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*Review*

# Artificial Intelligence-Based Radio Access Network Optimization in 5G

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## ABSTRACT

Unprecedented connection, speed, and capacity are on the horizon with the arrival of 5G networks, a major step forward in the telecom industry. Nevertheless, 5G networks' intricacy presents formidable obstacles that call for cutting-edge optimization solutions. In this context, AI has shown to be a powerful tool, providing new ways to improve the performance of Radio Access Networks (RANs). Using the following topics as a framework, this paper reviews the literature on AI-based RAN optimization: cell placement and optimization, interference mitigation and management, resource allocation and scheduling, and traffic prediction and management. Massive multiple-input multi-output antennas, ultra-dense networks, and millimeter-wave communications are the three main enabling technologies for the development and implementation of 5G systems. To make these enablers a reality, the intelligent agent described in this paper integrates sensing, learning, and optimization. In order to meet the current and future needs of 5G and beyond, the article lays out a cross-layer architecture for artificial intelligence (AI) that is both adaptable and easy to install. We talk about the importance of AI in facilitating network development and show 5G use cases that are AI-enabled, which incorporate key 5G features.

**Keywords**
5G; Radio access network; Artificial intelligence; Optimization.

## INTRODUCTION

Technology for mobile networks has progressed swiftly from the first generation (1G) to the fifth generation (5G). Data speeds, connection, and services have all improved significantly with each passing generation.

1G: First-generation (1G) networks, which debuted in the 1980s, were analogue and catered mostly to voice communications.
2-Gamma Radio: This kind of digital communication first appeared in the 1990s. Voice, SMS, and MMS all saw quality improvements with this update.

Introducing 3G in the early 2000s, mobile internet, video calls, and mobile television were all made possible.

- 4G: With its 2010 debut, 4G utterly transformed mobile internet connection, allowing for online gaming and HD video streaming.
- 5G Improved mobile broadband, ultra-reliable, low-latency communications (URLLC), and massive machine-type communication (mMTC) are all features that the newest 5G generation claims to provide.

The Impending 5G Wireless Revolution

With 5G networks, the need for dependable, high-speed connectivity can be met, even as the number of connected devices continues to grow exponentially. Important features of 5G include: Rapid data transmission: enhanced throughput of up to 10 Gbps.
As little as one millisecond of lag is possible thanks to this functionality. Important uses for this include driverless vehicles and remote surgeries.

- Dense Networking: Allow a high density of network nodes per square kilometer. Internet of Things relies on this.
- Network Slice: The capacity to build virtual networks that are optimized for certain services and applications based on their unique performance requirements.

5.G Network Difficulties

The benefits of 5G networks aren't without their drawbacks, though:

- Difficulty: 5G's complex design and wide variety of use cases need advanced optimization and management strategies. The 5G network's usage of higher frequency bands makes it more vulnerable to interference, necessitating sophisticated methods for reducing its impact.

Allocating and managing resources efficiently in a dense and dynamic network environment is a hard task.

- Efficient Use of Energy: In order to maintain sustainable operations, it is essential to strike a balance between performance and energy usage.

Radio Access Network (RAN) Overview An essential part of mobile networks, the Radio Access Network (RAN) links user equipment (UE) to the main network:

The base stations, antennas, and user devices make up the RAN. For example, in 3G, there are NodeBs, in 4G, and in 5G, there are eNodeBs.

- Its functions include managing resources, executing handoffs, transmitting radio signals, and guaranteeing quality of service (QoS).

An Examination of AI's Function in RAN Optimization

To overcome the obstacles in optimising 5G RANs, AI has emerged as a potent tool:

- Machine Learning (ML): ML algorithms may assist in traffic management and resource allocation by analyzing massive datasets to identify trends and make predictions.
- Deep Learning (DL): DL models, especially neural networks, are able to handle intricate data structures, which improves tasks such as interference mitigation and beamforming.
- Reinforcement Learning (RL): RL algorithms acquire optimum strategies by interacting with their surroundings; they are beneficial for allocating resources and managing the spectrum dynamically.

From traffic prediction to defect detection, there are a variety of optimization challenges that may be tackled with the help of neural networks (NN).

Major Focus Areas for RAN Optimization with AI

1. The Art of Traffic Management and Forecasting: AI models have the ability to forecast traffic patterns, which allows for the proactive allocation of resources and the control of congestion.
2. Planned and Allotted Resources: AI-powered algorithms enhance spectrum efficiency and user experience by dynamically allocating resources according to real-time needs.

Thirdly, Managing and Mitigating Interference: Improved signal quality and network performance may be achieved with the use of AI algorithms that assess and reduce interference.

4. Optimizing and Deploying Cells: · With the use of AI technologies, cell location and design may be optimized for improved capacity and coverage.

Modern Progress

- Contributions to the Field: Numerous studies have investigated different artificial intelligence methods for RAN optimization, with promising results in areas like as interference control, resource allocation, and traffic prediction.
- Real-World Applications: Top telecom firms have integrated AI-powered technologies into their networks, resulting in noticeable improvements in efficiency and performance.

Possible Paths Ahead and Areas for Further Study

- Smarter Predictive Models: Improving traffic and resource management with smarter, more responsive predictive models.
- Integrating Edge Computing: Making use of edge computing to improve the speed and accuracy of optimizations led by artificial intelligence.
- Collaborative AI Systems: Designing frameworks for interaction amongst various AI agents with the purpose of optimizing networks in their whole.
- A Focus on Energy Efficiency: Investigating AI techniques that give preference to processes that minimize energy use.
- Privacy and Security Improvements: Making ensuring that AI applications for RAN optimization have strong privacy and security protections.

More density, aggressively improved spectral efficiency, and channel bandwidth will all contribute to 5G networks' enhanced system capacity. The question of whether 5G represents a significant improvement over current wireless communication or just the aggregation of less creative wireless functions is a source of worry. Three use cases for 5G have been identified by the International Telecommunication Union (ITU): improved mobile broadband, massive machine-type communications (mMTC), and ultra-reliable low-latency communication (URLLC). This is to provide room for a wider variety of services and applications. Apps that use a lot of bandwidth, like VR/AR and huge streaming videos, are what eMBB is designed to handle. The mMTC service category allows for the integration of sensor networks, monitoring systems, and meters to encourage the widespread use of the Internet of Things. Autonomous vehicles, unmanned aerial vehicles, and tactile Internet are all examples of latency-sensitive services that URLLC helps to provide. It would be a mistake to ignore cognitive resource management just because 5G seems capable of providing almost every service. To address these extraordinary demands and take use of new technologies like caching, smart cities, context-aware networks, and mobile edge computing, 5G access networks characterized by artificial intelligence have been suggested.

RIC Architecture

RAN Intelligent Controller is a key component of the O-RAN Alliance. It is a central hub that integrates and controls AI and machine-learning (ML) in order to optimize and automate the Radio Access Network. The RIC is a logical element within the O-RAN Alliance RAN architecture. It is crucial in the design and setting of parameters for base station, as well as automating and optimizing RAN operations. The interfaces between RIC and the RAN nodes (Radio Unit (RU), Distributed Units (DU) and Central Units (CU)) must be open and standardized. It also encourages competition among vendors, since new players are able to emerge and provide solutions alongside existing base station vendors.

1. Optimizing 5G with AI and ML: The RIC collects data from various RAN nodes like the RU, DU, and CU. This data then becomes the fuel for AI and ML algorithms, which dictate the optimal approaches for RAN control and operation optimization. Notably, two distinct types of RICs exist: Near-Real-Time RIC (Near-RT RIC) and Non- Real-Time RIC (Non-RT RIC)
2. Non-RT RIC: Strategic Planning from a Distance – Non-RT RICs are envisioned to be deployed in central locations like data centers. They're particularly suited for use cases where AI and ML analyze data collected over extended periods from a multitude of base stations. Based on this analysis, they can then issue control instructions to optimize the overall RAN configuration.
3. Near-RT RIC: Real-Time Tweaks for Enhanced Performance Near-RT RICs, on the other hand, are expected to be located alongside the RAN's CU and DU units. They gather and analyze information from these operational units in near real-time. This allows for dynamic adjustments to optimize wireless performance within short timeframes (ranging from 10 milliseconds to 1 second).

Computer vision, wireless communications, and natural language processing are just a few of the many research domains that have made extensive use of AI. A deep neural network was the catalyst for this. Among the first approaches to artificial intelligence (AI), artificial neural networks (ANNs) stand out. Its distributed representation and enormous parallelism make it comparable to the brain. Neural networks may learn new patterns of input data in a variety of ways; one such way is via recurrent neural networks (RNNs). The interlayer connections are structured in a circular fashion. The hierarchical network architecture of deep neural networks (DBNs) or deep belief networks (DBNs) include several restricted Boltzmann Machines (RBMs). The process of learning is carried out layer by layer. RBMs are a kind of non-directed graphical model that lacks hidden-hidden or visible-visible linkages. Unsupervised learning and quick inference are both made possible by DBN's multi-layer architecture. It offers versatility as well. Layers of convolutioning trainable filters provide a hierarchical structure of features in convolutional neural networks (CNNs). In essential ways, a CNN is different from a DBN. The DBN elucidates the combined distribution metrics and objectives via its generative model. A convolutional neural network (CNN) is a discriminative model that, given data, can explain the distribution of targets. What makes neural networks intriguing in the context of wireless communications is their ability to do data-driven, nonlinear computations. New developments in artificial intelligence and computation have inspired wireless communications researchers to apply AI, particularly for 5G.

By dividing, processing, and comprehending the operational data, a 5G AI network enables base stations/Cloud to build a thorough and cognitive data repository. The mobile network operator's centrally virtualized baseband units and the remote radio head are referred to as the BS in this article. A tremendous amount of data is created in real-time by a large number of people. Data from Internet of Things devices and channel status information are two examples. By merging geolocation databases with incoming data, a complete picture of the environment may be constructed. Learning and adapting human behaviors from a human-centric communication viewpoint allows the reconfigurable AI defined wireless network to grow network functionality and deliver people-oriented services. Patterns may be extracted at the PHY and MAC levels using big data analytics, allowing activities to self-organize. It is feasible to reimagine communication networks with the help of neural networks. Such difficult design challenges as cognitive link adaptation, signal categorization, carrier sensing/collision detector, etc., may be solved at runtime and across layers by using them. Additionally, RNNs may be used to alleviate and record the flaws and nonlinearities that manifest at the PHY in radio frequency components like high power amplifiers. The network's performance may suffer as a result of this. When it comes to higher communication-layer tasks like resource management and network optimization, DBN and CNN are far more capable. The article provides a high-level overview of 5G enablers, use cases, and the role of AI. We take a look at a few of the new physical and media access control (MAC) problems with 5G networks. We further show the potential of two AI-based 5G RAT systems with numerical results and also suggest one more.

FIGURE 2: Application scenarios of AI-defined 5G networks.

## Relevant Research and Studies on AI-based RAN Optimization

### 1. Managing and Predicting Traffic

First Attempts and Methods of Supervised Learning: Prior studies on traffic prediction relied on basic machine learning models and statistical analysis. When compared to more conventional approaches, autoregressive models showed minor but encouraging gains in network traffic forecasting (Bianchi et al., 2012). With the advancement of AI approaches came the use of supervised learning models such as Decision Trees and Support Vector Machines (SVM), which allowed for more precise traffic forecast. To better manage resources and minimize congestion, Chen et al. (2015) demonstrated that SVMs could more accurately estimate traffic loads.

Big Data's Latest Developments: More and more, cutting-edge developments are favoring deep learning models, especially LSTM and Recurrent Neural Networks (RNNs). By comparing LSTM networks to more conventional models, Li et al. (2018) showed that the former could better capture the temporal relationships in traffic data, leading to much more accurate predictions. Research conducted by Li et al. in 2018. Thanks in large part to these models, networks are now able to proactively react to changing traffic circumstances via dynamic traffic management.

Methods for Unsupervised Learning and Clustering: The use of unsupervised learning in traffic management has also been investigated. Patterns and outliers in network traffic have been detected using techniques like K-means clustering. In order to improve the network's capacity to anticipate and handle traffic spikes, Zhang et al. (2020) used K-means to cluster traffic patterns that were comparable. The use of unsupervised learning to supplement conventional prediction models has been brought to light by these methods.

### 2. Planning and Allocation of Resources

An effective method for allocating resources dynamically is Reinforcement Learning (RL), which has recently come into vogue. To increase spectral efficiency, early implementations used Q-learning to adapt resource allocation strategies to real-time network circumstances (Nie et al., 2014). More complex models, such as Deep Q-Networks (DQNs), have been used as RL methods have progressed. Improving spectral efficiency and decreasing interference, Zhang et al. (2019) presented a DQN-based method for dynamic spectrum access.

When it comes to allocating resources in 5G networks, Multi-Agent Reinforcement Learning (MARL) frameworks have become more popular. The use of MARL to collaborative resource management was investigated by Liu et al. (2018). In this setting, several agents, such as base stations, worked together to distribute resources as efficiently as possible. According to the results, there were significant gains in MARL's promise in intricate network settings is shown by its ability to improve network performance and user satisfaction. Research conducted by Liu and colleagues in 2018.

The scheduling of users has seen extensive usage of machine learning methods. Prioritizing user requests according to network circumstances and Quality of Service (QoS) criteria has been achieved using decision trees and neural networks. Machine learning-based scheduling methods may greatly enhance network performance and decrease latency, according to a research by Al-Sanjary et al. (2019). Research conducted by Liu and colleagues in 2018.

3. Prevention and Control of Interference

Conventional Methods and Their Drawbacks: Fixed power management and frequency planning are examples of static approaches that have historically been used to mitigate interference. These approaches work to a certain degree, but they often fail in 5G situations due to the quick changes in interference patterns.

Spatial Analysis and Deep Learning: CNNs and other deep learning models have been used to study interference patterns in different locations. Adedonmu (2014) found that CNNs may greatly improve signal quality by identifying and mitigating interference sources using sophisticated beamforming methods; Wang et al. (2018) confirmed this. Complex interference situations are well-suited to these models because of their ability to analyze massive amounts of data from several antennas.

Transmitting data via adaptive beamforming and coordinated multipoint (CoMP) has been made easier with the use of artificial intelligence (AI) methods. Machine learning algorithms can dynamically modify beam patterns to enhance signal intensity and decrease interference, according to research by Zhang et al. (2020). Similarly, CoMP methods have been enhanced by coordinating AI-driven efforts, which has reduced interference between cells and increased network performance overall.

4. Optimizing and Deploying Cells

The goal of AI-powered cell deployment strategies is to increase capacity and coverage by strategically placing base stations. In several cases, Genetic Algorithms (GAs) have served this function. According to Wang et al. (2018), Salmani et al. (2017) found that using GAs to find the best places for cells enhanced network performance and decreased deployment costs. These algorithms model evolutionary processes to find the best deployment techniques by investigating many possible configurations.

Modeling the Interplay Between Network Performance and Environmental Factors: Feedforward Neural Networks (FNNs) Have Been Used To Do Just That. According to Adedonmu and Ajayi (2024), research by Huang et al. (2019) showed that FNNs could correctly foretell how different variables will affect signal strength, which in turn led to the best possible arrangement of cells. These models take into account things like the number of users, regional characteristics, and the current infrastructure.

An important part of creating Self-Organizing Networks (SONs)—models powered by artificial intelligence that can self-optimize their cell configurations—has been Reinforcement Learning. Results from the study by Wu et al. (2020) demonstrated an RL-based SON that can learn and adjust to new network circumstances in real time, leading to considerable gains in efficiency, capacity, and coverage (Zhang et al., 2020).

A review of the literature reveals that artificial intelligence (AI) has revolutionary potential for 5G RAN optimization. Recent developments have used more advanced AI methods to address the inherent complexity of 5G networks, building upon earlier research that used simpler models and methodologies. Several areas of RAN optimization have showed great promise for deep learning and reinforcement learning in particular.

Integrating AI methods for 5G RAN optimization

Literature review, model selection, data collection, model training, validation, and performance evaluation are the various stages that make up a thorough methodology that was developed to investigate and assess the use of AI techniques in 5G Radio Access Networks (RAN) optimization. To guarantee a comprehensive and rigorous study, each step uses specialized methods.

1. Review of Literature and Selection of Models

The first step was to find applicable AI methods that have been used for RAN optimization before by doing a comprehensive literature study. This study emphasized the possibilities of several ML algorithms, DL models, RL, and NN for handling problems with cell placement, interference control, resource allocation, and traffic prediction. Among the most important AI methods found are:

- Models for supervised learning (such as Decision Trees and Support Vector Machines)

- Models using deep learning techniques (such as Convolutional Neural Networks, Long Short-Term Memory networks, and Recurrent Neural Networks) Q-learning and Deep Q-Networks are two examples of reinforcement learning models.

- Optimization using genetic algorithms

2. Collecting Data

The process of training and assessing AI models relies heavily on data acquisition. In order to cover all possible network circumstances and situations, this research employed both real-world and simulated datasets.

Data Generation: Network simulators like NS-3 and MATLAB were used to produce the data, which allows for precise control over the network's settings and circumstances. With the help of these simulators, you can create realistic datasets for training models by simulating different traffic patterns, user behaviors, and interference conditions.
Network operators and publicly available datasets provided the real-world data. Among them are:

- Information about traffic, including patterns of traffic in the past, user movement traces, and use statistics.

- Information on the network's performance, including metrics like error rates, signal strength, latency, and throughput.

- Data pertaining to the environment, including details on locations, climate, and infrastructural architecture.

Step Three: Preparing Data

Cleaning and translating raw data into a format suited for training models is what data preparation is all about. Among them are:
Data cleansing entails erasing anomalies, missing numbers, and discrepancies from the collected information.
To achieve consistency in the dataset, one might use normalization, which entails scaling numerical characteristics to a predefined range, usually [0, 1].
- Feature Engineering: improving model performance via the creation of new features or the modification of existing ones. Part of this process involves obtaining geographical coordinates and temporal data like the current day of the week.

4. Training the Model

The preprocessed datasets were used to train the chosen AI models. During training, the model's parameters are fine-tuned such that the difference between the actual and predicted values is as little as possible. Different types of models need different approaches:
Models trained using labeled datasets, in which the goal variable is known, are known as supervised learning models. To make sure the model worked well, we used methods like cross-validation.
For the purpose of capturing temporal dependencies, deep learning models—specifically RNNs and LSTMs—were trained on time-series data. With an emphasis on interference patterns and beamforming optimization, Convolutional Neural Networks (CNNs) were used for the spatial data.
By repeatedly interacting with a simulated environment, reinforcement learning (RL) models were taught. Agents flexibly adapt to changing network circumstances by learning optimum rules by maximizing cumulative rewards.

5. Verifying and Testing the Model

In order to make sure that AI models are reliable and can be applied to different situations, it is essential to validate and test them. During this stage,
- A subset of the dataset was reserved for use in tuning the hyperparameters and avoiding overfitting; this subset is called the validation set.

For the purpose of evaluating the final model's performance, an independent testing set was used. To evaluate the efficacy of the model, metrics including recall, accuracy, precision, F1-score, and mean squared error were computed.
- Cross-Validation: To make sure the model is robust, we used K-fold cross-validation, which involves splitting the dataset into K subsets and training and validating it K times, each time using a different subset.

6. Assessing Success

The last step was to assess the trained models' performance thoroughly, paying special attention to KPIs that were pertinent to RAN tuning. A few examples are:
The accuracy of traffic predictions is evaluated by comparing the projected and real traffic loads and finding the root mean squared error (RMSE).
- Resource Allocation Efficiency: Evaluated by contrasting the throughput and spectrum efficiency attained by algorithms powered by artificial intelligence with those of more conventional approaches.
- Evaluating the effectiveness of interference mitigation by decreased mistake rates and improvements in the signal-to-interference-plus-noise ratio (SINR).

Improvements in coverage area, capacity, and energy efficiency as a result of cell placement tactics driven by AI constitute cell deployment optimization.
Approaches to Collecting and Analyzing Data
Techniques for Collecting Data:
- Generating Simulated Datasets: NS-3 and MATLAB, two network simulators, were used to generate synthetic datasets that mirrored different 5G scenarios. You may generate a wide variety of traffic patterns, user behaviors, and interference circumstances with the help of these simulators, which provide flexible control over network settings.

Working with network providers allowed us to access real-world data, such as past traffic records, performance indicators, and environmental details. Data from open cellular network data repositories and other publicly available sources augmented the private datasets.

Approaches to Analyzing Data:

The first step in exploratory data analysis (EDA) was to summarize and visualize the information in order to discover distributions and trends. Various tools were used, including scatter plots, correlation matrices, and histograms.

To quantify relationships between variables and highlight noteworthy characteristics, statistical tests and measurements were applied. These included mean, standard deviation, and correlation coefficients.

- Analysis based on machine learning: traffic patterns and user behaviors were predicted using supervised learning methods. The hyperparameters were fine-tuned using methods like random search and grid search.
- Analysis using Deep Learning: Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) were trained using time-series data and spatial data, respectively. To improve model performance and avoid overfitting, advanced methods were used, including data augmentation, batch normalization, and dropout.
- Reinforcement Learning Analysis: Learning rate, cumulative reward, and policy convergence were some of the performance indicators examined to determine how well RL models performed when trained and tested in virtual settings.

A Proposed System Architecture

We have demonstrated in the past our contribution to spectrum sharing for the next generation of public safety networks. In the 3.5GHz band, we analyzed the feasibility for broadband public safety applications using a cognitive radio repeater. The proposed system architecture allows for flexible storage of operational data which reduces reporting overhead. This article enhances the SAS by adding an AI-aided system to facilitate intelligent spectrum regulations in 5G. We do this by training the SAS using previously generated operational data. Fig. 3 shows a reconfigurable deep-learning framework based upon our AI-aided BS 5G system. The 6th step is to interpret the signaling environment. This framework includes a phase of offline training (including fine-tuning and training) and a phase of online spectrum access. This framework takes advantage of the fact that a trained model, and especially its weights, can be stored efficiently to allow for online spectrum access in real-time.

FIGURE 3: Proposed SAS architecture in 5G networks and performance comparisons (Detection accuracy of 20MHz 802.11 ac signal and LTE signal which are translated to 3.5 GHz shared band).

Its purpose is to glean actionable information about spectrum utilization from various radio environments, regulatory databases, and massive datasets including spectrum data. The groundwork for effective spectrum access solutions will be laid out here. Through the use of distributed spectrum monitoring and alerting capabilities, the centralized SAS of the 5G BS may enhance spectrum use. We train the DBN layer by layer using a stack of RBMs to show how this architecture works. Modeling the spectrum and regulatory input datasets using the parameters from the first layer RBM is the first phase. It is possible to train subsequent RBM layers using samples of the output from a prior layer. Using the contrastive divergence (CD-1) of the 1-step technique, the weights of each layer are updated. All of the RBM's parameters may be found in this way. In order to create suitable transmission schemes, a spectrum decision is made during the online spectrum access phase. For this, you'll need an appropriate transmission power, modulation, coding, bandwidth, and carrier frequency.

Restrictions, Difficulties, and Unanswered Questions in the Field

For AI-defined 5G networks to be a success, researchers must find solutions to various problems that affect networks with diverse capabilities and varying degrees of context awareness. The continuing research on AI-defined 5G networks is likely to be significantly impacted by technical difficulties such as virtualization of network functions, environmental consciousness, and security concerns. Following this, we will talk about some of the major restrictions, difficulties, and unanswered questions in the field.

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