A Study on the Artificial Intelligence for 5G Wireless Systems

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ABSTRACT

AI is being used in various industries due to its development of AI. In this study, we reviewed and analyzed the cases of AI applications for five major technologies of 5G wireless systems. The main technologies of 5G were MassiveMIMO, Automatic Modulation Classification (AMC), Channel Coding, Intelligent Radio Resource, Network Management, and Radio Channel Modeling. We would like to help research using AI in 5G wireless systems by reviewing and analyzing the various research results.
As a result of the study, it was confirmed that the use of AI for 5G wireless systems has the intelligence, efficiency, and flexibility necessary to manage wireless resources and provide high quality services to users.

KEYWORDS

artificial intelligence (AI), 5G wireless systems, machine learning (ML), deep learning (DL)

1 INTRODUCTION

Today, artificial intelligence (AI) and 5G wireless systems are the core technology of the advanced technologies of the 4th industrial revolution. AI is distinguished by machine learning (ML) and deep learning (DL). The 5G specification released by 3GPP considers design flexibility as one of the fundamentals of 5G [1-3]. The flexibility of this design allows for flexible 5G wireless systems that can self-tune in real time to optimize resource allocation while improving the quality of user experiences that require accurate predictions of network behavior, traffic demand, and user mobility. Many leading wireless research groups predict that AI is a technology that could provide the flexibility and intelligence needed for 5G wireless systems. For this reason, many researchers have investigated the effectiveness of this theory in many aspects of 5G wireless systems, including modulation, channel coding, interference management and scheduling, and 5G slicing.
In this study, we review and present previously published papers that the use of A.I. can solve the complex problems of 5G wireless networks by considering various aspects of 5G wireless systems. As a result, we show you how to apply machine learning to each aspect of 5G wireless systems.

2 Utilization of AI for 5G Systems

In this section, we reviewed several use cases for 5G wireless systems with A.I. applied. A table is presented and shown for each example.

2.1 Massive MIMO

Massive MIMO is one of the features of 5G, using a vast number of antennas, which allows 5G to focus transmission and reception of signal power in much smaller spaces. However, in Massive MIMO, it is difficult to estimate the exact channel with a simple estimation method and a reasonable number of pilots. The minimum squared (MS) estimator with low complexity does not achieve satisfactory performance, while the minimum mean squared error (MMSE) channel estimation is very complex. A.I. was applied to Massive MIMO to solve these problems. In Table 1, deep learning of Massive MIMO is to perform more accurate channel estimations of channel conditions and reduce the number of pilots required to achieve satisfactory performance.

Table 1: AI for Massive MIMO

Reference Number	Proposed Contents
4	Deep learning-based channel estimation scheme for the massive multiple-input multiple-output system was proposed.
5	A direct-input deep neural network is first proposed to estimate channels by using the received signals of all antennas.
6	Deep learning-based channel estimation scheme for the massive MIMO system in Rician fading environment was proposed.

7	Deep learning technology was used to develop CsiNet and Novel channel state information sensing and recovery mechanism that learns to effectively use channel structure from training samples.
8	MMNet was proposed, a deep learning MIMO detection scheme that significantly outperforms existing approaches on realistic channels with the same or lower computational complexity.
9	Deeping learning can achieve high parallelism and robustness, which is especially suitable for massive multiple-input multiple-output. detection. Deep learning can be used for mapping channels in space and frequency.
10	Deep learning can be used for power allocation in Massive MIMO.
11	Deep learning and machine learning can predict the user distribution and accordingly optimize the weights of antenna elements.

2.2 Automatic Modulation Classification

Automatic Modulation Classification (AMC) is one of the tasks that helps classify the modulation types of incoming signals, and is a necessary step in understanding and detecting 5G wireless environments with high-quality detection and adaptation that improves spectral efficiency and interference mitigation. In Table 2, the DL-based AMC system consists of three parts. The first part is signal processing, frequency offset calibration, gain control, amplifier and filtering to improve the quality of the received sample. The second part is to extract features such as amplitude, phase, and frequency of the received signal. The third part is to classify modulation types using a signal classifier. DL can achieve high accuracy of modulation classification.

Table 2: **AI for Automatic Modulation Classification (AMC)**

Reference Number	Proposed Contents
12	ANN (two hidden layers with 50 and 25 neurons) uses a system-based AMC, which consists of a Nesterov accelerated adaptive moment estimation algorithm to improve the training runtime.
13	Long short term memory (LSTM) could achieve a classification accuracy close 90% at varying signal-to-noise ratio conditions (0dB to 20dB).
14	Used AlexNet, which is a large CNN based Model that has eight convolution layers and three fully connected layers, to classify 11 modulation types which can achieve an average accuracy of 87%.

2.3 Channel Coding

The feature of the 5G wireless interface is the use of new channel coding technology. DL is well known for its highly parallel architectures that can implement one-off coding/decoding. In Table 3, many researchers predict that deep learning-based channel coding is a good way to enable 5G NR. The DL-based channel coding can achieve a good range of performance-complexity trade-offs that lead to overfit and underfit if correctly performed with the choice of code word length.

Table 3: AI for channel coding

Reference Number	Proposed Contents
15	Reinforcement learning for effective decoding strategies for binary linear codes such as ReedMuller and BCH codes, and as a case study, they considered bit-flipping decoding.
16	Three types of deep neural networks for channel decoding for 5G, multi-layer perceptron, convolutional neural network, and recurrent neural network.
17	A low latency, robust, and scalable convolutional neural network-based decoder of convolutional and LPDC codes.
18	Deep learning models consist of an iterative belief propagation concatenated with a convolutional neural network LDPC decoding under correlated noise, CNN for denoising the received signal, and BP for decoding.

2.4 Intelligent Radio Resource and Network Management

In 5G, there is a lack of wireless resources and increasing demand for wireless traffic. In Table 4, a method for efficiently addressing resource allocation by applying artificial intelligence to 5G wireless communication network. DL can be applied to interference management, spectrum management, multipath use, link adaptation, multichannel access, and traffic congestion.

Table 4: AI for Intelligent Radio Resource and Network Management

Reference Number	Proposed Contents
19	An A.I. scheduler to infer the free slots in a multiple frequencies time division multiple access to avoid congestion and high packet loss.
20	Deep reinforcement learning for decentralized cooperative localization scheduling in vehicular networks.
21	Deep reinforcement learning based on LSTM to enables small base stations to perform dynamic spectrum access to an unlicensed spectrum.

22	A.I. framework for smart wireless network management based on CNN and RNN to extract both the sequential and spatial features from the raw signals.
23	Deep-reinforcement learning approach for SDN routing optimization.

2.5 Wireless channel modeling

The application of AI to 5G wireless channel modeling is expected to improve the channel model and contribute to more efficient channel estimation. In Table 5, a study of AI for wireless channel modeling proposes a model with appropriate parameters.

Table 5: AI for wireless channel modeling

Reference Number	Proposed Contents
24	If the target is to estimate large scale fading, the average the power delay profile is calculated.
25	Using deep learning to identify and classify the modulation nodes, improve the interference alignment, and locate the optimum routing path.
26	Addressed that DNNs are capable to learn the channel model characteristics of the wireless channel that get affected by fading.
27	Recommend involving the convolution neural network in the 3GPP channel model.
28	The CNN techniques are used to predict the speed and direction angle using a sequence of images as an input.
29	Used multiple machine learning algorithms such as KNN and Random Forests to estimate the path loss model from a dataset and showed results that prove the accuracy with small estimation errors.
30	Used neural network methods such as learned denoising-based approximate message passing network to estimate and learn CSI and solve the limited number of frequency chains in cellular systems from training data.
31	Used deep learning for estimating the carrier frequency offset.
32	Presented several novel ideas for applying deep learning to end-to-end communication systems such as autoencoder and redesigning those communications in a single process. Where the autoencoder helps to decrease the block error rate by 1-7 time in scenarios that has Rayleigh fading.
33	Showed how to predict the transmitted signals using deep learning techniques such as neural networks other than the classical method where existing receivers estimate the parameters and then recover the data using estimation. Whereas with deep learning, the channel state information is estimated, and recovering the transmitted signals directly.
34	Other channel modeling challenges that reach the complexity level such as blockage, atmospheric effects, handover, beam direction, MIMO and it is time for machine learning to get evolved.
35	A unique way to train deep learning of channel modeling without any assumptions which improves the system performance. The authors used a back-propagating stochastic approximation method to overcome the corrupted signals due to hardware, fading, improper schemes, etc. The cross-entropy loss function is used to measure the performance of the system as shown below.

3 CONCLUSIONS

AI has been used in various industries due to development of AI. In this study, we reviewed and analyzed the cases of AI applications for five major technologies of 5G wireless systems. The main technologies of 5G were selected: MassiveMIMO, Automatic Modulation Classification, Channel Coding, Intelligent Radio Resource, and Network Management, and Radio Channel Modeling.

As a result of the study, it was confirmed that the use of AI for 5G wireless systems has the intelligence, efficiency, and flexibility necessary to manage wireless resources and provide high quality services to users through related research reviews.

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