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A Review of Deep Learning in 5G Research: Channel Coding, Massive MIMO, Multiple Access, Resource Allocation, and Network Security

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ABSTRACT The current development of 5G technology is flourishing with widespread deployment across the world at a rapid pace. However, there is still a demand concerning 5G research for service and performance improvement. Research tasks include but are not limited to quality-of-service (QoS), energy efficiency, massive connectivity, reliable communications, and security. Due to the advancement of deep learning, numerous such research has utilized this technique. This article provides a comprehensive review of 5G communications research using deep learning. Specifically, we address the issues of low-density parity-check (LDPC) coding, massive multiple-input multiple-output (MIMO), non-orthogonal multiple access (NOMA), resource allocation, and security.

INDEX TERMS Deep learning (DL), machine learning (ML), fifth generation (5G), massive multiple-input multiple-output (MIMO), low-density parity-check coding (LDPC), non-orthogonal multiple access (NOMA), resource allocation, security.

I. INTRODUCTION

WIRELESS technology and communications have evolved drastically throughout the years. Wireless cellular technology began with the first generation mobile voice-system in the early 1980s, and in roughly four decades we are headed into the fifth generation of technology, 5G. Originally, the focus was on the basics of mobile voice calls, then short message service (SMS), Web browsing, video consumption, and high-speed data. In 2020 we are pushing the limits to achieve all previously mentioned along with lower latency, higher capacity, and increased bandwidth compared to the fourth generation technology, 4G. The world's connectivity needs continue to advance and, to sustain the consumption of consumers, wireless cellular technology introduces 5G. The implementation of 5G has begun and anticipated explosive growth in data traffic will bring about great challenges worldwide.

5G network performance is measured by three essential components: enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (uRLLC), and massive machine-to-machine communication (mMTC). With the arrival of 5G come emerging applications such as device-to-device (D2D) communications, machine-to-machine (M2M) communications, Internet of Things (IoT), Internet of Vehicles (IoV), healthcare and wearable technology, as well as smart grids, homes, cities and financial technologies [1]. 5G will revolutionize the way we live today and the deployment of 5G is already in progress. Although 5G networks have been implemented in select locations by various telecommunications operators, there are caveats such as massive multiple-input multiple-output (MIMO), low-density parity-check (LDPC) coding, and non-orthogonal multiple access (NOMA) communications require further study.

Deep learning (DL) techniques are being used to advance and enable the full potential of 5G. The impact of deep learning began to boom in the early 2000s, but it was not until recently did the utilization of deep learning become more prevalent. Deep learning can process, create, and provide an advanced analysis on nearly any task it is given with concise and reliable results. It has state-of-the-art performance and some of its outstanding successes include automatic speech recognition, image classification, and the detection of various objects. Deep learning is used in a myriad of domains including wireless systems and 5G with faster, more consistent, more reliable results and by easy to configure means.

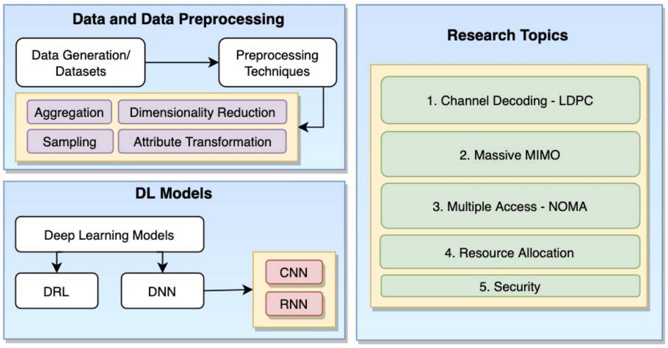

FIGURE 1. 5G research using deep learning.

Unlike other survey papers [1]–[5], this article combines both 5G wireless communication and deep learning to analyze the different challenges that 5G entails. Related survey papers discuss the vision of 5G wireless networks along with its features [1], security/privacy of 5G technologies [2], the artificial neural networks [3], and the machine learning techniques used in wireless communication [4]. The paper most prevalent to ours is [5] due to its providing a broad overview of deep learning techniques in mobile networks. This article presents new research results in the following five topics areas specifically in 5G: massive MIMO, LDPC coding, NOMA communications, resource allocation, and security. Notice that the topics of massive MIMO such as mmWave blockage prediction [6], [7] and NOMA such as power allocation spectral or energy efficiency [8] and system capacity [9] are also extremely prevalent in beyond-5G (B5G)/6G wireless communications networks. B5G/6G also includes key technologies such as reconfigurable intelligent surfaces (RIS) [10], [11], Terahertz (THz) communications [11], [12] and unmanned aerial vehicle networks (UAV) [13], [14] that can utilize DL. Figure 1 illustrates the contents and structure of the 5G research presented in this article.

The remainder of this article is organized as follows. Section II will cover the various datasets and data preprocessing methods. Section III discusses deep learning models used in 5G research. Sections IV–VIII presents the research and different challenges in 5G and how deep learning can help. The 5G research topics will be discussed in the following order: LDPC, massive MIMO, NOMA, resource allocation, and security. Section IX will provide a brief discussion of the application of DL in other key B5G technologies. The paper concludes with Section X.

II. DATA AND DATA PREPROCESSING

A. DATA

Being as 5G is still an evolving technology, the datasets available for experimentation are limited. There exist datasets such as ViWi [15], Raymobtime [16] and DeepMIMO [17] or datasets provided for AI challenges such as ITU AI/ML in 5G. However, most of the data used in the literature surveyed in this article are either self-generated through experiments or using tools such as MATLAB and TensorFlow. Security research has the most available datasets such as the Benchmark Aegean Wi-Fi Intrusion dataset [18], CTU dataset [19], NSL-KDD dataset [20], and the WSN-DS dataset [21]. Although security has available data sets, these datasets are not niched to 5G. Nonetheless, these datasets provide a more uniform understanding of the widespread study of security that can be applicable for 5G as well.

B. PREPROCESSING

Data preprocessing is a data mining technique that takes place to transform raw data into a state that the DL model requires to easily parse and learn. The most commonly used preprocessing method is the resizing or reformatting of data. As previously mentioned, security has available datasets that researchers use; however not everything in the dataset will be important to the researcher so they will preprocess and select what they want through different means. For example, [22] will need to extract the data in a CSV file format and then reshaped into RGB images of size 100 x 100 x 3 for the convolutional neural network (CNN) with any excess data discarded. Data that [18] is using will consist of both numerical and nominal values so different types of encoding or normalization steps, such as a conversion to 16-bit integer form, are necessary to make the data coherent for the DL model. Similarly, [20] will convert their data into the right value; given a dataset with numeric and non-numerical values, all non-numerical values will be converted to a binary vector that will be appended to create a 12 x 12 matrix for the CNN model. Both Rezvy *et al.* and Zhu *et al.* also use a logarithmic scaling method for reducing the scaling scope and conduct detailed statistical analysis to monitor minimum and maximum values for each feature.

In areas like NOMA, LDPC, resource allocation, and massive MIMO, data was self-generated so less preprocessing is used because they specify what they collect during the experiments. Nonetheless, researchers like Jin, Ni, Wang, Liao, and Henarejos still had minor tweaks made to their data before inputting them in the DL model. References [23], [24] and [25] studied channel decoding, specifically LDPC decoding, and their methods were the division of blocks of N bit sequences into segments with a segment length of 4 bits, constellation demapping followed by the conversion into log-likelihood bits, and the addition of bits before the receiver receives different codewords to create their unique indicator section respectively. References [26] and [27] both combined the real and imaginary parts of the channel matrix into a larger matrix for massive MIMO and reshaped the matrix to their specific needs.

There is a multitude of ways to transform data but a few techniques are aggregation, dimensionality reduction, sampling, and attribute transformation. If data is unclean (i.e., containing duplicates, outliers, missing attributes, or incorrect data) the quality of the results will be degraded. Regardless of what technique is used, data preprocessing is crucial because it has a direct impact on the success rate of the DL model.

III. DEEP LEARNING MODELS

Deep learning, a subset of machine learning (ML), utilizes supervised, unsupervised, and reinforcement learning via neural networks. It facilitates decision making and the classification of data using various algorithms to obtain high accuracy and in-depth results with little to no human supervision. Machine learning algorithms are designed to learn by understanding labeled data and then used to produce outputs; however, if the output is not desirable, it requires human intervention. On the other hand, DL algorithms do not require human interaction because the nested layers will process the data through hierarchies and learn distinct features while learning from its errors. DL will require a substantially larger set of data than ML thus requiring high computational capacity. Industries ranging from transportation to medicine are utilizing deep learning applications. From automated driving by using deep learning for object and pedestrian detection to medical research for the detection of cell abnormalities, the growth of deep learning has just begun.

The neural network architecture resembles the perception process in a human brain. A specific set of units are activated given the current environment, influencing the output of the neural network model and its goal to approximate complex functions through a configuration of simple and predefined operations of units (or neurons) [5]. Neural networks are organized into layers that utilize feed-forward or back-propagation to indicate the direction of data flow. A node will assign a value known as weight and as data flows through the node, the value will be multiplied by the associated weight thus producing multiple different values. Data will travel from the input layer through the hidden layer(s) and finally the output layer.

An important aspect of neural networks is the activation function, which allows the network to learn complex patterns in the data. Some of the different types of activation functions include but are not limited to Rectified Linear Unit (ReLu), Sigmoid, Tanh, Softmax and Leaky ReLu. The most commonly used activation function is ReLu due to its computational efficiency. If the value is below a specified threshold value, it will not pass any data to the following layer. If the value is above the threshold value, that value, or sum of weighted inputs will be assigned to the next layer. Since the range of ReLu is bounded from 0 to infinity, there exists a dilemma. The issue with ReLu is that all the negative values immediately become zero which decreases the model's ability to fit or train the data properly. Leaky ReLu attempts to fix the problem by altering the range to be from negative infinity to infinity and providing a negative slope of 0.01 for values below the threshold; however, the results provided by Leaky ReLu are not consistent for negative input values. The Sigmoid activation function is bounded between 0 and 1, thus normalizing the output and providing a smooth gradient; however, it is computationally expensive and has a vanishing gradient problem. The Tanh activation function is similar to the Sigmoid function with the additional benefit of being zero centered. The Softmax function is unique because, unlike other activation functions, it is able to handle multiple classes.

With the emergence of 5G communications and all it entails, deep learning can prove to be an extremely powerful tool in solving its challenges including the encoding and decoding of LDPC coding, power control in massive MIMO, power-based and code-based NOMA, resource allocation, and security. The most commonly used models for 5G research are deep reinforcement learning (DRL), deep neural network (DNN), convolutional neural network, and long short-term memory (LSTM).

A. DRL

Deep reinforcement learning follows the idea of learning by interacting. Reinforcement learning learns not by being told what actions to take but by discovering for itself which actions produce the greatest reward through a simple trial and error concept. There are two core components in a reinforcement learning framework: the agent and the environment. It is commonly seen in AI games such as AlphaGo, chess, and TORCS. DRL incorporates the concepts in RL and DNN so the agents are self-sufficient; since DRL replaces tabular methods of estimating state values with function approximation, it permits the agent to generalize the value of states it has yet to encounter.

In 5G, DRL frameworks are generally used in resource allocation since resource allocation focuses on resource optimization. Abiko *et al.* [28] and Yu *et al.* [29] utilized a DRL network slicing architecture to accommodate diverse Quality-of-Service (QoS) requirements in 5th generation cellular networks, rationally allocating resources to minimize energy usage of the remote radio heads (RRHs). Since the state of the radio access network changes from moment to moment and automatic control of network slicing is necessary to respond to service requirements in real-time, [28] proposes using DRL to design state, action and reward to allocate resource block (RB). The agent estimates the optimal RB amount for the state using the information in the slice as the state and controls the RB allocation to satisfy the slice requirements as an action. The reward is the slice requirement satisfaction with the intent of maximizing the percentage of user equipment per slice. Although [29] aims to minimize the energy usage of RRHs, its motivation is for TV multimedia service and broadband media forms.

5G antennas consume three times more energy on average than a 4G antenna and utilizing DRL to design a computation offloading and resource allocation strategy could assist in minimizing system energy consumption while still delivering high throughput to its multiple users [30]. Regardless of the motivations, a DRL framework is commonly applied in the area of resource allocation.

B. DEEP NEURAL NETWORKS

Artificial neural network (ANN) is the overarching canopy that encompasses any deep learning model. ANNs can be shallow, containing only one hidden layer, or deep, more than one hidden layer - better known as deep neural network. DNNs are highly popular and successful in research due to their excellent performance in benchmark problems and applications. The simplest type of ANN is feed-forward neural network (FNN) where the data travels in one simple direction when there is more than one hidden layer, it becomes a deep feed forward (DFF). Some more specific types of DNNs are convolutional neural network and recurrent neural network (RNN).

1) CONVOLUTIONAL NEURAL NETWORK - CNN

CNNs use images and videos since CNNs are applied in image classification, computer vision, and mainly for finding characteristics or patterns in images by using filters. The basic structure of a CNN is composed of three types of layers: convolutional layer, pooling layer, and fully connected layer. The convolutional layer is to extract high-level features through the means of a filter. A filter is a defined $N \, x \, M$ grid of numbers that are multiplied with the number representing the pixel value of the original image. Filters are applied throughout an image or images in a video to extract dominant features and reduce data redundancy using a pooling layer. The pooling layer will compress the extracted important characteristics into one image to be processed in the next layer that could for instance be a multilayer perception (MLP), convolutional layer. It will use a max-pooling or average pooling layer in an attempt to reduce the spatial size and decrease the computational power required to process the data. The fully connected layer will learn non-linear combinations of the high-level features and flatten the image into a column vector and used as an input for training and future iterations. There is also a dropout layer, which is a regularization technique used to reduce over-fitting. Typically, a dropout layer is used on the fully connected layers, but is also possible to use dropout after the max-pooling layers, creating image noise augmentation.

In 5G, CNN is the most popular and diversely used DNN; it is used when studying LDPC coding, massive MIMO, resource allocation, and security. In 5G security, CNN was used to detect network anomalies and compared to see if it will outperform previously used machine learning methods such as Näive Bayes, Random Forest, Random Tree, and SVM [20] so software-defined security can be applied to an intrusion detection system to create a more flexible, scalable, portable and end-to-end defense for a 5G network [22]. The purpose is for any identified anomalies to be stored with corresponding traffic features for future automated detection and database updates so incoming malicious flows can be properly defined and the system can be protected. Similarly, in LDPC coding, Ni *et al.*, also used CNN for the blind detection and the identification of quasi-cyclic LDPC, and spatially coupled LDPC for cognitive radio or military communications systems. It is an essential decoding interaction for the receiver to be capable of blindly identifying the channel code adopted by the transmitter to reduce extra channel resources [23]. A novel resource allocation method used CNN to optimize channel state information (CSI) was developed in [31] and reported that DL outperforms the traditional resource optimization methods. The idea of optimizing channel resources proves to be fundamental in massive MIMO when [27] utilized a 2D and 3D CNN network to learn the non-linear structural characteristics of the channel, extract the channel feature vectors to compress the data for further use and when [26] used a flexible denoising CNN on a cell-free mmWave massive MIMO system to exploit an accurate estimation of CSI. Vieira *et al.*, specifically utilized CNNs to show that massive MIMO channel measurements can be used to achieve precise positions inference for fingerprint-based inference of user positions by using its sparse channel structure [32]. In addition, [33] and [34] used CNN based models to attempt and solve the non-convex sum rate maximization and sum spectral efficiency optimization problems in massive MIMO. With a deep convolutional neural network consisting of 32 convolution layers, 37 residual layers, average pooling layer, fully connected layer and sigmoid part, [33] is able to determine a mapping from the large scale-fading coefficients and optimal power using the quantized channel. CNN's hierarchical structure and feature extraction capabilities prove to be an exceptionally robust algorithm when dealing with a variety of situations including 5G research.

2) RECURRENT NEURAL NETWORK - RNN

RNNs are different from CNNs and they are generally used for text and speech analysis. RNNs unique characteristic is the ability to learn based on past instances of itself to predict the future. This means that RNN is capable of processing a sequence of inputs so that each data is dependent on the previous one. The disadvantage of RNNs is that they have a gradient vanishing and exploding problem, which introduces long short-term memory networks (LSTM). LSTM specializes in processing and predicting time series time lags of unknown duration using three types of gates: input gate, forget gate, and output gate.

In 5G, LSTM has a diverse reach; it is used when studying massive MIMO, multiple access, resource allocation, and security. Yu *et al.* and Gui *et al.* implemented LSTM for framework purposes in resource allocation and multiple access, specifically NOMA, respectively. In resource allocation, LSTM was used to gain predictions of the best precision and compare that to the performance of several other recent approaches with traffic data obtained from a self-organizing network (SON) entity before the design of a DRL framework to allocate wireless resources for energy-efficient TV broadcast services [29]. Whereas, [35] used the LSTM framework to simulate and evaluate data detection under different channel conditions via offline learning and then used during the online learning process to realize automatic encoding, decoding, and channel detection in an additive white Gaussian noise channel for enhancing system capacity and spectral efficiency in NOMA systems. Similarly, Maimó *et al.*, also used LSTM for data detection, in this

TABLE 1. Summary table of major DL methods.

Category	CNN	RNN	DRL
LDPC	[23]		
Massive MIMO	[26], [27], [32] - [34]	[27]	
NOMA		[35]	
Resource Allocation	[31]	[29]	[28] - [30]
Security	[20], [22]	[19]	

case, for a cyber-defense architecture to identify cyberthreats in 5G mobile networks; hoping to manage traffic fluctuation and optimize computing resources and performance of analysis and detection, LSTM was used for network anomaly detection [19]. Offline learning was used in both NOMA and massive MIMO, and the difference was that massive MIMO used LSTM along with CNN. A Bi-LSTM and Bi-ConvLSTM network was used in the decompression process to recover the original CSI for single-user and multi-users hoping to improve reconstruction quality and feedback accuracy of the CNN compressed structural characteristics of the massive MIMO channel information [27]. LSTM proved to be extremely useful when researchers deal with sequential data and, since LSTM allows the preservation of gradients, it allows one greater flexibility in controlling the desired outcomes.

Table 1 summarizes major DL methods used in 5G research and related references are listed in the table.

IV. CHANNEL DECODING - LDPC

Channel coding introduces redundancy in the transmitted signals to protect the information from channel noise and interference that create unwanted errors. Noise and interference disturb the reliability of digital communication systems and the error-correcting codes applied to control these occurrences are classified into linear block codes (i.e., Hamming codes, Golay codes, BCH codes, and Reed Solomon codes), and convolutional codes. Channel coding can be evaluated based on their signal to noise ratio (SNR) and block error rate (BLER) performance.

In 3G and 4G wireless communication, turbo code, a mix between convolutional and block codes, was implemented given that it is one of the best forward error correction (FEC) codes that perform closest to the Shannon limit and had remarkable power efficiency in additive white Gaussian noise (AWGN) and flat-fading channels for moderately low bit rate error (BER). However, for 5G wireless communication, due to its high throughput and low latency requirements, low-density parity-codes (LDPC) are adopted over turbo codes. Although LDPC codes achieve better performance and faster decoding, it contains a higher encoding complexity than turbo coding and typically requires more iterations than iterative turbo decoding which could lead to higher latency.

Since 5G communications systems have adopted polar codes, specifically LDPC codes, DL has been used to discover methods to blindly identify LDPC codes [23], reduce the decoding delay [25], [36], [37], [38], analyze the trade-off of LDPC codes for channel coding [24], develop error correction codes for nonlinear channels [39] and optimize the decoding algorithm to solve a non-convex minimization problem [40]. As expected, when comparing traditional decoding to DL-based decoding, DL has a greater reward. Since one of the crucial characteristics of 5G network performance is its enhanced mobile broadband (eMBB), it requires reliable control signaling simultaneously with high throughput data transmission. Wang *et al.* [25] implements powerful decoders using DL by concatenating an indicator section to identify coding types and then compared it with the traditional belief propagation-based (BP) decoding algorithm. When the results of BER versus SNR performance were compared, the DNN LDPC decoding scheme outperforms the traditional scheme by 0.8 dB at a BER of 10^{-2}. Thus, the unified 3-layer DNN LDPC decoder with a rectified linear unit (ReLU) activation function in the hidden layers, a sigmoid activation function in the output layer, and MSE loss function was able to provide similar BER performance against traditional belief propagation methods while achieving a significant improvement for throughput [25]. The issue of greatest concern is the high decoding complexity and delay that accompanies LDPC codes, which prompts [36] to use a scheme that parallels multiple neural networks that incorporate both the forward and backward propagation of polar codes to reduce the overall time complexity of decoding. Its DNN structure contains three hidden layers, in which each hidden layer has 256 nodes, input and output layers with 16 nodes, a ReLU activation function, and mean square error (MSE) loss function. With its proposed DNN structure of parallel multiple neural networks, the time complexity of the proposed scheme is $O(N) + O(h+1)$, where N is the inner code length and h is the number of layers in the DNN, which is lower than the traditional time complexity of $O(N) + O(n(\log_2 n))$, where n is the code length of the polar codes.

Literature [37] and [38], unlike [25] and [36], utilizes a low-complexity BP-based decoding method. Reference [37] relies on its early stopping prediction stage and decodability detection stage to eliminate the unnecessary decoding operations that increase the complexity of LDPC decoding for polar codes; it successfully achieves a 71% decoding delay reduction while maintaining the same decoding performance as traditional schemes. Reference [38] studies the min-sum algorithm decoding approach and proposes both a neural normalized min-sum network (NNMS) and a shared neural normalized min-sum network (SNNMS). The latter network is used to reduce the number of correction factors while also making use of the advantages of model-driven DL methods. Experimental results show that the BER performance of the proposed NNMS decoder uses fewer iterations and is 1.5 dB better than the conventional LDPC decoder. Furthermore, the proposed SNNMS decoder outperforms the proposed NNMS decoder by up to 0.4 dB with a lower and computational complexity. Table 2 summaries a number of LDPC research tasks using DL methods.

TABLE 2. Summary table of LDPC research using deep learning.

Research Tasks	DL Method	Performance and Observations	References
• Blind LDPC code identification	• CNN	• Identification accuracy at SNR=2dB and code sequence length N=100: – QC-LDPC: 99.07% & SC-LDPC: 98.75% • Identification accuracy at SNR=0dB and N=100: – QC-LDPC: 85.00% & SC-LDPC: 93.48%	[23]
• Optimization-based decoding algorithm for hardware architectures	• FNN	• Impressive improvement in BER performance • Control trade-off between decoding complexity and decoding performance	[40]
• Comparison of traditional decoding to DL based decoding	• ANN • DNN	• Lower BER compared to traditional demapping and decoding implementations • Saves significant implementation resources	[24], [25]
• Decoding of both polar and LDPC • Decoding delay and complexity reduction	• DNN	• Reduces time complexity • Block error rate performance is the same compared with traditional methods. • Achieves 71% decoding delay reduction while maintaining the same decoding performance as traditional methods • Shared neural normalized min-sum decoding network has lower complexity compared with a basic neural normalized min-sum decoder	[25], [36], [37], [38]
• Developing error correction codes for nonlinear channels	• ANN	• Large spectral efficiency gain • Higher-order modulation formats are operable for one-bit receivers	[39]

V. MASSIVE MIMO

Massive MIMO, an extension of MIMO, expands by adding a much larger number of antennas at the base station. Before massive MIMO, MIMO uses multiple antennas at the transmitter and receiver sides to send and receive signals by exploiting multipath propagation. As one would assume, 4G wireless communication utilized MIMO but with the huge increase in data usage that 5G will bring, emerges massive MIMO. The massive number of antennas helps focus on energy, which brings drastic improvements in throughput and efficiency due to its more responsive behavior towards devices transmitting in higher frequency bands. It will also make the 5G network more resilient against interference and jamming that the current network experiences. As expected, there are challenges with massive MIMO such as finding new deployment scenarios, reducing internal power consumption to achieve total energy reductions, the acquisition and synchronization for all the newly joined terminals, and the exploitation of the extra degrees of freedom provided by the massive number of antennas.

DL has been utilized to improve localization [32], [41], solve the non-convex optimization problem in power control [33], [34], and exploit CSI feedback [26], [27], [31], [42] for an accurate estimation of channel and direction of arrivals (DOA) estimation. The most prevalent DL architecture used in massive MIMO is DNN and CNN in both localization and CSI. In wireless communication, CSI is extremely important because the channel properties in a communications link provide information on how a signal propagates. This information can then be used for channel estimation which is required to compensate for any distortion. The concept of optimizing channel resources was studied in [27] when it utilized a 2D and 3D CNN network with a ReLU activation function to learn the non-linear structural characteristics of the channel, extract the channel feature vectors to compress the data for further use and when [26] used a flexible denoising convolutional neural network on a cell-free mmWave massive MIMO system to exploit an accurate estimation of CSI. Liao *et al.* [27] implemented a Bi-LSTM and Bi-ConvLSTM network in the decompression process to recover the original CSI for single-user and multi-users hoping to improve reconstruction quality and feedback accuracy of the CNN compressed structural characteristics of the massive MIMO channel. Both 2D and 3D were used but for separate cases; 2D was for the single-user case and 3D was for the multi-user case. Once the data was filtered and feature vectors were extracted with the 2D and 3D CNN, it was compressed through the 2D and 3D max-pooling networks respectively so the data would be 1/4 the original and reshaped into a one-dimensional vector [27]. This compressed information would then be fed through the Bi-LSTM and Bi-ConvLSTM networks for CSI prediction. Similarly, Jin *et al.* [26] also use a ReLU activation function with a combination of two other operations being convolution and batch normalization to create his flexible denoising CNN with zero paddings after each layer.

mmWave is a major aspect of the 5G wireless network and represents the wave spectrum between 30 GHz and 300 GHz. Jin and Huang *et al.* both studied a combination of a mmWave massive MIMO system using DL methods like CNN and DNN to reduce hardware complexity, reduce energy consumption [42] and exploit accurate estimation of channel state information [26]. Unlike Jin, Huang *et al.* focused on a mmWave massive MIMO framework for effective hybrid precoding using a DNN. The DNN is comprised of a fully connected layer with 128 units followed by two hidden layers that are fully connected layers but with 400 and 256 units respectively. Following is a noise layer to disturb the signals with AWGN or other mixing distortions and the last two hidden layers contain 128 and 64 units respectively followed by an output layer. Each hidden layer and input layer contained a ReLU activation function [42]. Both [26] and [42] had great success with their mmWave massive MIMO system. As determined by the normalized mean square error (NMSE) performance, the flexible denoising CNN outperforms conventional estimation methods and has a larger noise perception range than a conventional denoising CNN. The only downfall is the normalized mean square error (NSME) performance against the number of iterations; the denoising CNN does better than the flexible denoising CNN but with only a 1 dB gap between the two schemes until they converge within 150 iterations [26]. As determined by the spectrum efficiency performance, the DL-based hybrid precoding scheme outperforms other methods due to the phenomenal mapping, structural information, and learning capability of DL and that also implies that the proposed mmWave massive MIMO strategy will solve the existing non-convex optimization in hybrid precoding [42].

When researching the application of deep learning on power control for massive MIMO systems, [33] solved the non-convex sum rate maximization problem on four different power control schemes to determine the best channel statistics to convert the power allocation problem into a standard geometric program using a deep convolutional neural network and [34] analyzes the sum spectral efficiency optimization problem in multi-cell massive MIMO systems using CNN. The deep convolutional neural network shows less than 0.02% loss when comparing the training sets to the test sets and the loss decreases as the total number of training sets increase. The DL-models attain the same or better performance compared to when solving these problems using basic optimization theory. Likewise, the CNN model in [34] shows results that the joint pilot and data power optimization obtains 30% higher sum spectral efficiency with less than 1% loss in a symmetric multi-cell system serving 90 users. Each literature demonstrates the feasibility of using deep learning for real-time power control in massive MIMO.

Although we have only gone in depth about power control and channel estimation [43] regarding massive MIMO, other research topics exists like beamforming [44], specifically beam selection [16], [45], [46] and beam prediction [44], [45], [47], [48] along with blockage prediction [6], [7], [47], [48], [49], [50] and power prediction [51] in mmWave massive MIMO. DL can be applied to many areas of massive MIMO to target various challenges so 5G can provide an increased network capacity, improved coverage, and better overall user experience. Table 3 summaries various massive MIMO research tasks using DL methods.

VI. MULTIPLE ACCESS - NOMA

In cellular communication, it is required to have a mechanism that provides communications services to multiple users at the same time. Throughout the years, there have been several multiple access schemes being used such as frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA), and orthogonal frequency division multiple access (OFDMA). In 4G wireless communication, OFDMA and single carrier FDMA (SC-FDMA) were ideal in the downlink and uplink for high-speed data transmission because it provides resilience against narrowband fading.

With 5G, wireless networks will be heavily congested with an explosive amount of data traffic that accompanies the increasing number of users and non-orthogonal multiple access (NOMA) can exploit the existing resources in a more efficient basis than conventional multiple access techniques to effectively support services for the congestion of data traffic and users. In NOMA, there are two types of training: offline training, where the channel state information (CSI) of different environments is collected from simulations and arbitrary sequences of the input are extensively trained and online training, where the input signal is trained with the CSI in real-time with the help of the data being carried by pilot signals. As [54] states, "*In NOMA, a multiuser signal is multiplexed using superposition coding in the transmitter and then sent to the users using different power levels in a non-orthogonal basis*." This means that when a signal is received, the user with the stronger channel gain will retrieve it immediately and the user with the weaker channel will recognize other signals as interference and perform successive interference cancellation (SIC) to retrieve its original signal. Before NOMA, orthogonal multiple access systems would use guard periods to avoid interference which decreases spectral efficiency. NOMA operates on the principle of sharing time-frequency resources between users by separating them in another domain with two regimes [55]: power-based and code-based [56], [57].

DL can be applied in enhancing the system capacity and spectral efficiency [35], reliability, and connectivity [52], [58], while also reducing overall latency [59], [60] in NOMA systems to offer the best quality of service (QoS) to all the users [61]. For example, when it comes to enhancing spectral efficiency and system capacity, Gui *et al.*, utilized a LSTM network consisting of 8 layers, 6 of which are hidden layers like dense and noise layers processed by the ReLU function to carry out training and recognition, to simulate and evaluate data detection under different channel conditions via offline learning and then used during the online learning process to realize automatic encoding, decoding, and channel detection in an additive white Gaussian noise channel [35]. This LSTM-aided NOMA scheme achieved an area under the curve (AUC) of 0.98 indicating that it has a good performance in terms of robustness and accuracy. When it comes to satisfying the QoS while minimizing the total transmitted power, [61] achieved this using a deep belief network with two hidden layers and noted that both single-carrier NOMA (SC-NOMA) and multi-carrier NOMA (MC-NOMA) systems are more power-efficient than

TABLE 3. Summary table of massive MIMO research using deep learning.

Research Tasks	DL Method	Performance and Observations	References
• Estimation of CSI • mmWave band	• DNN • CNN	• FFDNet and DnCNN outperform conventional channel estimation methods (LS and MMSE) by a large margin • Minimizes the BER and enhances spectrum efficiency of mmWave massive MIMO • Achieves better performance in hybrid precoding compared with conventional schemes	[26], [42]
• Downlink of MIMO-NOMA • Precoding and SIC decoding	• FNN	• Achieves lower MSE and lower BERs • Addresses the issue of imperfect SIC decoding in a nonlinear manner	[52]
• Channel estimation and DOA estimation • CSI feedback	• DNN • CNN • LSTM	• MSE performance of the DOA estimation is more stable with larger batch sizes • Performance of the channel estimation is optimized when employing longer training sequences • BER performance is better than in the DCT, PCA, KLT and CsiNet algorithms. • Maintains a high system performance gain under the different antenna configurations at the BS.	[27], [53]
• WiFi positioning • Improve localization	• CNN • MLP	• Average accuracy decreases as number of users increase • Positioning capabilities generalizes well in highly-clustered propagation scenarios with or without line-of-sight	[32], [41]
• Power control • Solve non-convex problem	• CNN	• Number of iterations needed to reach the stationary point does not vary significantly when increasing the network size • Largest relative improvement is when going from 1 to 5 initializations, but the average improvement is still less than 1% • Single neural network can handle varying number of users per cell • Increases the median of the cumulative distribution of the achievable uplink sum rate of the cell-free massive MIMO system by more than three times compared to existing schemes • Large scale-fading based power control scheme provides a better performance with multiple antennas per access point	[33], [34]

OFDMA systems and the performance of MC-NOMA is superior to that of SC-NOMA. It was also noted that there was a direct relationship between the total transmitted power and the noise power regardless of the number of UEs but if the noise power is kept constant, the number of users will directly affect the minimum total transmitted power.

Another important aspect is the massive connectivity that NOMA supports by serving more users simultaneously. This is made possible by successive interference cancellation. The uplink/downlink transmission of 5G data will face numerous hindrances using the current multiple-access techniques due to their incapability to support efficient spectrum usage but DL can assist the timing and recovery of NOMA systems by reducing the effect of imperfect SIC. Both Kang *et al.* and Saetan and Thipchaksurat utilize DL to reduce the effect of the imperfect SIC for downlink NOMA systems. Reference [58] aims to also maximize the energy efficiency for downlink multiuser NOMA systems by using a DNN with a scaled conjugate gradient optimization algorithm, a hyperbolic tangent activation function for the hidden layers, a logistic function for the output layer and three inputs: the set of channel response, the uncancelled fraction of signal power and the total transmit power. It was then tested for a 2-users and 3-users NOMA system and achieved an energy efficiency performance close to the optimal exhaustive search power allocation scheme of 97-99% but with lower complexity and noticed that the energy efficiency performance of the DL scheme and the exhaustive search power allocation (ESPA) scheme decreases due to the effect of the uncancelled fraction of signal power. For [52], the authors proposed the DL-model FNN of 2 hidden layers with 100 nodes to learn the coding and SIC decoding process of MIMO-NOMA systems to minimize the total mean square error of the user's signals. This scheme yields a lower MSE when learning the joint precoding and SIC decoding in a non-linear manner by addressing the issue of imperfect SIC decoding than the existing linear schemes. It also achieves lower BERs, which indicates high reliability that NOMA systems offer.

When it came to code-based NOMA, both literatures used DNN to improve the uplink code domain of NOMA whether it be by proposing an uplink multiple access scheme to support a highly overloaded multi-user system [56] and by formulating a finite-alphabet signature design [57]. In [56], one DNN-based detection was used for near users and one DNN-based detection was used for far users. Both DNNs had 3 hidden layers; one using a tanh function with 480 neurons and two using a sigmoid function with 10 neurons. In [57], the data would go through an encoder module, then a channel module, followed by a decoder module. Despite the diverse research tasks, DL has proved to be extremely successful in achieving lower BER than conventional methods. Table 4 summaries various NOMA research tasks using DL methods.

VII. RESOURCE ALLOCATION

Resource allocation is the process of manning and assigning resources in a form that helps to reach the most strategic

TABLE 4. Summary table of NOMA research using deep learning.

Research Tasks	DL Method	Performance and Observations	References
• Downlink of NOMA • Reduce effect of imperfect SIC • Precoding and SIC decoding	• DNN • FNN	• Attains optimal energy efficiency (EE) performance with lower complexity • Yields substantially lower MSE and BERs than the existing schemes • As the modulation order becomes higher, more errors are induced in the SIC decoding	[58], [52]
• Minimize transmission delay • Balance between performance and computational complexity	• DNN	• Observes that multidimensional signatures achieve slightly better SER performance than linear signatures. • Higher accuracy than conventional schemes • Reliability gain with respect to user activity detection and symbol reconstruction can reduce re-transmission numbers and lead to further latency reduction.	[59], [60]
• Minimize total transmit power • Satisfy QoS requirements • Enhance system capacity and spectral efficiency	• DBN • LSTM	• Takes less time to approximate the optimal solution, which facilitates to meet the requirement of ultra-low latency. • Under the same setting of noise power, the minimum total transmit power is monotonically increasing with the increase in the number of UEs • Sum rate improves as the training sequence length increases • LSTM scheme outperforms the conventional schemes in terms of the sum rate	[35], [61]
• Improve uplink code-based NOMA	• DNN	• Achieves a lower BER than the conventional multi-user shared access and Welch-Bound Equality-based schemes. • Performance is robust when the percentage of the change of channel statistics is between 0%-5%. • High performance degradation occurs when the percentage of the change of channel statistics is greater than 5%.	[56], [59]

solution. With all the rapid changes in technology, many seek ways to find methods that prove to be exceedingly efficient in reducing both time and effort. 5G can be summed up with an assessment purpose triangle consisting of capacity enhancement, massive connectivity, and low latency with ultra-high reliability [62]. Being as the number of mobile devices is increasing at an enormous rate with various traffic patterns, the infrastructure must determine how to properly support all the countless requirements. As a result, the already congested radio spectrum will only get more congested with 5G network services and must thus be optimized.

The optimization of resources will prove to be a difficult feat, but DL can assist with resource allocation and the minimization of energy usage of the remote radio heads. In current works of literature, DL has been compared to traditional resource optimization methods [31], [63] with great success and advantageous such as flexibility and computing speed. DL has also been used to allocation resources to satisfy diverse quality of service constraints [28], [29], [64] or to minimize system energy consumption [29], [30], [64]. QoS requirements are technical specifications of the system quality in areas like performance, scalability, serviceability, and availability. 5G brings a growth of video service traffic and a vast volume of M2M connections. Considering this growth, the expectations of the 5G QoS requirements are a throughput of 10-20 Gbps, a reduction in end-to-end latency, 100% network availability, reliability, and bandwidth from 100Kbps to several hundred megabits per second.

Dong *et al.* [64] focused on developing a framework using DL, specifically FNN and cascading neural networks, to obtain a near-optimal energy-efficient bandwidth and power allocation scheme where they focus on the QoS requirements of delay-tolerant, delay sensitivity, and uRLLC services. uRLLC allows for the processing of immensely large amounts of data with minimal delay. The intent behind the two kinds of neural networks is to approximate the optimal policy that maps the system states to the optimal resource allocation. The parameters of the neural networks are initialized with Gaussian distributed random variables with zero mean and unit variance, and since the cascaded neural networks are comprised of multiple FNNs with 4 hidden layers each with 800 neurons, the complexity of the FNN is analyzed before the training of the cascaded neural networks where a backward propagation is implemented. When comparing the results of the QoS achieved by the FNN and the cascaded neural networks, the latter satisfies the requirements with a probability of 99.98% whereas the FNN satisfies 99.2% [64].

Abiko *et al.* [28] and Yu *et al.* [29] tried to optimize radio resources while also focusing on the QoS constraints as a measure of their success. Abiko focused on radio access network (RAN) slicing to allocate divided slices for services using DRL. The method developed to control resource allocation to RAN slices and confirmed that with their method, resource block allocation is unaffected even as the number of slices changes. Yu, also using DRL and proposing slice resource allocation architectures, specifically focused on resource allocation for TV multimedia services, noticed that DRL-based resource power allocation outperforms the existing algorithms by causing high energy efficiency while maintaining a similar quality of service. As expected, the energy efficiency, network power, and bandwidth become

TABLE 5. Summary table of resource allocation research using deep learning.

Research Tasks	DL Method	Performance/Results	References
• Network slicing flexibility	• DRL	• Slice 5 performs best-effort communication and has a period of 0 allocation resource blocks (RBs) for allocating excess RBs • Allocates RBs and satisfy slice requirements even if the number of slices changes	[28]
• Comparison of traditional methods to DL based method • Make use of full scale information instead of traditional resource optimization	• DNN • CNN	• Maximum test accuracy of 86.31% for 4 hidden layers and 86.14% for 3 hidden layers • Compared to MMSE, there is about 1.04% loss but they have the advantage of flexibility and computing speed	[31], [63]
• Accomodate diverse QoS constraints • Minimize system energy consumption and power consumption • Optimize bandwidth	• DRL • FNN • LSTM	• Energy efficiency, network power and bandwidth get worse as the number of users increases • Outperforms existing methods by achieving high energy efficiency while maintaining a similar quality of service • Cascaded NNs can satisfy the QoS requirement with a probability of 99.98%	[29], [30], [64]

worse as the number of users increases due to network pressure increments as more resources are required [29]. DRL was an extremely prevalent DL method when it came to resource allocation because optimization problems focus on improving long term rewards rather than immediate rewards and DRL, the idea of learning by interacting, has the advantage of not requiring expert labels but instead learns directly from its interaction in the world or these cases, in a system. Table 5 summaries various research allocation tasks using DL methods.

VIII. SECURITY

Cybersecurity has gotten increasingly significant in the past few years and with the rise in the widespread use of technology, there has also been a rise in cybercrime and cyber-attacks. These cybersecurity threats consist of but are not limited to malware, phishing, data leakage, hacking, structured query language (SQL) injection, denial-of-service attacks, and domain name system (DNS) Tunneling. Cybersecurity is important because it pertains to protecting user's sensitive data and personal information.

The next-generation technology, 5G, is designed to bring faster speeds, to lower latency, and be more robust than the previous 3G and 4G communications; however, there will be an elevated security threat due to the vast number of vectors through which adversaries can attack. 5G could make existing intrusion detection and defense procedures obsolete and with the increasingly alarming rate of cyberattacks, various services including online access to healthcare, communications, e-commerce, and banking systems will require new DL-based methods implemented in network intrusion detection systems.

Like LDPC coding, security will require network traffic classification [19], [20], [22], and cyberthreat identification [18], [21]. In 5G networks, the cloud radio access network (C-RAN) is considered a promising future architecture in terms of minimizing energy consumption and allocating resources efficiently; however, it is vulnerable to malicious attacks. Hachimi *et al.* [21] focuses on being able to detect and classify four types of jamming attacks: constant jamming, random jamming, deceptive jamming, and reactive jamming using multilayer perceptron (MLP) with several hidden layers. MLP was chosen over other DL algorithms due to its flexibility which allows it to be applied to different types of data. The data that Hachimi used is the Wireless Sensor Networks Dataset, a dataset dedicated to wireless intrusion detection and achieved a classification accuracy of 91.9% with just MLP. When implemented with the kernel support vector machine (KSVM), a machine learning algorithm used for binary classification, the model achieves a classification accuracy of 94.5%. The purpose of the additional KSVM is to reduce the false negatives that MLP has to a 7.84% false-negative rate [21]. Similarly, Rezvy *et al.* [18] also utilized DL to classify and predict network intrusion. Using the Aegean Wi-Fi Intrusion dataset, Rezvy designed a supervised three-layer DNN with a softmax activation layer as the output layer with an unsupervised pre-training using an autoencoder. This deep autoencoder DNN allows input data to be compressed into a low-dimensional representation and uses techniques such as dropout and batch normalization to speed up the training process and avoid overfitting. It achieved a detection accuracy of 99.9% for flooding, injection, and impersonation attacks. When it comes to cyberthreat identification, DL has an excellent performance rate [18].

With 5G, there will be more devices, more mobile data, higher user rate thus higher network traffic than with previous wireless networks. Network traffic can be inspected to determine what will happen on the network to ensure that there will be no unexpected security breaches. Literature [19], [20], and [22] used a variety of CNN, FNN, LSTM, DBN, and SAE models as well as various datasets such as CICIDS2018 dataset, CTU dataset, and the NSL-KDD dataset. Maimó *et al.* [19], used a combination of LSTM, DBN, and SAE for data detection. LSTM was used to implement the network anomaly detection and both DBN and SAE were used for anomaly symptom detection. Reference [19] hoped to manage traffic fluctuation and optimize computing resources and performance

TABLE 6. Summary table of security research using deep learning.

Research Tasks	DL Method	Performance/Results	References
• Detection of specific wireless network intrusion • Classification of jamming attacks in C-RAN	• DNN	• Detection accuracy of flooding, impersonation and injection type of attacks: 99.9% • Classification accuracy of attacks is 94.51% with a 7.84% false negative rate	[18], [21]
• Detection of anomalous network traffic • Analyze network traffic	• CNN • LSTM • FNN • DBN	• Identifies benign traffic with a 100% accuracy rate and anomalous traffic with a 96.4% detection rate • CNN (77.8%) and FNN (80.34%) obtain higher accuracy and detection rate with lower false positive rates • Higher accuracy than classic ML algorithms which achieve about 75% accuracy	[31], [63]

of the analysis. On the other hand, Lam and Abbas [22] and Zhu *et al.* [20] focused on the detection of anomalous network traffic. Zhu *et al.* compared the effects of DL models like CNN and FNN with ML algorithms like J48, Näive Bayes, NB Tree, Random Forest, Random Tree, and SVM. It was observed that CNN with feed-forward propagation, backpropagation, and a softmax layer for classification as well as the FNN with one hidden layer or the FNN with two hidden layers achieved a classification accuracy of 77.8% and 80.34% respectively [20]. The models obtain a higher accuracy and detection rate with lower false-positive rates than all of the machine learning algorithms. Lam and Abbas [22], like Zhu *et al.* [20], utilized a CNN model to detect anomalous network traffic in hopes of producing software-defined security that could be implemented into an intrusion detection system to create more proactive and end-to-end defense for a 5G network. The model was extremely effective with an identification accuracy of 100% for benign traffic and a 96.4% detection rate for anomalous traffic [22]. These phenomenal results detecting network traffic and cyberthreats will lead to a safer 5G network. Table 6 summaries a number of security research tasks using DL methods.

IX. DISCUSSION ON B5G/6G

Although this article has focused solely on 5G, several topics will continue to be prevalent in B5G. B5G can be viewed as a pathway to 6G technologies and like previous generations and will render its preceding generation of wireless communication pale in comparison. The vision of B5G/6G will consist of increased network intelligence, increased data, enhanced senses, quantum networks, extended battery duration and energy as well as fast spectrum reallocation. Similar to 5G, this will require adequate resource allocation and an enhanced security infrastructure and privacy management. The five topic areas covered in this article will evidently be of importance for B5G and 6G and the deep learning techniques can be extended in some key technologies of B5G such as reconfigurable intelligent surfaces, Terahertz, and unmanned aerial vehicles.

The 5G spectrum is a range of radio frequencies in the sub-6 GHz range and the mmWave frequency range of roughly 24-40 GHz for cell carriers with 5G availability. For the next generation of wireless communications systems, frequencies are expected to range from 100 GHz to 3 THz [12] to support the increasing number of applications such as virtual reality, wireless cognition, IoT and wireless backhaul that requires more significant data rates and lower latency than offered by 5G. The ultra-high data rates enabled through mmWave and Terahertz will also revolutionize wireless cognition in areas like robotic control and autonomous vehicles as well as make radar and imaging more effective than the current light or infrared-based imaging because it will minimize the impact of weather and ambient light [12].

There has been research on ML techniques on UAV-based communications to study the throughput, radio coverage, QoS, latency, energy efficiency and spectral efficiency with varying success. As concluded in [65], there exists several open issues towards optimizing UAV networks and DL could reveal useful correlations among such large amounts of heterogeneous data. DL methods have thus far provided to enhance the results of ML methods. There has already been some research [11] using deep learning on hybrid precoding, specifically a RIS-based hybrid precoding architecture for Terahertz communications due to its energy efficient [66] characteristic. Using a parallel DNN system each with one input layer, one output layer and three hidden layers, [11] was able to approximate the complex non-convex function of the traditional hybrid precoding algorithm well at a lower runtime and negligible performance loss. This is just the beginning of what deep learning can accomplish and with future research using such DL methods presented in the exploration of 5G, there is no doubt that B5G and 6G can achieve great success.

X. CONCLUSION

This article provides a comprehensive review of 5G research using various DL methods such as CNN, RNN, DRL and LSTM. We focused on the five main challenges that 5G entails: channel coding, massive MIMO, non-orthogonal multiple access, resource allocation, and security. It is seen that, in channel coding, deep learning will greatly reduce the time complexity of LDPC codes without the deterioration of performance. For massive MIMO, deep learning models like DNN and CNN will greatly improve the BER performance and system capacity while optimizing channel estimation and feedback. NOMA, along with massive MIMO, will deliver enhanced performance and a reduction of internal power consumption to achieve total energy efficiency reductions. With deep learning, resource allocation and NOMA will satisfy QoS requirements and optimize bandwidth usage. Finally, deep learning is exceptional at the security of 5G especially at detecting wireless network intrusions and analyzing network traffic. With further DL research in 5G wireless networks, future deployments of 5G will produce exceptional connectivity at unprecedented speeds and with low latency that will redefine the world of technology.

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