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Real-World Wireless Network Modeling and Optimization: From Model/Data-Driven Perspective

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Abstract — With the rapid development of the fifth-generation wireless communication systems, a profound revolution in terms of transmission capacity, energy-efficiency, reliability, latency, and connectivity is highly expected to support a new batch of industries and applications. To achieve this goal, wireless networks are becoming extremely dynamic, heterogeneous, and complex. The modeling and optimization for the performance of real-world wireless networks are extremely challenging due to the difficulty to predict the network performance as a function of network parameters, and the prohibitively huge number of parameters to optimize. The conventional network modeling and optimization approaches rely on drive test, trial-and-error, and engineering experience, which are labor intensive, error-prone, and far from optimal. On the other hand, while the research community has spent significant efforts in understanding the fundamental limits of radio channels and developing physical layer techniques to operate close to it, very little is known about the performance limits of wireless networks, where millions of radio channels interact with one another in complex manners. This paper reviews the very recent mathematical and learning based techniques for modeling and optimizing the performance of real-world wireless networks in five aspects, including channel modeling, user demand and traffic modeling, throughput modeling and prediction, network parameter optimization, and IRS empowered performance optimization, and also presents the corresponding notable performance gains.

Key words — Mathematical methods, Learning based methods, Network performance modeling, Network performance optimization.

I. Introduction

The performance of a real-world wireless network depends on not only the capabilities of its hardware (e.g., base stations, mobile handsets), but also how it is configured. A wireless network serving a metropolitan area consists of large numbers of base stations, each covering several cells and providing various communication services for users in this area. The service range, signal strength, antenna settings, and many other configurations of the base stations greatly impact the communication quality and user experience [1].

In real-word wireless networks, the surrounding environment (such as terrains, building distributions, crowd densities, user distributions and trajectories, and network traffic loads) of different base stations are also diverse. Therefore, millions of tunable parameters need to be optimized to improve the overall performance of the wireless networks. Only by setting them to match the local

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radio environment and user traffic patterns can the network reach its optimal performance.

Traditional optimization methods rely on human knowledge. Professional network optimization engineers monitor and analyze the radio environment and log data of each base station, locate the problems, and propose the optimization solution based on the expert experience. However, in a real-world wireless network, the optimization for millions of parameters is extremely costly and time consuming, making the conventional approaches only suitable for very small-scale networks [2]. On the other hand, while significant efforts have been made to understand the fundamental limits of radio channels, it is still challenging to develop efficient methods to model and optimize the performance of the real-world wireless networks. What are the performance gains that can be brought by adjusting the parameters of a network? Can mathematical/learning models defeat the best network engineers and fully reap the capacity of a large-scale wireless network?

Effective approaches for modeling and optimizing the network performance are greatly needed. In particular, some fundamental problems are still open with many challenges, such as:

1) Lack of Historical Data: Most parameters in wireless networks are configured to be default values, and there is no diversified historical data;

2) Large Network Fluctuation: The fast-varying propagation environment and user behaviors make the network performance non-stationary and hard to predict;

3) Large Search Space: The number of network parameter combinations is huge, reaching sizes of $10^{2,000,000}$ for a metropolitan 5G wireless network;

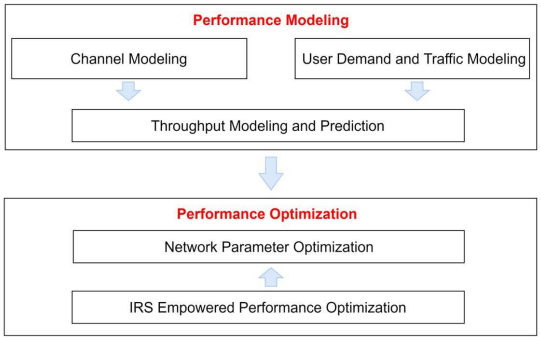

Fig. 1 The relations among the five aspects in performance modeling and optimization of real-world wireless networks.

4) Complex Interactions: Parameter configuration for a single cell affects its own performance but also that of the neighbor cells, inducing complex interactions.

Faced with these challenges, this paper reviews the very recent mathematical and learning based techniques, including various cutting-edge technologies such as deep learning, reinforcement learning, and black-box optimization to effectively improve the service quality and user experience of the real-world wireless networks. Specifically, we focus on five aspects in the performance modeling and optimization for real-word wireless networks, which consist of channel modeling, user demand and traffic modeling, throughput modeling and prediction, network parameter optimization, and an advanced intelligent reflecting surface (IRS) empowered performance optimization. The relations among the five aspects are illustrated in Fig. 1. Firstly, channel modeling provides the accurate estimate of the wireless environment. On the other hand, user demand and traffic modeling establishes a precise prediction for the dynamic data traffics. Based the the well established channel models, user demand and traffic models, the mapping function from the parameters in channels and data traffics to the overall performance of the wireless networks can be investigated through the throughput modeling and prediction. Once the mapping function is obtained, various parameters can be optimized to maximize the overall performance of the wireless networks. In particular, some advanced scenarios such IRS involve a lot of special continuous and/or discrete parameters. By judiciously designing these parameters, the overall performance can be much improved.

The rest of the paper is organized as follows. Section II reviews state-of-the-art channel modeling methods. Section III introduces the main traffic prediction and traffic models. In Section IV, we discuss how to achieve the throughput modeling and prediction through the cutting-edge mathematical and learning based technologies. After the performance modeling, we further move to the network parameter optimization in Section V, and introduce the optimization methods for an advanced IRS empowered scenario in Section VI. Finally, the conclusions are included in Section VII.

II. Channel Modeling

In this section, we introduce the 5G channel modeling methods and the channel models commonly used in existing network optimizers. Then, we propose our design of data-driven localized statistical channel modeling.

1. 5G channel modeling methods

According to the modeling methods, channel modeling can be classified into deterministic manner and stochastic manner. The deterministic channel models usually depend on the map information of environment, and describe the propagation paths by solving the Maxwell's equations or approximated propagation equations. As for the stochastic channel models, they characterize the channel parameters by using certain probability distributions,

and can be applied to various scenarios with relatively low accuracy. Generally speaking, the deterministic channel models cost much higher computational complexity than the stochastic channel models.

The new techniques and applications in 5G mobile communication systems have introduced new challenges to the channel modeling [3]. A wide frequency range and broad bandwidths of channel measurement need to be conducted for millimeter wave (mmWave) communication in 5G systems. Taking massive MIMO for example, due to the large dimension of antenna array, the distance between the transceiver and the clusters could be smaller than the Rayleigh distance, resulting in that the assumption of plane wavefront does not hold. Besides, the array non-stationarity would occur. The clusters may appear and disappear from the viewpoint of one antenna element to the next one, which means the path parameters such as power and delay can drift over different antennas. These two properties set new requirements to the channel modeling for massive MIMO. In [4], the spherical wavefront with an ellipsoid model is considered in the massive MIMO channel model. The appearance and disappearance of the clusters over the array is modeled by a birth-death process with cluster generation rate λ_G and cluster recombination rate λ_R.

2. Channel models in the network optimizer

As channel models are indispensable for system design and performance evaluation in the network optimizer, here we focus on two types of channel models that are exploited in the network optimizer:

1) Empirical path loss model. Coverage and capacity optimization (CCO) is a typical application of network optimization by tuning the tilt angle and azimuth angle of antenna array. To describe the channel characteristics, the simplified empirical path loss model (e.g., COST231-Hata model) can be exploited in the CCO. However, such ideal one-dimensional path loss model is not accurate enough and fails to embrace the actual complexity and randomness of practical 5G networks. The only one-dimensional path loss model needs to be extended into multi-dimensional channel model, because the massive MIMO and beamforming in the 5G networks yield high-resolution multi-path channels in the angular domain.

2) Neural network channel model. A neural network enabled wireless channel model framework is proposed in [7]. The input parameters are transmitter (Tx) and receiver (Rx) coordinates, Tx-Rx distance, and carrier frequency, while the output parameters are channel statistical properties, including root mean square (RMS) delay spread (DS), and RMS angle spread (AS). Datasets used to train and test the neural network are collected from both real channel measurements and a geometry based stochastic model (GBSM). Different datasets from different scenarios will show different channel statistics.

3. Localized statistical channel modeling

We propose a novel data-driven localized statistical channel modeling (LSCM) for the network optimizer, which is capable of sensing the physical geographical structures of the targeted cellular environment [5]. The proposed channel modeling solely relies on the reference signal receiving power (RSRP) of the user equipment, unlike the traditional methods which use full channel impulse response matrices. The key is to build the relationship between the RSRP and the channel's angular power spectrum. Based on it, we formulate the task of channel modeling as a sparse recovery problem where the non-zero entries of the spare vector indicate the channel paths' powers and angles of departure (AoD). By taking advantage of the spatial consistency of channel, LSCM is able to be constructed in a manner of multiple grids [6].

Similar to the 3GPP's technical report [8], we focus on the tilt AoD, azimuth AoD, and channel gain from the base station to the user equipment with one receive antenna, ignoring the arrival angle and delay. Suppose the uniform rectangular array of the base station contains $N_T = N_x \times N_y$ antennas. The CIR of antenna (x, y) from the base station to the user equipment is given as

$$h_{x,y}(t) = \sum_{i=1}^{N_V}\sum_{j=1}^{N_H}\sqrt{\alpha_{i,j}(t)} \times g_{i,j} \times e^{-j2\pi\frac{d_x x}{\lambda}\cos\theta_i \sin\varphi_j} \times e^{-j2\pi\frac{d_y y}{\lambda}\sin\theta_i} \times e^{-j\omega_{i,j}(t)-j\omega_{x,y}(t)}. \quad (1)$$

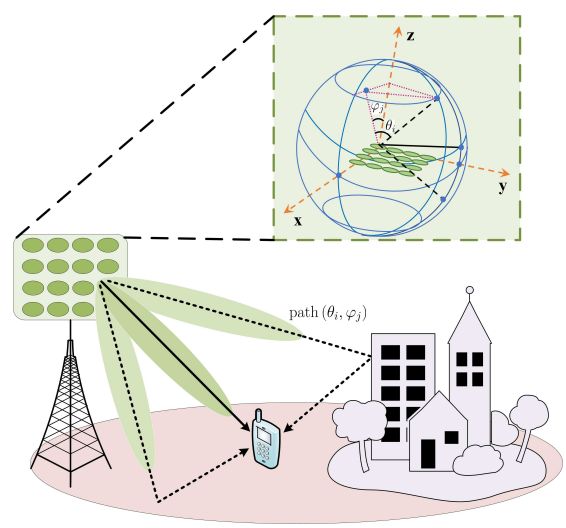

Fig. 2 Angular discretization of the channel model in the downlink.

We consider the channel modeling of the massive MIMO downlink communication system with beamforming, where the signal is transmitted from a base station to the user equipment through several propagation paths, as shown in Fig. 2. The tilt and azimuth AoD over the free space are discretized into N_V and N_H angles, respectively. If there does not exist a path in the angles (θ_i, φ_j), the corresponding channel gain $\alpha_{i,j}(t)$ is zero, otherwise $\alpha_{i,j}(t) > 0$ for the path (θ_i, φ_j) in the channel. It is readily known that the channel gain $\alpha_{i,j}(t)$ is sparse, and contains multiple propagation paths in the angular domain.

The channel gain $\alpha_{i,j}(t)$ consists of path loss and the shadowing effect. Path loss is determined by the physical environment (distance, carrier frequency, buildings) which is assumed to be relatively static, while shadowing is caused by the obstacles and is usually modeled as the log-normal distribution. Thus, we assume $\alpha_{i,j}(t)$ follows the log-normal distribution, with its mean representing path loss and its covariance representing the shadowing effect. Notcie that $\omega_{i,j}(t)$ is the random phase error between different angles caused by the reflection, diffraction, and scattering effect of electromagnetic waves, while $\omega_{x,y}(t)$ is the random phase error of different antennas caused by the imperfect hardware of the antenna array. Inspired by [8], we assume $\omega_{i,j}(t)$ follows the uniform distribution between $-\pi$ and π, and $\omega_{x,y}(t)$ follows the Gaussian distribution with zero mean and variance σ^2.

The channel measurement of our proposed LSCM is the RSRP measured from multiple beams. In the downlink of 5G cellular systems, the RSRP can be measured from synchronization signals block (SSB) beams or channel state information-reference signal (CSI-RS) beams. Denote the precoding matrix of the k_{th} beam as $\boldsymbol{W}^{(m)} \in \mathbb{C}^{N_x \times N_y}$, whose size is the same as that of the antenna array. The entry of $\boldsymbol{W}^{(m)}$ is $\left(w_{x,y}^{(m)}\right) = \left(e^{j\phi_{x,y}^{(m)}}\right)$. Denote the CIR matrix from the base station to the user equipment as $\boldsymbol{H} \in \mathbb{C}^{N_x \times N_y}$, where the entry of $\boldsymbol{H}$ is $h_{x,y}(t)$ in Eq.(1). The RSRP of the m_{th} beam at time t is defined as

$$rsrp_m(t) = P\left|\sum_{x,y} h_{x,y}(t) w_{x,y}^{(m)}\right|^2 = P\left|\operatorname{tr}\left(\boldsymbol{H}^T \boldsymbol{W}^{(m)}\right)\right|^2, \tag{2}$$

where P denotes the transmit power. The quality of the channel can be represented through $rsrp_m(t)$, and a larger value of $rsrp_m(t)$ reflects better channel quality.

Notice that $rsrp_m(t)$ is a random variable, since $h_{x,y}(t)$ contains three independent random variables, i.e., $\omega_{x,y}(t)$, $\omega_{i,j}(t)$, and $\alpha_{i,j}(t)$. We want to show the relationship between the first-order statistics of $rsrp_m(t)$ and $\alpha_{i,j}(t)$, i.e., their expectation $\mathbb{E}\left(rsrp_m(t)\right)$ and $\mathbb{E}\left(\alpha_{i,j}(t)\right)$, implying the statistical relationship of the RSRP and angular information. Suppose the expectation of $rsrp_m(t)$ is $\mathrm{RSRP}_m \triangleq \mathbb{E}\left(rsrp_m(t)\right)$, and the expectation of channel gain is $X_{i,j} \triangleq \mathbb{E}\left(\alpha_{i,j}(t)\right)$, then we have

$$\mathrm{RSRP}_m = \sum_{i=1}^{N_V}\sum_{j=1}^{N_H} \mathrm{A}_{i,j}^{(m)} X_{i,j}, \tag{3}$$

where

$$\mathrm{A}_{i,j}^{(m)} \triangleq P g_{i,j}^2 \Bigg(N_x N_y \left(1 - e^{-\sigma^2}\right) + e^{-\sigma^2} \sum_{x,y}\sum_{x',y'} \cos\left(\psi_{i,j,x,y}^{(m)} - \psi_{i,j,x',y'}^{(m)}\right) \Bigg).$$

The statistical relationship between the expectation of RSRP measurements RSRP_m and the first-order statistics of channel gain $X_{i,j}$ is connected by the coefficient $\mathrm{A}_{i,j}^{(m)}$. The angular power spectrum (APS) can be expressed by $X_{i,j}$, where the subscripts i and j indicate the tilt angle θ_i and azimuth angle φ_j, respectively. According to this finding, it is possible to extract the angular information from beam-wise RSRP if we can infer $X_{i,j}$ from RSRP_m.

The channel statistics of APS from the proposed channel model are consistent with those of the true propagation environment, and can provide enough information for the network optimization simulator to generate channels similar to reality.

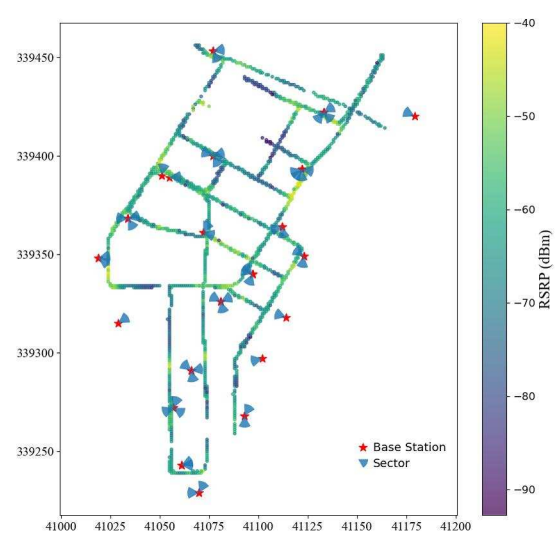

Fig. 3 RSRP distribution in real-world drive testing.

As shown in Fig. 3, it is an example of collecting the real-world RSRP measurement by using the drive-test in the street of Chengdu city, China. The carrier frequency of the cellular network is 2.6 GHz with 100 MHz bandwidth. The number of antennas in the base station is

32. Compared with the traditional network optimization which needs many rounds of drive testing, the proposed LSCM only need one round of drive testing, and thus, saving a lot of money and enabling the assessment of network optimization. Depending on the velocity of the driving car, dozens of samples are collected when passing through a 10×10 square meters grid in the interval of several seconds. The samples of RSRP measurements are averaged to alleviate the effect of fast fading. If the number of samples is smaller, then the noise effect will be dominant which leads to a higher mean absolute error.

III. User Demand and Traffic Modeling

Optimizing the performance of a real-world wireless network is extremely challenging because of the difficulty to predict the network performance as a function of network parameters, and the prohibitively large problem size. Therefore,traffic prediction and modeling plays a fundamental role in the overall performance optimization of wireless networks.

Industry and industry communication field attach great importance to traffic prediction. Huawei predicted that mobile network traffic will increase a hundredfold in 2030 during the Global Mobile Broadband Forum 2021 (MBBF2021), saying that wireless networks are an important pillar for moving towards an intelligent world. Ericsson not only predicted that the traffic in 2026 would increase by 4.5 times compared with 2020, but also proposed that there would be 3.5 billion 5G users in the world by 2026. On the other hand, Nokia Bell Labs made predictions on the infrastructure and interconnection equipment in the future. Among them, 4G expenditure will account for 80% of the infrastructure expenditure of operators in the next few years. It is estimated that there will be 50 billion interconnection devices in the world by 2025. Prediction of network traffic is being rapidly advanced by the world's leading research institutions.

Therefore, how to predict the traffic with low cost and high accuracy under the rapidly changing propagation environment, user environment as well as huge number of network parameter combinations. It has become an urgent international open problem in the industry, with great market demand and academic value. It is also a very attractive research hotspot.

1 Traffic models.

Our goal is to accurately characterize and predict the stochastic behaviour of the real world 4G/5G wireless network. High precision traffic prediction method has become a research hotspot in the industry and academia. In order to improve the prediction accuracy, great efforts have been made in model establishment and prediction methods, and fruitful results have also been achieved, which has promoted the progress of traffic prediction and parameter estimation.

The prediction models used in the existing research are roughly categorized into the following three types:

1) Statistical models

At present, the statistical models used in the research are mainly time series, probability estimation and particle filter models. Some representative models include Holt Winters (HW) [9] and ARIMA[10]. ARIMA(p, d, q) model is an extension of ARMA(p, q) model, which can be expressed as:

$$(1 - \sum_{i=1}^{p} \lambda_i B^i)(1 - B)^d y_i = (1 - \sum_{i=1}^{q} \theta_i B^i)\epsilon_t, \quad (4)$$

where B is the lag operator, $\sum_{i=1}^{p} \lambda_i B^i$ and $\sum_{i=1}^{q} \theta_i B^i$ are autoregressive coefficient polynomial and moving average coefficient polynomial respectively. ϵ_t is zero mean white noise sequence, $d \in \mathbb{Z}, d > 0$.

Network slicing is the key technology of the fifth generation (5G) mobile network. In order to meet the demand of network operators for dynamic deployment of network slicing, scholars proposed to use HW model [9] to reduce the cost of network operators by 15% and energy consumption by 13%. The utilization rate of resources also increased by more than 6 per cent. Clemente et al. [11] used the method of combining naive Bayesian classifier and Holt Winter to accurately predict cell traffic, and limited the prediction RMSE to 5%.

For short-term flow forecast represented by seasonal problems, Wang [10] et. al used MSE and MAE to evaluate the performance of the proposed ARMA model, and proved that short-term prediction has high prediction accuracy. The literature [12] proved that the prediction accuracy of conditional probability estimation model is higher, and the daily seasonal model error is 9.92%.

ARIMA model and HW model are univariate time series models. In addition to these two models, there are ES method [13] and particle filter method based on sequence Monte Carlo (SMC) [14] for traffic demand prediction. As the classical method, the prediction accuracy of statistical model is much less than machine learning and deep learning model since most of them are based on the linear relationship between input values and output values. Considering statistical models are not suitable for large-scale problems and are difficult to be trained in parallel, scalability is also its drawback.

2) Machine learning models

Common machine learning prediction models are mainly tree based, such as random forest(RF) [15] and

LightGBM [16], and others are based on Gaussian process or other mechanisms. Decision trees are the most basic concepts in tree based models, which can be used to solve classification or regression problems. Predict y_i by giving x_i to get the objective function:

$$Obj(\Theta) = L(\theta) + \Omega(\Theta). \tag{5}$$

where L represents the training error function, and Ω represents the regularization term to control the complexity of the model and prevent over fitting. For logical regression, the most commonly used loss function is the Logistic function, which is expressed as:

$$L(\theta) = \sum_i [y_i ln(1 + e^{-\hat{y}_i}) + (1 - y_i) ln(1 + e^{\hat{y}_i})]. \tag{6}$$

The regularization is expressed as:

$$\Omega(\Theta) = \theta_j (1 - \alpha \frac{\lambda}{m}) - \frac{\alpha}{m} \sum_i^m [(h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}]. \tag{7}$$

where λ is constraint multiplier and $h_\theta(x)$ represents the prediction function.

In the literature [17], Prophet model and GPR model are combined to predict single cell traffic, and RMSE, MAE and MAPE are used to verify the superiority of prediction accuracy and explain the inherent space-time correlation of traffic data. In order to realize ultra reliable low delay communication (URLLC) in large-scale machine communication networks, the Tree based ML model was proposed by Weerasinghe et. al [18].

In order to improve users' life comfort, Abozariba et. al [19] proposed ML model to accurately predict users' traffic demand. Performance index analysis shows that the prediction results can provide higher resource utilization. In addition, in order to improve the service quality of smart cities and understand the distribution of service demand in time and space, a spatio-temporal Bayesian hierarchical learning method [20] is used to learn and predict the distribution of MEC resource demand in time and space, and the resource allocation efficiency predicted by the model is higher.

Compared with deep learning models, these models have the characteristics of "shallow" structure. Machine learning models usually perform better than statistical models, but only in a few cases can obtain better prediction results than deep learning models.

3) Deep learning models

The main advantages of deep learning model include high precision prediction performance and high scalability. The deep learning models used in the study include Convolutional Neural Network (CNN)[21]-[24], Graph Convolutional Network (GCN)[25]-[32], Long Short-Term Memory (LSTM)[33]-[45]. The GCN model is expressed as:

$$f(H^{(l)}, A) = \sigma(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}), \tag{8}$$

where input layer is $H(0) = X$, output layer is $H(L) = Z$, and L is the number of layers. W and σ represent linear transformation and nonlinear transformation respectively.

Due to the wide coverage of deep neural network, it has been used for deep learning and has achieved great success in a series of prediction problems in the past decade, such as intelligent transportation system [26], urban traffic prediction [36] and cellular network prediction [45]. In addition, there are Generative Adversarial Network (GAN) [28], Deep Neural Network (DNN) [36], Attention-based Periodic-Temporal neural Network (APTN) [37], Multi-Stage Attention Spatial-Temporal Graph Networks (MASTGN) [39], Neural Architecture Search (NAS) [46].

CNN can extract local spatial features of data, but it needs a large sample size, high computational complexity, high redundancy, and no memory. Therefore, it is suitable for nonlinear time series prediction with large sample size, high prediction accuracy, and time delay insensitivity. RNN can flexibly capture the time dependence of data, and may also cause gradient disappearance or gradient explosion. It is suitable for dynamic short correlation time series prediction. DNN can learn deep nonlinear feature transformation, but it can not use historical information to assist the current task. LSTM can better deal with the influence of large time scale data, but its convergence speed is slow, the parameters cannot be directly determined, and it is easy to fall into local optimization. It is suitable for time series prediction with large number of samples and long-term dependence. Considering the structural correlation between nodes, GCN is very effective in processing graph data and has over smoothing problem. Because GCN has the function of a low-pass filter, the characteristics tend to be the same after multiple iterations. It is suitable for spatial prediction scenarios. GCN-GAN can predict plateau, single engine, and double engine traffic. The model is suitable for large-scale burst traffic prediction, and can predict three types of traffic.

In particular, GCNs and LSTM are employed to model the spatial and temporal aspects [32]. To get a better understandings of deep learning model, we discuss several works in Table. 1.

Table. 1 List of papers on deep learning traffic prediction

Reference	Year	Spatial/Temporal	Proposed model	Application	Short/Long Term	Evaluation metrics
21	2020	Both	MDL, CNN	Traffic Flow	Both	RMSE, MAE
22	2020	Spatial	CNN, GCN	Cell traffic	Long-term	MAE, MSE
23	2021	Both	CNN	ITS	short-term	RMSE, MAPE
24	2017	N/A	CNN, LSTM	Mobile traffic	Both	RMSE, MAE, MA
25	2020	Both	LSTM, GCN	Intelligent Route Planning	Both	RMSE, MAE
26	2022	Both	LSTM, GCN	ITS	Both	MAE,RMSE,MAPE
27	2020	N/A	GCN-GAN	Burst Events	Long-term	MSE
28	2020	N/A	ML, GCN	Intelligent Transportation Systems	Short-term	N/A
29	2021	Both	LSTM, MASTGN, GCN	ITS	Both	RMSE,MAE,MAPE
30	2020	Temporal	T-GCN	ITS	Short-term	RSME,MAE
31	2021	N/A	GCN-GAN	Elastic Optical Networks	Short-term	MSE
32	2018	Both	LSTM, GCN	Cellular Networks	Both	MAE
33	2021	N/A	LSTM, DL	Transportation Planning	Long-term	TSMAPE,TRMSE
34	2019	N/A	LSTM	Optical Networks	Both	N/A
35	2017	N/A	LSTM	Big Date Oriented Networks	Short-term	N/A
36	2022	N/A	DNN, LSTM	Road Network	Both	N/A
37	2020	Both	LSTM, APTN	ITS	Both	RMSE,MAE,MASE
38	2021	N/A	LSTM	Cellular Network	Both	NRMSE
39	2021	Temporal	LSTM	Cellular Network	Both	RMSE
40	2021	Spatial	LSTM	Cellular Traffic	Both	RMSE,MAE
41	2020	N/A	LSTM	Mobile Traffic	Short-time	RMSE
42	2020	N/A	LSTM,ANFIS	Network Traffic	Both	MSE,RMSE,MAE
43	2019*a*	N/A	LSTM,ARIMA	Cellular Traffic	Both	RMSE
44	2019*b*	N/A	LSTM,ARIMA	Cellular Traffic	Both	RMSE

2. Prediction problems

1) Predicting network behaviours at the millisecond timescale is both technically infeasible and practically unnecessary, considering the stochasticity and non-stationarity of networks caused by the rapidly changing propagation environment and user behaviour;

2) How to clean, store, analyze and calibrate the prediction model in the case of the gigantic problem size and massive data sets of network parameters;

3) How to provide an accurate, efficient, yet inexpensive assessment of network performance for any network configuration.

3. Discussion

In the past decade, researchers have designed many network traffic prediction algorithms based on deep learning and made great progress. Network traffic prediction has made a great breakthrough from the traditional method to the application of deep learning technology. However, the current network traffic prediction research is faced with the problems of few public data sets, privacy of traffic data, and limited disclosure.

We forecast the temporal and spatial traffic distribution in the beam-space. It is the basis for characterizing the time/frequency/spatial resource utilization of each cell, which in turn, helps quantifying the perceived interference per beam-space cluster.

To deal with the intrinsic difficulty of the traffic forecasting task in cellular networks, GCN is first used to leverage the spatial correlation of the traffic in neighboring beam-space clusters. The output of the GCN is then used by a LSTM neural network, which captures the temporal behaviour of the data traffic, and enables accurate forecasting. We present the following data-driven spatial and temporal traffic forecast diagram in Fig. 4.

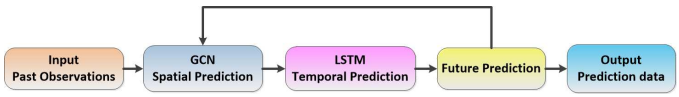

Fig. 4 Forecast diagram.

Therefore, the influence of spatial and temporal factors on the prediction results should be fully considered when making traffic prediction, and GCN and LSTM are combined to predict. In addition, traffic modeling should be human-centric, fully consider the needs of users, and conduct traffic modeling under the conditions of high security, confidentiality and privacy.

IV. Throughput Modeling and Prediction

With the development of machine learning, deep neural networks are widely used in wireless communication systems for modeling and prediction. Neural networks have powerful data fitting capability suitable for complex multi-factor communication scenarios. The downlink Internet Protocol (IP) throughput, defined as the payload data volume on IP level per elapsed time unit on the U-u interface, is an important performance metric for the quality of service experienced by the end user. In this

section, we propose a deep neural network-based modeling approach to predict the downlink IP throughput. Real-trace data of cellular systems in South Africa, i.e., user-uploaded data including physical layer measurement, user scheduling information, user throughput and so on, are used for model training and testing. The experimental results show that our proposed model performs well for downlink IP throughput prediction.

The downlink IP throughput, defined as the payload data volume on IP level per elapsed time unit on the U-u interface, is an important performance metric for the quality of service experienced by the end user. To make sure that only impacts from the RAN is included in this measurement, time units to be included in "elapsed time unit on the Uu interface" shall only be the ones where there is data in the buffer to be transmitted e.g., in application data flows such as a web session, there are times when there is no data to transmit by the eNodeB due to bursty traffic pattern, then this "eNodeB idle time" shall not be included in "elapsed time unit on the Uu interface".

To achieve a throughput measurement that is independent of file size it is important to remove the samples where one time and temperature indicator (TTI) on the radio interface is not utilized.

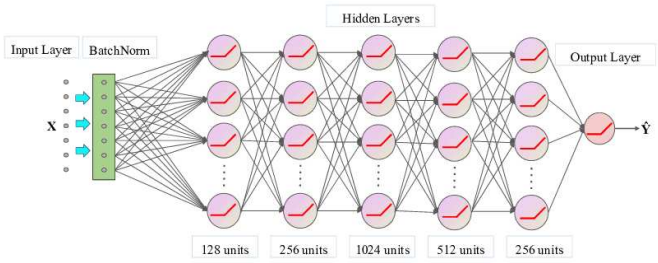

Fig. 5 The net architecture of proposed model.

1. Dataset introduction

By enabling cell history record (CHR) subscription at the 5G base station side, we can get the information reported by the user base station measurements in event blocks. The recording rule is either periodically triggered (e.g. 5s) or event triggered (user switching between cells). A total of seven event blocks exist in our dataset, the contents of which are shown in Table. 2. The first four events are user measurements, where all users in the cell report cumulative measurements every 5s. The fifth event file is the base station measurement file, where the base station counts the beam IDs of all beams uplinked in a time period as well as the RSRP. The last two events are records of users cutting in and out of the base station. These two event blocks are event triggered and therefore much smaller in volume than the other five event blocks. Our dataset includes measurements from 3 base stations for 31 consecutive days.

2. Neural network-based rate prediction model

We propose a data-driven network rate prediction model. The model uses user and base station measurements collected from real environment as input and uses the real measured experience rate as output. Thanks to the huge amount of data collected by the network operators and the powerful data fitting ability of deep learning, many channel modeling studies combining deep learning have emerged. Unlike traditional methods, the neural network-based approach can fully explore the deep coupling relationship among a large number of measurement metrics, and can facilitate the analysis of the impact of network parameters on communication performance. On the one hand, IP throughput is different from traditional rate metrics and it is not clear which parameters are of higher impact on this metric. The small time scale feature makes IP throughput prediction quite challenging. These two factors require us to fully explore the relationship between different measurements and IP throughput from massive data, so we choose the NN-based prediction model.

Table. 2 Dataset event block list

5G CHR event block list	Description
PERIOD INTRA FREQ MEASUREMENT	Downlink Service Cell SSB RSRP
PERIOD PRIVATE UE MEASUREMENT	User scheduling data, including MCS, RNK, etc.
PERIOD PRIVATE THROUGHPUT MEASUREMENT	User flow measurement data
PERIOD PRIVATE UE MIMO MEASUREMENT	User MIMO related data
PERIOD PRIVATE UL BEAM INFO	BS measurement uplink beam level SRS RSRP
PRIVATE HO IN	Cell switch-in events
PRIVATE INTRA RAT HO OUT	Cell switch-out events

1) Input measurement data. After the CHR is turned at the base station we can get the complete daily measurement data for all cells at the base station. We match the data with user IDs by time index to obtain the

complete data. Currently, the basic network measurement data required for our prediction network include:

a) Signal power per beam: 5G BSs can transmit and receive their reference signals through multiple radiating beams. BSs and UEs typically record measurements for the beam with the maximum signal power. Such measurements include, among others, RSRP and SINR estimates for the synchronization signal block (SSB), the channel state information reference signal (CSI-RS), and the detection reference signal (SRS).

b) User connection information: For each UE connection, BS also records its experience by storing statistical information, such as the amount of data transmitted, resources allocated, class, modulation and coding schemes (MCSs), packet failures, retransmissions, and data rates.

c) Base station statistics: The user experience rate is also related to the bandwidth resources that users can allocate during the count transmission time, which is related to the average number of activated users in the cell, thus the higher the number of users, the lower the user experience rate. We use not only the average number of activated users over a single measurement period, but also the number of tied activated users over a larger time range (e.g., over 10 and 30 minutes). This information allows capturing more temporal information, such as user behavior habits throughout the day.

2) Framework for the Model. We use a multilayer neural network to build the rate prediction model, and the network structure is shown in Fig. 5. The network contains a total of 5 hidden layers, and the number of neurons in each hidden layer is indicated in Fig. 5. We use Rectified Linear Unit (ReLU) as the activation function to increase the nonlinearity. In addition, we add a BathNorm layer between the input layer and the first hidden layer to normalize the data samples. The loss function is Mean Absolute Percentage Error (MAPE).

3. Experimental results

1) Data filtering. The experience rate is calculated by removing the tail packet traffic and tail packet count transmission time. Predicting the rate is a difficult task for data with a relatively large percentage of tail packet traffic and tail packet count transmission time. Therefore, we consider predicting the data with a larger percentage first. We set two fixed thresholds a and b to filter the data set, and select the sample data with the tail packet traffic ratio exceeding a and the tail packet transmission time ratio exceeding b for prediction.

In Table. 3, we use different thresholds ($a = b$) to filter the data, and count the remaining percentage of the filtered data and the remaining percentage of data transmission traffic. It can be seen that, according to this method, even a large amount of data is filtered out, the proportion of the remaining traffic is still very large, which is acceptable in practical engineering, so we will use the threshold $a = b = 0.2$ for experiments.

Table. 3 Statistical of different filtering thresholds

Threshold	Data items remaining	Traffic remaining
0.1	54%	94%
0.2	39%	86%
0.3	30%	77%
0.37	25%	70%

2) Results. We use MAPE as a test indicator. Set the filtering threshold $a = b = 0.2$. The results obtained from the experiments on base stations $2343, 3434, 3955$, and the three base stations combined are shown in Table. 4.

Table. 4 Multi-base station multi-day experiment

Base Station	Days	Test MAPE
3955	1∼20	21.50%
2343	1∼20	25.72%
3434	1∼20	25.00%
2343, 3434, 3955	1∼20	23.50%

We can see that the 3955 base station has the best performance. Its test MAPE can reach 21.5%, while the other two base stations perform slightly worse, but can also reach about 25%. The result of combining the three base stations together is about the average of the respective results of the three base stations. In general, the MAPE between the predicted value and the actual value can reach below 25% which meets the needs of the industry.

The following experiments are aimed at the verification of generalization performance.

First, we verify whether it is generalizable for different days. For the three base stations respectively, the data of the first 20 consecutive days is selected as the training data, and then the trained model is tested with the data of the first 20 days and the last 10 days, and the results are shown in Table. 5.

Table. 5 Generalization experiment of day

Base station	Train days	Test days	Test MAPE
3955	1∼20	1∼20	**21.50%**
	1∼20	21∼30	23.13%
2343	1∼20	1∼20	**25.72%**
	1∼20	21∼30	37.14%
3434	1∼20	1∼20	**25.00%**
	1∼20	21∼30	30.83%

We can see that the performance of the base station 3955 is still the best. The ratio of MAPE tested on different days increase by about 2%, but the performance of the other two base stations is not ideal. The performance of base station 3434 increases compared to the original. At first glance, the trained model does not generalize for simply dividing the days continuously.

Table. 6 Generalization experiment of day (cycle on week)

Base Station	Train days	Test days	Test MAPE
3955	3, 10, 17	3, 10, 17	***24.17%***
	3, 10, 17	24	26.41%
2343	3, 10, 17	3, 10, 17	***23.99%***
	3, 10, 17	24	45.02%
3434	3, 10, 17	3, 10, 17	***29.91%***
	3, 10, 17	24	38.94%
3955	6, 13, 20	6, 13, 20	***18.68%***
	6, 13, 20	27	24.80%
2343	6, 13, 20	6, 13, 20	***25.05%***
	6, 13, 20	27	34.84%
3434	6, 13, 20	6, 13, 20	***23.67%***
	6, 13, 20	27	32.00%

Take into account that traffic may have weekly periodicity as traffic usage will vary between weekdays and weekends. We divide the days into weeks, selected Wednesday (day 3, 10, 17, 24) and Sunday (day 6, 13, 20, 27) for the experiment. From Table. 6, it can be seen that whether it is Wednesday or Sunday, the MAPE tested by each base station on different days is about 10% higher than that on the original day, which is not much different from the effect of continuous day division. That is to say, the model we trained based on the provided measured data does not have generalization to days.

Table. 7 Generalization experiment of base station

Train Base Station	Test Base Station	Days	Test MAPE
3955	3955	1∼20	**21.50%**
	2343	1∼20	40.45%
	3434	1∼20	56.28%
2343	2343	1∼20	**25.72%**
	3955	1∼20	39.49%
	3434	1∼20	50.64%
3434	3434	1∼20	**25.00%**
	3955	1∼20	35.83%
	2343	1∼20	40.72%

Next, we verify its generalizability for different base stations. The first 20 days are selected for the range of days, and the data of the three base stations are cross-validated respectively. From Table. 7, it can be seen that the effect of testing the model with different base stations is far worse than the test results of the same base station, which shows that the differences between different base stations may be huge due to differences in geographical location and number of users and so on. The model trained by one base station cannot be used to predict the experience rate of other base stations.

4. Discussion

In this section, we combine machine learning and wireless communication systems modeling and prediction, to predict downlink IP throughput in cellular networks with deep neural networks. Our proposed method models the real-trace data of the South African cellular system, and reaches the MAPE between the predicted downlink IP throughput and the measured value less than 25%, indicating the effectiveness of our method. In addition, our method filters most of the data, which are all small packets. Although filtering out small packets has little impact on the data transmission traffic, it occupies for the majority of the data so its value cannot be ignored. It is difficult to predict small packets with the original method.

V. Network Parameter Optimization

As mentioned before, the performance of a real-world network depends not only on the capabilities of its hardware, but also on how it is configured. Thus, careful network optimization is exceedingly desirable to ensure efficient radio resource management and high quality of service (QoS). Traditional optimization methods, which are heavily dependent upon the experience of professional network engineers, are often costly and time-consuming. In light of this, a self-organizing network (SON) has been proposed as a promising solution for increasing the network's efficiency and, hence, for maintaining and/or increasing the network's QoS while saving capital and operational costs at the same time. Various methods for network optimization have been proposed in existing literature which can be categorized into three classes, i.e. optimization-based methods, learning-based methods, and meta-heuristic methods.

1. Optimization-based methods

The computation of the objective function is usually a time-consuming and non-differentiable process due to the complex relationships between network parameters and key performance indicators (KPIs). Therefore, many

existing approaches are zero-order methods which only rely on the computation of the objective values. Niemela et al [47] studied the impact of antenna downtilt on the performance of cellular WCDMA network by utilizing a radio network planning tool. The optimal downtilt angles of antennas can be obtained based on solid simulation experiments by varying the downtilt angles inside a given range. Since the objective function values for all the combinations of the tuning of parameters are obtainable, the exhaustive method is supposed to always reach the optimal in theory. However, it is usually unfeasible because the solution space is too large. To reduce the time complexity, rule-based algorithm [48], greedy algorithm [49], Taguchi's method [50], and Nelder-Mead approach[51] are adopted to search the solution space to find a near-optimal solution. Line search algorithms are also proposed, which choose a search direction and then find a better solution along that direction iteratively. The coordinates are typically selected as the search directions, which is referred to as Coordinate Descent (CD) [52]-[54]. These search methods can efficiently reach the optimal or a near-optimal point in small-scale network with accurate network model, but are not applicable in large-scale network since the search space grows exponentially with the number of parameters.

In coping with large-scale network parameter optimization, line search methods in the optimal direction, i.e., the gradient direction or its approximate version, are often better than methods in the random or preordered coordinate directions. However, the objective function, especially the coverage, is usually discrete-valued and thus non-differentiable. One popular approach is to convert the non-differentiable objective function to a smoothed approximation to make the gradient-driven methods or other convex optimization approaches feasible [55],[56]. The approximation is usually based on simplified path loss model and antenna radiation pattern proposed by 3GPP. In addition to the fact that the performance of these methods depends largely on the accuracy of the approximation model, they need to be further validated in real scenarios. Another approach is to estimate the gradient by applying subtle changes to each network parameter [57],[58], which can be carried out on accurate network simulators. However, this kind of gradient estimator is also time-consuming and inefficient in large scale network. Li et al. [5] proposed a zeroth-order continuation method which is able to estimate the gradient with only two objective calculations. However, the gradient descent over the $[0, 1]$-valued coverage ratio is severely inefficient and the convergence of the algorithm can only be guaranteed under very strict assumptions. In addition to these gradient-driven methods, Engles et al. [59] formulated the CCO problem as a mixed-integer linear program (MILP) by introducing a low-complexity interference approximation model. They utilized state-of-the-art MILP solvers such as CPLEX or Gurobi Optimizer to compute (optimal) solutions. Partov et al. [60] reformulated the non-convex utility fairness problem in a convex manner by proposing a linear approximation of the antenna gain model, and solved it using a primal-dual approach.

In general, most of the optimization-based algorithms are designed to be executed offline, based on the assumption that factors such as the physical environment and user distribution are constant during the optimization process, or based on statistical network environments. Only the network configuration that is the solution of the offline optimization is then applied to the real network. These methods are usually highly effective, but require accurate modeling of the network to be optimized, i.e., the locations of all users need to be known and the received power of users with different parameter settings needs to be precisely evaluated.

2. Learning-based methods

Unlike optimization-based methods that require a large amount of prior knowledge to accurately model the system, the learning-based methods have the advantage that, in general, no prior knowledge or only sparse prior knowledge about the system's behavior is required. Moreover, learning-based approaches are often used for online network optimization, which makes it necessary to balance not only the various KPIs, but also the immediate gains and long-term performance. Therefore, many studies resort to multi-armed bandit (MAB) theory to address the resulting exploration and exploitation trade-offs. [61]-[63]. Dhahri et al. [61] proposed a novel multi-player MAB framework to model the trade-off in the CCO problem and a Pareto search framework to deal with the multi-objective optimization. In order to accelerate the convergence to the optimal selection, Shen et al. [62] proposed a novel multi-armed bandit model called generalized global bandit, which allows for the modeling of similarities across arms. They developed a series of greedy algorithms to achieve the optimal trade-off between sufficient small cell coverage and limited macro-leakage without prior knowledge of the deployment environment. In order to exploit the prior knowledge of the system, Wang et al [63] proposed the MAB algorithm with Bayesian principle on the small base station transmit power allocation problem. They incorporated performance correlations between similar power values and considered a power switching penalty to discourage frequent variations.

In addition to MAB, reinforcement learning is also widely used in online network optimization [64]-[68]. Dandarov et al. [64] proposed an RL approach awarded by the sum data rate normalized to the sector capacity and the number of satisfied users normalized to the potential total number of served users to address CCO problem. The network can predict the optimal antenna tilts for a particular user distribution. But the employment of explore-then-commit algorithm makes it highly inefficient for large-scale networks. The authors of [65] treat the coverage and capacity objectives as black-box functions, with no analytical formula and no gradient observations. They identified the set of Pareto optimal solutions through Bayesian optimization (BO) and the deep deterministic policy gradient algorithm (DDPG). These methods are still difficult to adapt to large-scale networks because the search space and data volume increase dramatically with the number of parameters. Therefore, Bouton et al. [66] proposed a coordinated RL approach modeling cellular networks as coordination graphs. Message passing and parameter sharing across the graph edges enabled the coordinated RL to operate in distributed manner and scale to large-scale networks with more than two hundred agents. Naderializadeh et al. [67] proposed a distributed RL algorithm for resource management and interference mitigation in wireless networks. In this framework, agents were able to make decisions simultaneously in a distributed manner and the DNN structure did not vary with the actual size of the wireless network, which made the algorithm scalable to large-scale networks. In addition, safety issues are also an important factor that has limited the real-world deployment of RL methods for network optimization. The primary source of unsafety in RL methods can be imputed to the agent;s exploration, resulting in undesired network performance degradation. Vannella et al. [68] formulated the remote electrical tilt (RET) optimization problem in the safe reinforcement learning (SRL) framework. The SRL aimed at solving RL problems in which a minimum performance level must be guaranteed during learning and deployment and thus undesired network performance degradation was avoided.

In order to address the curse-of-dimensionality, hybrid approaches, known as fuzzy reinforcement learning (FRL) framework, that combine Fuzzy Logic (FL) and RL have also been developed [69]-[73]. The fundamental idea is to address the curse-of-dimensionality by utilizing FL to encode a threshold-based discrete state space and then utilize it in RL algorithms. Razavi et al. [69] proposed an FRL method in which an FL module models the intrinsic uncertainty of the states in cellular networks, and then uses a Q-learning approach based on this encoded state. In [70], the author proposed a fuzzy Q-Learning (FQL) algorithm for self-optimization of the tilt angle in an LTE network scenario, which can operate in a fully distributed, asynchronous and autonomous fashion without any need for a priori information for the network conditions or any human interventions. Fan et al. [71] used a fuzzy neural network architecture in a cooperative Q-learning approach to execute the joint optimization of sector-edge and sector-center performance indicators. Sparse sampling is another technique that can handle the-curse-of-dimensionality problem. Thampi et al. [72] applied a reinforcement learning approach for the coverage self-optimization through antenna tilting and used sparse sampling algorithm to handle the the-curse-of-dimensionality problem. It has the ability to adapt to network environments without prior knowledge, handle large state spaces, perform self-healing and potentially focus on multiple coverage problems in LTE networks. In addition, Balevi et al. [73] designed a multi-agent RL framework to transform the weighted sum-rate optimization problem into a markov decision process (MDP). The two-step deep RL algorithm first aggregates inter-cell interference through mean-field theory to tackle the curse of dimensionality problem and then applies Q-learning with linear function approximation to utilize the single agent features.

The main disadvantage of learning-based solutions is the large number of iterations and measurement data, which keeps increasing with the size of the network. Besides, there is usually no convergence guarantee if they are applied to multi-agent systems. Generally, parameters must be set very precisely and are often based on an application, which means they must be customized for each system. Furthermore, theoretically, the more knowledge of the system is effectively utilized, the better the performance of the corresponding method will be. Therefore, the solution quality of learning-based methods is usually inferior to that of optimization-based methods.

3. Meta-heuristic methods

Meta-heuristic methods mainly include, genetic algorithm (GA) [74]-[78], particle swarm optimization (PSO) [79]-[81], simulated annealing (SA) [82], Tabu search [83], multi-objective evolution algorithm (EA) [84] and ant colony algorithm (ACA) [85], [86].

Yoon et al. [74] proposed an efficient GA based on quotient space property of their optimization problem to maximize the coverage deployment in wireless sensor networks. Yin et al. [75] solved the outage compensation problem by continually optimizing the antenna tilt based on GA to reduce the coverage holes. Liu et al. [76]

took the geometric distribution of the candidate sites into consideration and proposed a geometry-induced GA to efficiently maximize the cellular system coverage. Lakshminarasimman et al. [77] introduced a modified non-dominated sorting GA to solve various parameters of cellular base station placement problem such as site coordinates, transmitting powers, heights, and antenna tilts. Zhang et al. [78] proposed a hybrid two-layer optimization framework to enhance the network capacity and coverage and the genetic programming (GP) approach was exploited for the eNB operation at small time granularity.

Sousa et al. [79] implemented a PSO algorithm to optimize areas of low coverage and high interference simultaneously, through the adjustment of the antenna tilts and/or antenna orientation. Huang et al. [80] modified the PSO algorithm by employing a heuristic power control scheme to guide the algorithm to search for the global optimal solution. Qin et al. [81] investigated the metric structure of quotient subspace of the solution space and further proposed the metric-guided PSO for the cellular coverage problem.

The authors of [82] optimized the antenna tilt and azimuth network-wise, with the objective of minimizing the CPICH power consumption by simulated annealing algorithm. Hurley et al. [83] introduced a mathematical model for the automated design of fixed wireless access networks through the automatic selection and configuration of base station sites, and adopted the Tabu search method to generate the fixed wireless access network infrastructure design. Mai et al. [84] proposed a BS planning model based on TD-LTE system and designed a evolutionary algorithm with local search to solve this model. The model aimed at reducing the co-channel interference, expanding network capacity, and saving the network construction cost at the same time. Rui et al. [85] utilized ACA to find the optimal pilot power of each small cell to obtain the optimal coverage. Bo et al. [86] applied an ant colony optimizing algorithm for balancing the network load based on the ground user density by adjusting the handover parameters.

In all of these methods, the solution space is searched extensively in a fixed or stochastic manner in order to find the optimal or near-optimal solution. As a result, they are difficult to adapt to large-scale network parameter optimization and lack performance guarantees.

VI. IRS Empowered Performance Optimization

We now turn to a frontier technology called intelligent reflecting surface (IRS) that has brought a completely new perspective on how to improve the performance of wireless systems. Rather than optimizing the network infrastructure (including base stations, remote radio heads, and user terminals, etc.), IRS aims to improve the wireless environment. By manipulating the phase shift between the incident signal and the reflected signal on each reflective element of IRS, we can render the multipath propagations add up constructively at the target receiver, thereby augmenting the signal-to-noise ratio (SNR).

Clearly, in the IRS configuration, the key event of interest is *passive beamforming*, i.e., how to coordinate phase shifts across the reflective elements in order to achieve the signal focusing effect at the destination. For ease of discussion, let us restrict our attention to a single-input single-ouput (SISO) setup with an IRS comprising N reflective elements. We use $h_0 \in \mathbb{C}$ to denote the direct channel from the transmitter to the receiver, $h_n \in \mathbb{C}$ the reflected channel induced by the nth reflective element, $\theta_n \in [0, 2\pi)$ the phase shift of the nth reflective element, Z the additive white Gaussian noise at the receiver. The relationship between the transmit signal $X \in \mathbb{C}$ and the receive signal $Y \in \mathbb{C}$ is given by

$$Y = h_0 X + \sum_{n=1}^{N} h_n e^{j\theta_n} X + Z. \tag{9}$$

The SNR boosting goal can now be characterized as maximizing the following objective function $f(\cdot)$ over the passive beamforming vector $\boldsymbol{\theta} := (\theta_1, \ldots, \theta_N)$:

$$f(\boldsymbol{\theta}) = \frac{\mathbb{E}[|Y - Z|^2]}{\mathbb{E}[|Z|^2]} = \left| h_0 + \sum_{n=1}^{N} h_n e^{j\theta_n} \right|^2. \tag{10}$$

Inspection of $f(\boldsymbol{\theta})$ shows that the optimal strategy is to align each $h_n e^{j\theta_n}$ with h_0 by setting $\theta_n^\star = \angle h_0 - \angle h_n$, where $\angle \cdot$ represents the phase of a complex number. Nevertheless, the practical implementation of passive beamforming poses two significant challenges. First is the discrete constraint on θ_n as elaborated in Section VI-1; second is channel acquisition as elaborated in Section VI-2.

1. Passive beamforming for IRS with CSI

As compared to the other wireless devices, IRS bears a distinguishing feature that it does not generate any new signals but rather modifies the incident ones. Such feature has triggered a wave of research interest in incorporating the passive trait of IRS into the conventional beamforming paradigm. Although the link-level beamforming problem can be readily solved as stated under (2), a general system-level beamforming in the presence of multiple users is much more difficult to tackle because of nonconvexity. Among a variety of sophisticated mathematical tools developed for passive beamforming, semidefinite relaxation (SDR) [87] and fractional programming

(FP) [88], [89] have been most extensively applied in the literature to date. For instance, the authors of [90]-[96] find SDR particularly useful because the passive beamforming problem can be rewritten as a quadratic program, while the fractional structure of the passive beamforming problem (due to the ratio terms such as SNR or SINR) motivates the use of FP in [97]-[104]. Other nonconvex optimization approaches for passive beamforming include successive convex approximation (SCA) [105], [106], alternating direction method of multipliers (ADMM) [94], [107], minorization-maximization (MM) [108]-[110].

So far we treat the passive beamforming for IRS as a continuous problem wherein each phase shift θ_n can be arbitrarily chosen in $[0, 2\pi)$. However, this is not the case in the real world. On the contrary, the prototype realizations of IRS [111]-[116] typically limit the phase shift choices to a small set Φ_K with K discrete values, i.e.,

$$\Phi_K = \{\omega, 2\omega, \ldots, K\omega\}, \tag{11}$$

where

$$\omega = \frac{2\pi}{K}. \tag{12}$$

There are three reasons for the above restriction. First, the hardware cost increases with the number of phase shift choices. Second, the real-time configuration is difficult for continuous beamforming. Third, the reflection loss becomes higher when more PIN diodes are integrated into each reflective element for the continuous beamforming purpose. This discrete constraint on $\boldsymbol{\theta}$, however, results in a huge challenge in optimizing phase shifts. Because of the wide belief that the discrete IRS beamforming problem is NP-hard, those works aimed at the global optimum resort to the exponential-time algorithms such as the exhaustive search [107] and the branch-bound method [108], [109]. But the recent work [110] shows a somewhat surprising result that the binary beamforming problem of the single-user case can be globally solved in linear time.

In the existing literature [111]-[114], [118]-[120], a popular approach is to first relax the discrete beamforming problem as the continuous and then round the solution to the closest point in the discrete set Φ_K, but the resulting error is difficult to analyze. Another approach is to optimize one phase shift θ_n at a time while holding the rest phase shifts fixed [121], [125], [127], namely block coordinate descent. A penalty term is added to the relaxed problem in [126] to enforce the discrete constraint. Moreover, [120] not only shows that SDR works for discrete beamforming, but also develops a novel approximation algorithm called APX with a strictly better performance guarantee than SDR and the aforementioned closest point projection (CPP) method, as illustrated in Fig. 6.

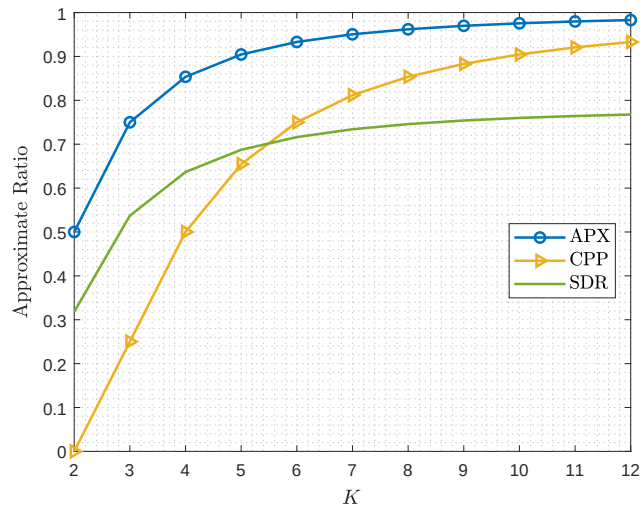

Fig. 6 The approximation ratios, i.e., $\frac{achieved\ SNR\ boost}{global\ optimal\ SNR\ boost}$, of the different algorithms when there are K phase shift choices for each reflective element.

2. Passive beamforming for IRS without CSI

The above algorithms, either for continuous beamforming or for discrete beamforming, all heavily depend upon CSI, so channel acquisition in IRS-aided systems has attracted considerable research interests over the past few years. We are mainly faced with the following challenges in this area:

1. Each reflected channel h_n alone can be much weaker than the direct channel h_0, so h_n is difficult to estimate accurately.

2. It requires the access to the in-phase and quadrature components stored in the communication chip, but this is not supported by the current 5G protocol.

3. The channel estimation for the cascaded channels enhances the time complexity and the overhead cost of passive beamforming.

The prior studies mostly concentrate on challenge #1. An early work [108] suggests estimating one single h_n at a time, assuming that the rest reflective elements are OFF and could absorb their incident signals; the more recent works [131], [132] further develop this ON-OFF policy by estimating a group of h_n's simultaneously in order to address the weak reflection issue as noted earlier. The state-of-the-art estimation method is based on the discrete Fourier transform (DFT) matrix [118], [122], [133], [134]. The main idea is to generate a pilot sequence by setting the beamforming vector to each row of the DFT matrix; in particular, [128] shows that the Cramér-Rao lower bound can be achieved for the least-squares estimation. Moreover, a line of studies [104], [117], [119], [125]

examine the channel estimation task from a compressed sensing perspective, aiming to find a sparse representation of the cascaded channels. Notice that none of the above methods accounts for challenges #2 and #3. To the best of our knowledge, not any channel estimation methods have been implemented in a real-world 5G network.

Because of the aforementioned bottlenecks in channel acquisition, the area of IRS has branched out to a new front wherein passive beamforming is performed without any channel information. For instance, [87], [88] suggest a random rotation strategy that does not require instantaneous CSI. There is also a deep learning based approach. In contrast to [111], [117] that apply the deep neural network to channel estimation and [135]-[137], [143] that apply the deep neural network to the IRS configuration given CSI, the recent work [138] proposes using the deep neural network to learn the direct mapping from the received pilot signal to the passive beamforming solution, thus sidestepping the channel estimations stage. Moreover, a cluster of works [89],[130]-[141] are based on beam training, the main idea of which is to sweep all possible directions of the reflected beam. However, the beam training method is limited to the millimeter/terahertz frequency bands with sharp beams.

Alternatively, we could exploit the statistics of received signal. The so-called RFocus method in [142] aims to decide the ON-OFF state of each reflective element; it simply tries out different ON-OFF combinations and then chooses the state for each reflective element according to the average performance. This statistical approach is further developed in [112] to account for the discrete phase shift $\theta_n \in \Phi_K$. Specifically, we first generate T random samples of $\boldsymbol{\theta}(t)$ over the discrete set Φ_K, where the sample index $t = 1, \ldots, T$, and then measure the corresponding received signal power $|Y(t)|^2$ with respect to each $\boldsymbol{\theta}(t)$. Furthermore, consider a subset $Q_{nk} \subseteq \{1, \ldots, T\}$ for each reflective element n and each phase shift option k, which comprises the indices of all those random trials with the nth phase shift chosen to be $k\omega$, i.e.,

$$\mathcal{Q}_{nk} = \{t : \theta_n(t) = k\omega\}. \tag{13}$$

We now compute the conditional sample mean of the received signal power within the above subset:

$$\widehat{\mathbb{E}}[|Y|^2|\theta_n = k\omega] = \frac{1}{|\mathcal{Q}_{nk}|} \sum_{t \in \mathcal{Q}_{nk}} |Y(t)|^2. \tag{14}$$

Intuitively, the conditional sample mean $\widehat{\mathbb{E}}[|Y|^2|\theta_n = k\omega]$ quantifies the average performance of setting $\theta_n = k\omega$, so it is natural to choose each phase shift to maximize the conditional sample mean, i.e.,

$$\theta_n = k_n^\star \omega, \tag{15}$$

where

$$k_n^\star = \arg\max_k \widehat{\mathbb{E}}[|Y|^2|\theta_n = k\omega]. \tag{16}$$

Aside from the theoretical justification that the above method guarantees a quadratic SNR boost in the number of reflective elements, [112] further demonstrates through field tests the practical effectiveness of the above conditional sample mean algorithm.

We conclude this section by remarking the implementation of the proposed conditional sample mean method in practice. The proposed method does not require any assistance or collaboration from the base station side, so it works in a plug-and-play fashion. The random sampling in (9) can be performed by using one or more sensor devices to measure the received signal quality in the vicinity of the target user terminal(s). Notice that the sensors used in our method are much simpler and cheaper than most user terminals because they only measure the received signal power, not even requiring the phase information. After receiving the random sample data from the sensors, the IRS then locally decides the passive beamforming vector according to (10) and (11), which, according to the field test in [112], takes merely a few seconds in total.

VII. Conclusions

This paper has reviewed state-of-the-art mathematical and learning based methods for performance modeling and optimization of real-world wireless networks. The current cutting-edge techniques from five different perspectives, including channel modeling, user demand and traffic modeling, throughput modeling and prediction, network parameter optimization, and IRS empowered performance optimization, have been elaborated. With the principles and properties of different methods explained and illustrated, we hope that this paper will facilitate the suitable choice of methods for further research on performance modeling and optimization of future wireless networks involving advanced techniques such as IRS.

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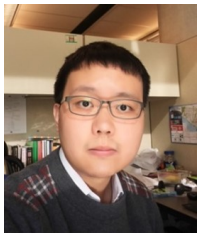

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