named DRL-CCP, for named data networking (NDN) [133]. In DRL-CCP, the training of neural networks is separated from real-time data transmission. The workflow of DRL-CCP can be described as follows: designing the integrated congestion control objective of the consumer in terms of user requirements; determining the specific DRL training model, variables and parameters; and pretraining the neural network of the DRL model. In [121], Jay *et al.* formulated a framework for DRL-based congestion control protocol design, which extends the performance-oriented congestion control (PCC) approach [134]. In [122], Bachl *et al.* proposed reactive adaptive eXperience-based congestion control (Rax), a method of congestion control that uses online RL to maintain an optimum congestion window with respect to a given reward function and is based on current network conditions. The above DRL-based solutions aim at implementing different optimization objectives in terms of the specific requirements. [120] and [121] employ the general DRL model; however, [122] uses a new variant of DRL called partial action learning (PAL). An obvious advantage of PAL is that it supports delayed and partial rewards.

b: DL-BASED SOLUTIONS

In [124], Liu *et al.* proposed an adaptive congestion control protocol (ACCP) for NDN. ACCP is divided into two phases to control network congestion before affecting network performance. The objective of the first phase is to use the time series prediction model based on DBN to forecast the source of congestion for each node. In the second phase, the level of network congestion is estimated by the average queue length in terms of the outcomes of the first phase. The second phase returns the congestion level back to the receiver, and then the receiver adjusts the sending rate of interest packets to realize congestion control. Lan *et al.* noted that it is unrealistic for each router to use DL because of cost and computational capabilities [120].

c: DL AND RL COMBINED SOLUTIONS

In [126], Mao *et al.* proposed a system (namely Pensieve) that generates adaptive bitrate (ABR) algorithms using RL and DL. Pensieve trains a neural network model to determine bitrates for future video chunks based on observations (including the client playback buffer occupancy, several raw network signals and past bitrate decisions) collected by clients. Pensieve does not rely on preprogrammed models or assumptions about the environment. Instead, it learns to make ABR decisions solely according to the observations of the resulting performance of past decisions.

d: OTHER SOLUTIONS

In [123], Dong *et al.* proposed a congestion control architecture named Vivace. This solution adopts the high-level architecture of PCC, including a utility function framework and a learning rate control algorithm. However, it realizes both components differently. First, Vivace relies on a new, learning-theory informed framework for utility derivation that incorporates crucial considerations such as latency minimization and TCP friendliness. Second, Vivace employs provably (asymptotically) optimal online optimization based on gradient ascent to achieve high utilization of network capacity, swift reaction to changes, and fast and stable convergence.

In [128], Jayaraj *et al.* proposed an ML-based loss classification technique for optical burst switching networks. This technique differentiates between congestion and contention losses, which is derived from the observed losses. It uses both HMM and an unsupervised learning technique expectation-maximization clustering on the observed losses and classifies them into a set of states. Jayaraj *et al.* modified the congestion control mechanism of TCP suitably to arrive at two variants of TCP, HMM-TCP and EM-TCP. Simulation results demonstrated the effectiveness and accuracy of the loss classification technique in different network scenarios.

e: ANALYSIS

We can observe that many proposals have been proposed to control the transmission rates in terms of specific requirements. Because the dynamics of network conditions, the selection of ML algorithms should fully consider the dynamics adaptability. As a result, RL and RNN are desirable learning methods to control the rates.

4) DISCUSSION ON ML IN RATE CONTROL

This section reviews ML applications for rate control. Most of the existing ML-based rate control solutions were proposed in the last 3 years. We observe that the two most commonly used ML techniques in existing studies are DL (especially LSTM) and RL (especially DRL and Q-learning). The above situation occurs mainly because LSTM and RL can adapt well to the dynamics of network conditions. Supervised learning and semi-supervised learning have not been applied to rate control, which is easy to understand because data labeling makes less sense in rate control. We can notice that several existing solutions control the rate with the assistance of extra devices. This can improve the rate control performance to some extent, but it needs to further consider the deployment problem.

Although there have been many research efforts on ML-based rate control, ML techniques have not been well applied to two important fields in rate control, i.e., video streaming rate control and multicast rate control. As mentioned previously, video streaming traffic accounts for approximately 75 percent of total Internet traffic [20]. Multicasting is one of the basic communication methods and has wide applications, such as video on demand and video conferences. Compared with unicast, multicast is more complicated because it delivers data to many receivers simultaneously, which indicates that intelligence may play a more important role. For the above reasons, ML-based rate controls for video streaming and multicasting are noteworthy research directions.

B. ML IN CONGESTION-AVOIDANCE ROUTING

In this section, we introduce the ML techniques applied to congestion-avoidance routing. Table 5 presents a summary of ML-based congestion-avoidance routing solutions. Below, we introduce them in terms of the communication types (i.e., unicast and multicast).

1) UNICAST ROUTING

In the following, we introduce ML-based congestion-avoidance unicast routing solutions.

a: RL-BASED SOLUTIONS

In [137], Lin *et al.* proposed a QoS-aware adaptive routing (QAR) solution for SDNs. This solution assumes that the distributed hierarchical control plane architecture is employed in SDNs. The QAR algorithm is based on RL. The agent finds the routing path with the maximum QoS-aware reward. The QoS-aware reward function considers the available bandwidth in the next node. As a result, it can help build a congestion-avoidance path. In [143], Marbach *et al.* proposed RL-based call admission control and routing in integrated service networks. This solution calls admission control and routing on a list of paths (with limited bandwidth) fixed offline to optimize revenue.

In [144], Choi *et al.* proposed a congestion-avoidance routing protocol PQ-R. PQ-R retains the best Q-values and reuses them by predicting the traffic trend. In PQ-R, routes should not be selected for packet transfer for a period of time to enable them to recover from congestion when they are considered congested. These routes are called regulated routes. To check regulated route conditions and refresh delay estimate values, PQ-R probes them at a given frequency (i.e., regulated routes are occasionally selected for packet transmission).

In addition to PQ-R, there are several congestion-avoidance unicast routing solutions based on Q-learning. In [136], Al-Jawad *et al.* proposed an intelligent QoS management framework for multimedia-based SDNs, LearnQoS. LearnQoS employs policy-based network management (PBNM) to ensure the compliance of QoS requirements and optimizes the operation of PBNM through Q-learning. In [135], Murudkar *et al.* presented a user-centric approach to find the shortest path with optimal capacity for a given source and destination. The Q-learning algorithm proposed in [135] determines the shortest path, avoiding congested network nodes to achieve the required throughput and/or bit rate. In [140], the authors introduced a Q-learning-based unicast routing protocol, RLDRS, for optical networks. RLDRS attempts to avoid congestion paths. However, different from the above solutions, it makes decisions based on the switch buffer.

b: RANDOM RACE BASED SOLUTIONS

The solutions in [141] and [142] are based on a practical model named random race [139]. Random race was inspired by the theory of learning automata, in which a learning machine (automaton) is offered a set of actions. The automaton chooses only one of the offered actions at a time. The action it chooses is based on the action probability vector. The environment, which knows the "best action", either rewards the automaton or penalizes it with a certain penalty probability.

In [141], Oommen *et al.* proposed an adaptive online traffic engineering algorithm, namely RRATE, based on the random race model. RRATE generates superior solutions for the computation of the congestion-avoidance paths in MPLS-based networks. Oommen *et al.* further improved RRATE in [142]. The modified RRATE is run on a network having a certain number of nodes and links connecting certain pairs of nodes. A set of incoming bandwidth routing requests are run through the network. Then, it attempts to efficiently route the requests based on the random race model.

c: ANALYSIS

We can observe that RL, especially Q-learning, is the most commonly used technique in congestion-avoidance unicast routing. The main reason is that it can well avoid the congestion in terms of the dynamic traffic environment.

2) MULTICAST ROUTING

In the following, we introduce ML techniques applied to congestion-avoidance multicast routing.

In [146], the authors proposed a multicast routing protocol, Q-LMRWA, for optical networks with blocked light path optimization. Connections between sources and destinations use light paths allocated to them to send their data packets. Whenever some connections share the same optical link, they cannot simultaneously use the same wavelength. As a result, a connection is blocked if there are no available wavelengths. One performance metric of interest in WDM networks is "blocking probability", which is defined as the number of blocked connections divided by the total number of active connections. Q-LMRWA uses RL to find a multicast route that optimizes the number of required wavelengths while minimizing blocking probability.

In [145], Chao *et al.* proposed a self-learning multicast routing algorithm for a multirate WiFi mesh network to achieve higher time slot efficiency and guarantee the QoS. Fig. 5 shows the framework of the self-learning solution. To meet the QoS requirements, a self-predicted routing information mechanism is used. This mechanism calculates the delay and bandwidth of the multicast routing tree. A real-time automatic monitor was introduced to monitor the performance of the multicast routing tree, and the monitor can trigger the routing reconfigure ahead of schedule.

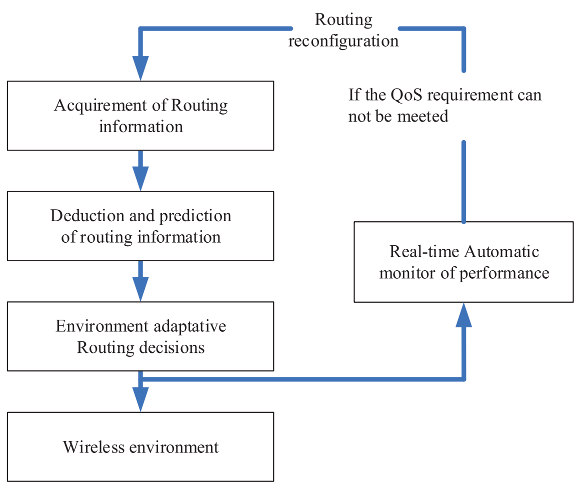

FIGURE 5. Relationships of routing components in [145].

3) DISCUSSION ON ML IN CONGESTION-AVOIDANCE ROUTING

This section reviews ML applications for congestion-avoidance routing. From Table 5, we observe that existing solutions usually adopt RL techniques, especially Q-learning, because RL techniques have high environment adaptability and relatively low computation load. In addition, we also observe that congestion-avoidance routing, especially multicast routing, has not been widely studied. To adapt to the dynamics of the network traffic, congestion-avoidance routing needs to frequently compute the routes according to current network conditions, which create a heavy load on routers or controllers. Arranging routes based on traffic

TABLE 5. Summary of congestion-avoidance routing solutions.

Ref.	Published in	Network environment	Type	ML techniques	Other metrics	Dynamics adaptability
[135]	2019	5G networks	Unicast	Q-learning	distance	Fair
[136]	2018	SDNs	Unicast	Q-learning	QoS parameters	Depending on the policy
[137]	2016	SDNs	Unicast	RL	Optional	Fair
[138]	2011	MPLS	Unicast	Random-Races [139]	No	High
[140]	2008	Optical networks	Unicast	Q-learning	Delay	Fair
[141] [142]	2006 2007	MPLS	Unicast	Random-Races	No	High
[143]	1998	Unspecified	Unicast	RL	No	Low
[144]	1996	Unspecified	Unicast	Q-learning	No	High
[145]	2009	WiFi networks	Multicast	A Self-learning	Delay	High
[146]	2003	Optical networks	Multicast	Q-learning	No	Fair

prediction is a feasible approach for solving the above problem. However, it has not been studied according to our survey. As a result, ML-based congestion-avoidance routing, based on traffic prediction, is a future research direction.

C. BANDWIDTH RESERVATION

1) ML-BASED BANDWIDTH RESERVATION SOLUTIONS

To date, there have been almost no studies that discuss learning-based bandwidth reservation. [147] is the unique related literature that we have found. In [147], Panayiotou *et al.* studied the problem of bandwidth allocation (i.e., bandwidth reservation) on flexible optical networks in the case where traffic demand is uncertain. They assume that the daily traffic demand is given in the form of distributions that describe the traffic demand fluctuations within given time intervals. The objective of the work [147] is to find a predictive BA model that infers from these distributions the bandwidth that best fits the future traffic demand fluctuations. The problem is formulated as a partially observable Markov decision process and is solved based on dynamic programming.

2) DISCUSSION ON ML IN BANDWIDTH RESERVATION

This section reviews ML applications for bandwidth reservation. The main reason for the lack of ML-based bandwidth reservation solutions is that the bandwidth reservation mechanism has not been widely applied on the Internet. In recent years, we have witnessed the rapid development of SDN. By limiting the sending rate of ports, the SDN can support the bandwidth reservation, which can effectively improve the aforementioned application problem of the bandwidth reservation. Intelligence in a simple bandwidth reservation solution is unnecessary. However, to better utilize network resources, it is necessary to make an intelligent bandwidth reservation decision according to the features of network traffic. In the above scenario, ML techniques can play a significant role.

V. FUTURE RESEARCH OPPORTUNITIES

Different approaches reviewed in this survey show that ML have achieved many interesting results in the BICC&A. However, ML applications for the BICC&A should be further studied in several important network environments. In the following parts, we will introduce these research opportunities.

A. ML FOR CENTRALIZED BICC&A IN SDN

As mentioned previously, legacy networks adopt distributed architecture, in which nodes act based on very limited knowledge of the whole network. Learning from nodes that can only view and act over a small portion of the system is very complex, particularly if the end goal is to exercise control beyond the local domain [148]. In recent years, we have witnessed the rapid development of SDN. Compared with legacy networks, SDNs have a better capability for solving the learning problem mentioned above mainly for the following reasons. First, the controller in SDN has a global view of the network topology and resources. Second, it is easier to monitor the dynamic use situation of network resources by inquiring statistical data on packets, ports and flows. Third, the controller can manage network resources in a centralized manner and conveniently install new routes on demand.

Because of the above advantages, ML-based SDN techniques have attracted wide attention in recent years. However, ML techniques for the BICC&A is only in its infancy stage, and there has been much intelligence to develop to optimize BICC&A from a global perspective. The fields where intelligence can be developed include path planning, rate orchestration and bandwidth reservation orchestration. For static path planning and bandwidth reservation orchestration, DL-based solutions are promising because the controller can collect and save mass data. For dynamic path planning and rate control, RL and RNN are desirable choices because of their high adaptability of dynamic network conditions.

In addition to specific BICC&A solutions, the ML-based traffic prediction in the SDN can be further improved by combining the convenient traffic monitoring capability of the SDN. Note that real-time traffic monitoring creates a heavy load on the controller. Existing ML-based prediction models for network traffic have only been developed for large aggregation time windows ($>$ 15 minutes in most cases) due to the very volatile nature of network traffic on smaller time scales [58]. The traffic prediction results can be used to determine a low-loaded sampling of traffic monitoring. Thus, the advantages of traffic prediction and monitoring can be fully used. In addition, the ML-based traffic prediction can benefit from traffic monitoring results because of more useful information.

B. ML FOR BICC&A IN OVERLAY NETWORKS

With the development of Internet applications, legacy networks have exposed an increasing number of problems. Network overlays operate on top of the legacy network, which means that it accomplishes new functions without modification of the legacy network. Because of the above flexibility, network overlays have been widely studied for a long time [149]–[151]. As noted in [151], overlay networks have been proposed to actively optimize traffic over alternative paths to avoid congested links. Because it requires a long time to finish the evolution from a legacy network to a new network, it is valued to study the BICC&A over network overlays based on ML techniques. The ML applications for the BICC&A over network overlays include topology discovery, available end-to-end bandwidth measurement, and bandwidth-guaranteed overlay routing.

To alleviate the performance decline, the BICC&A over network overlays should consider the underlying topology to fully use network resources. Unfortunately, it is difficult to accomplish this because the underlying topology is invisible. To date, there have been a large number of research efforts on topology discovery. However, almost no literature introduces ML-based intelligence to topology discovery. Because the GNN can model a network topology [105], it is a promising model to deduce the underlying network topology. According to the introduction in section III-C, we observe that only a very small amount of research work considers ML techniques in the available bandwidth measurement procedure. As mentioned previously, RL is a feasible approach to help measure available end-to-end bandwidth measurements because the states can be perceived after an action is applied. Supervised learning and DL-based solutions are also feasible because the training data can be easily obtained in the available end-to-end bandwidth measurement. Note that the overlay routing can adopt the ML techniques, especially RL, used in the common routing protocols.

C. ML FOR COLLABORATIVE BICC&A IN DISTRIBUTED NETWORKS

Most existing ML-based BICC&A solutions, designed for distributed networks, control or avoid network congestion in terms of a single communication session. This may cause two problems. On the one hand, separate congestion control and avoidance cannot fully utilize network resources, thereby limiting its capability. On the other hand, the bandwidth use fairness and utility (depending on the flow types) of the flows sharing the same congestion links are difficult to balance. To obtain an effective tradeoff between fairness and utility, it is necessary to implement collaborative BICC&A. Collaborative BICC&A can be well implemented in centralized network architectures such as SDN. However, the majority of the current Internet still consists of distributed networks. As a result, collaborative BICC&A in a distributed manner is a practical research topic for the current Internet.

To implement a collaborative BICC&A in a distributed network, the sender of each flow needs to perceive the features of other flows and make decisions based on the perceived results. For the above process, ML techniques, especially classifiers, can play an important role. The collaborative BICC&A requires the mutual cooperation of the entities (e.g., hosts and servers) in the distributed networks. For the distributed networks, the distributed learning techniques have their inherent advantages. The federated learning is a promising distributed learning technique proposed in [153], and have attracted some interesting works (e.g., [154]). The distributed learning techniques, including federated learning, can play an important role for the collaborative BICC&A.

D. ML FOR CROSS-LAYER BICC&A

The end-to-end connection in TCP/IP networks involve all layers, including application layer, transport layer, network layer, data link layer, and physical layer. The exchange of data and service calling takes place only between two adjacent layers and forms a significant black box feature of the TCP/IP model [155], [156]. As a result, the information in a layer is hidden for another layer. The strict boundary between different layers brings some advantages, such as the convenient deployment and the simplicity of development. However, the encapsulation of the layers prevents some necessary information sharing between layers [155]. Therefore, to mitigate the side effect of the encapsulation between the abstract layers in the TCP/IP model, a number of cross-layer designs have been proposed [155]. Because BICC&A can be performed at different layers, it is feasible to control or avoid network congestion by the collaboration of different layers. However, to the best of our knowledge, there are no ML-based cross-layer BICC&A solutions. As a result, ML for cross-layer BICC&A should be considered in the future. One typical field on ML for cross-layer BICC&A is the collaboration of congestion-avoidance overlay routing and rate control. The specific ML techniques applied to the cross-Layer BICC&A depend on the concerned optimization objectives. In general, the optimization objective with a dynamics adaptability can apply the RL techniques, while the optimization objective without considering the dynamics can use other ML techniques such as DL.

VI. CONCLUSION

This paper presented a comprehensive survey of the ML applications for the BICC&A. First, we presented an overview of the background knowledge of BICC&A, including challenges of dealing with Internet congestion, network condition acquirements for BICC&A, specific BICC&A methods, and various ML techniques and several concerns on ML algorithms for BICC&A. The network condition acquirements include traffic classification, traffic prediction, available bandwidth measurement and topology discovery; the specific BICC&A methods include rate control, congestion-avoidance routing and bandwidth reservation. Then, we provided detailed reviews on BICC&A-oriented network condition acquirement and specific BICC&A solutions based on ML algorithms. Finally, we outlined important research opportunities. In summary, research on applying ML algorithms in the BICC&A is quite broad, and many challenges still lay ahead. This paper attempts to explore how ML algorithms improve the performance of the BICC&A and which fields of BICC&A the network community should focus on. We hope that our exploration open a new avenue for the development of more intelligence in the BICC&A.

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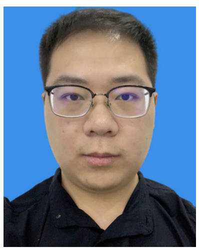

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