

ARTIFICIAL INTELLIGENCE-BASED RADIO ACCESS NETWORK OPTIMIZATION IN 5G

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Abstract

The advent of 5G networks marks a significant milestone in telecommunications, promising unprecedented speed, capacity, and connectivity. However, the complexity of 5G networks poses significant challenges, necessitating advanced solutions for optimization. Artificial Intelligence (AI) has emerged as a potent tool in this regard, offering innovative approaches to enhance Radio Access Network (RAN) performance. This article discusses relevant research and studies on AI-based RAN optimization, organized by key themes: traffic prediction and management, resource allocation and scheduling, interference mitigation and management, and cell deployment and optimization. The three key enablers for the deployment and development of 5G systems are millimeter-wave communications, ultra-dense network, and massive multiple-input multi-output antennas. This article describes the intelligent agent which combines sensing and learning with optimizing in order to facilitate these enablers. The article presents a flexible and rapidly deployable artificial intelligence (AI), cross-layer framework that will enable future and imminent demands for 5G, and beyond. We present AI-enabled use cases for 5G that include important 5G capabilities, and we discuss the value of AI in enabling network evolution.

Keywords: 5G, Radio Access Network, Artificial Intelligence, Optimization

Introduction

From the first generation (1G) to the fifth (5G), mobile network technology has advanced rapidly. Each generation has seen significant improvements in data rates, connectivity and services.

- 1G: 1G networks, introduced in the 1980s were analog and focused primarily on voice communication.
- 2G: Digital communication was introduced in the 1990s, with 2G. It brought improvements to voice quality as well as SMS and MMS.
- 3G: In the early 2000s, 3G was introduced, enabling mobile internet, video calls, and mobile television.
- 4G: 4G, launched in 2010, revolutionized mobile internet connectivity, supporting HD video streaming and online gaming.
- 5G The latest generation of 5G promises higher data rates and ultra-reliable, low-latency communications (URLLC), massive, machine-type communication (mMTC) and enhanced mobile broadband.

5G Networks: The Future of Wireless Communications

5G networks will support the exponential increase in devices connected and the demand for reliable, high-speed communication. The key characteristics of 5G are:

- **High data rates:** Increased data transfer speeds up to 10 Gbps.
- **Low latency :** This feature allows for latencies of as little as 1 millisecond. This is crucial for applications such as autonomous driving or remote surgery.
- **Massive Connection:** Support a large number of connected devices on a square kilometer. This is essential for Internet of Things.
- **Network Slice:** Ability to create virtual networks that are tailored to specific applications and services with different performance characteristics.

Challenges in 5G Networks

Despite the advantages, 5G networks introduce several challenges:

- **Complexity:** The intricate architecture and diverse use cases of 5G demand sophisticated management and optimization techniques.
- **Interference:** Higher frequency bands used in 5G are more susceptible to interference, requiring advanced interference mitigation strategies.
- **Resource Allocation:** Efficiently managing and allocating resources in a dynamic and dense network environment is complex.
- **Energy Efficiency:** The need to balance performance with energy consumption is critical to ensure sustainable operations.

Introduction to Radio Access Network (RAN)

The Radio Access Network (RAN) is a fundamental component of mobile networks, responsible for connecting user equipment (UE) to the core network:

- **Components:** The RAN includes base stations (e.g., NodeBs in 3G, eNodeBs in 4G, and gNodeBs in 5G), antennas, and user devices.
- **Functions:** It handles tasks such as radio signal transmission, resource management, handovers, and ensuring Quality of Service (QoS).

The Role of Artificial Intelligence (AI) in RAN Optimization

AI has emerged as a powerful tool to address the challenges in 5G RAN optimization:

- **Machine Learning (ML):** ML algorithms can analyze large datasets to uncover patterns and make predictions, aiding in traffic management and resource allocation.
- **Deep Learning (DL):** DL models, particularly neural networks, can process complex data structures, enhancing tasks like interference mitigation and beamforming.
- **Reinforcement Learning (RL):** RL algorithms learn optimal strategies through interaction with the environment, useful for dynamic spectrum management and resource allocation.

- **Neural Networks (NN):** Various NN architectures can be applied to different optimization tasks, from traffic prediction to fault detection.

Key Areas of AI-Based RAN Optimization

1. **Traffic Prediction and Management:**
 - AI models can predict traffic patterns, enabling proactive resource provisioning and congestion management.
2. **Resource Allocation and Scheduling:**
 - AI-driven algorithms dynamically allocate resources based on real-time demands, improving spectral efficiency and user experience.
3. **Interference Mitigation and Management:**
 - AI techniques can analyze and mitigate interference, enhancing signal quality and network performance.
4. **Cell Deployment and Optimization:**
 - AI tools assist in optimal cell placement and configuration, ensuring better coverage and capacity.

Recent Advancements

- **Research Contributions:** Significant research efforts have explored various AI techniques for RAN optimization, demonstrating improvements in traffic prediction, resource allocation, and interference management.
- **Industry Implementations:** Leading telecom companies have implemented AI-driven solutions in their networks, showcasing tangible benefits in performance and efficiency.

Future Directions and Research Opportunities

- **Advanced Predictive Models:** Developing more accurate and responsive predictive models for traffic and resource management.
- **Edge Computing Integration:** Leveraging edge computing to enhance the responsiveness and efficiency of AI-driven optimizations.
- **Collaborative AI Systems:** Creating collaborative frameworks where multiple AI agents work together for comprehensive network optimization.
- **Energy Efficiency Focus:** Researching AI methods that prioritize energy-efficient operations.
- **Security and Privacy Enhancements:** Ensuring robust security and privacy measures in AI applications for RAN optimization.

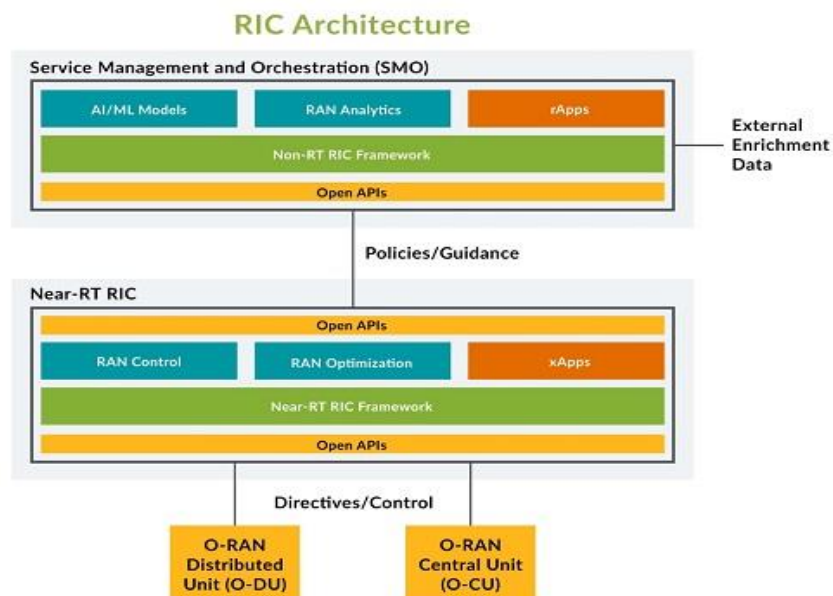
5G networks will achieve increased system capacity through aggressively increasing spectral efficiency and channel bandwidth, as well as higher density. There are concerns about whether 5G is a radical leap forward from wireless communication today or just a simple accumulation of less-innovative wireless functionalities. International Telecommunication Union (ITU), classifies 5G usage scenarios into three categories: enhanced mobile broadband, massive machine-type communications (mMTC) and ultra-reliable low-latency communication (URLLC). This is to accommodate more diverse applications and services. eMBB addresses bandwidth-hungry apps, such as massive streaming video and virtual/augmented realities (VR/AR). mMTC, a service category, enables massive sensing, monitoring and metering to

support the massive deployments of Internet of Things. URLLC is a category of services that support latency-sensitive services, such as autonomous driving, drones, and tactile Internet. While 5G appears to be able to provide virtually any service, cognitive resource management is important and must not be overlooked. Artificial intelligence-defined 5G access networks have been proposed to meet these unprecedented needs and to leverage the emergence and development of smart cities, context-aware network, mobile edge computing, and caching.

RIC Architecture

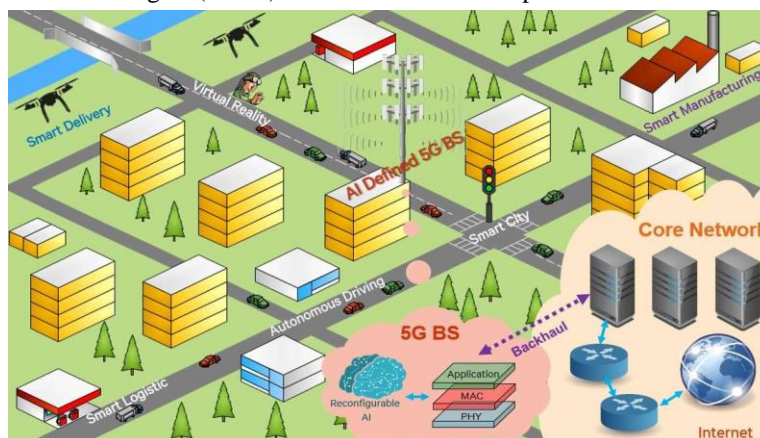
RAN Intelligent Controller is a key component of the O-RAN Alliance. It is a central hub that integrates and controls AI and machine-learning (ML) in order to optimize and automate the Radio Access Network. The RIC is a logical element within the O-RAN Alliance RAN architecture. It is crucial in the 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).



AI has been widely applied to a variety of research areas, including computer vision, wireless communications, and natural language processing. This was sparked by the introduction of deep neural network. Artificial neural networks (ANNs) are one of the oldest methods to create AI. It is similar to the brain because of its massive parallelism and distributed representation. Recurrent neural networks (RNNs), among other types of neural network, allow neurons to create memories from arbitrary input patterns. The connections between layers are arranged in a loop. Deep neural networks (DBNs) or deep belief networks (DBNs) use a hierarchical network structure that includes multiple restricted Boltzmann Machines (RBMs). They work through a layer-by-layer learning process. RBMs are a non-directed graphical model that does not have visible-visible or hidden-hidden links. DBN's multi-layer structure allows for unsupervised learning and fast inference. It also provides flexibility. Convolutional neural networks (CNNs) are built from layers of convolutioning trainable filters, which result in a hierarchical structure of features. A CNN differs fundamentally from a DBN. The DBN is a generative model that describes the joint distribution data and targets. CNNs are discriminative models which describe the distribution of targets conditional on data. The fact that neural networks can make nonlinear calculations and are data-driven is what makes them so interesting in wireless communications. Researchers in wireless communications have been encouraged by recent breakthroughs in AI and computing to use AI, especially in the context of 5G.

A 5G AI network allows base stations/Cloud to create a comprehensive and cognitive data repository, by splitting, processing and understanding the operational data. The BS in this article is the remote radio head and the centralized virtualized baseband units of a mobile network operator. The real-time data generated by a multitude of users is massive. It can range from channel state information to IoT devices readings. Geolocation databases and received data are combined to create a comprehensive understanding of the surrounding environment. The reconfigurable AI defined wireless network learns and adapts human behaviors from a human-centric communication perspective to evolve network functionalities and provide people-oriented services. Big data analytics is used to extract patterns at the PHY and MAC layers, enabling self-organizing operations. The use of neural networks to redefine communication networks is possible. They can solve a variety of complex design problems, both at runtime as well as across layers, such as cognitive link adaptation, signal classification, carrier sensing/collision detector, etc. A RNN can also be used to mitigate and capture the nonlinearities and imperfections of radio frequency components such as high power amplifiers, which occur at the PHY. This can have a negative impact on the performance of the network. DBN and CNN have a better ability to solve a variety of upper communication-layer tasks, such as resource management and network optimization. This article examines briefly the 5G enablers, use cases, and AI's role. We examine some of the PHY and MAC issues that are emerging in 5G networks. We also propose two AI-based architectures for 5G radio access technologies (RATs) and demonstrate their potentials with numerical results.



5GServicesType	Applications
Broadband	VR/AR
	Massive Streaming
Distributed	Mobile Cloud Computing
	Smart Infrastructure
Omnipresent	Massive IoT

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

Relevant Research and Studies on AI-based RAN Optimization

1. Traffic Prediction and Management

Early Efforts and Supervised Learning Approaches: Early research into traffic prediction leveraged statistical methods and simple machine learning models. For instance, Bianchi et al. (2012) utilized autoregressive models to forecast network traffic, demonstrating limited but promising improvements over traditional methods. As AI techniques evolved, supervised learning models like Support Vector Machines (SVM) and Decision Trees were employed, providing more accurate traffic predictions. Chen et al. (2015) showed that SVMs could predict traffic loads with greater precision, aiding in better resource management and congestion avoidance.

Advancements with Deep Learning: Recent advancements have seen a shift towards deep learning models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. Li et al. (2018) demonstrated the efficacy of LSTM networks in capturing temporal dependencies in traffic data, significantly improving prediction accuracy compared to traditional models Li et al. (2018). These models have been instrumental in enabling dynamic traffic management, allowing networks to anticipate and adapt to varying traffic conditions proactively.

Unsupervised Learning and Clustering Techniques: Unsupervised learning has also been explored for traffic management. Techniques such as K-means clustering have been applied to identify patterns and anomalies in network traffic. A study by Zhang et al. (2020) used K-means to group similar traffic patterns, enhancing the network's ability to predict and manage traffic surges Zhang et al. (2020). These approaches have highlighted the potential of unsupervised learning in augmenting traditional prediction models.

2. Resource Allocation and Scheduling

Reinforcement Learning and Dynamic Resource Allocation: Reinforcement Learning (RL) has emerged as a powerful tool for dynamic resource allocation. Early implementations, such as the work by Nie et al. (2014), applied Q-learning to adjust resource allocation policies based on real-time network conditions, demonstrating improved spectral efficiency. As RL techniques advanced, more sophisticated models like Deep Q-Networks (DQNs) have been employed. Zhang et al. (2019) introduced a DQN-based approach for dynamic spectrum access, which significantly enhanced spectral efficiency and reduced interference Zhang et al. (2019).

Multi-Agent Systems: Multi-Agent Reinforcement Learning (MARL) frameworks have gained traction for resource allocation in 5G networks. Liu et al. (2018) explored the use of MARL for collaborative resource management, where multiple agents (e.g., base stations) coordinated to optimize resource distribution. The study reported substantial improvements in

network throughput and user experience, demonstrating the potential of MARL in complex network environments Liu et al. (2018).

Machine Learning for User Scheduling: Machine learning algorithms have been widely applied to user scheduling. Neural networks and decision trees have been used to prioritize user requests based on Quality of Service (QoS) requirements and network conditions. A study by Al-Sanjary et al. (2019) showed that machine learning-based scheduling algorithms could significantly reduce latency and improve overall network performance Liu et al. (2018).

3. Interference Mitigation and Management

Traditional Approaches and Their Limitations: Traditional interference mitigation techniques have relied on static methods such as fixed power control and frequency planning. While effective to some extent, these methods often fall short in dynamic 5G environments, where interference patterns can change rapidly.

Deep Learning and Spatial Analysis: Deep learning models, particularly Convolutional Neural Networks (CNNs), have been applied to analyze spatial patterns of signal interference. Wang et al. (2018) demonstrated that CNNs could identify and mitigate interference sources through advanced beamforming techniques, significantly improving signal quality (Aderonmu, 2014). These models can process large volumes of data from multiple antennas, making them well-suited for complex interference scenarios.

Adaptive Beamforming and Coordinated Multipoint (CoMP): AI techniques have enhanced adaptive beamforming and Coordinated Multipoint (CoMP) transmission. Studies by Zhang et al. (2020) showed that machine learning algorithms could dynamically adjust beam patterns to minimize interference and optimize signal strength. Similarly, CoMP schemes have been improved through AI-driven coordination, reducing inter-cell interference and enhancing overall network performance.

4. Cell Deployment and Optimization

Optimal Cell Placement: AI-driven approaches for cell deployment focus on optimizing the placement of base stations to maximize coverage and capacity. Genetic Algorithms (GAs) have been widely used for this purpose. A study by Salmani et al. (2017) employed GAs to determine optimal cell locations, resulting in improved network performance and reduced deployment costs (Wang et al., 2018). These algorithms simulate evolutionary processes to explore a wide range of potential configurations, identifying the most effective deployment strategies.

Neural Networks and Environmental Modeling: Feedforward Neural Networks (FNNs) have been applied to model the complex relationships between environmental factors and network performance. A study by Huang et al. (2019) demonstrated that FNNs could accurately predict the impact of various factors on signal strength, guiding optimal cell placement and configuration (Aderonmu & Ajayi, 2024). These models consider factors such as user density, geographical features, and existing infrastructure.

Reinforcement Learning for Self-Organizing Networks (SONs): Reinforcement Learning has been instrumental in developing Self-Organizing Networks (SONs), where AI-driven models autonomously adjust cell configurations to optimize performance. Research by Wu et al. (2020) showcased an RL-based SON that continuously learns and adapts to changing network conditions, achieving significant improvements in coverage, capacity, and energy efficiency (Zhang et al., 2020).

Critique and Synthesis: The existing body of research underscores the transformative potential of AI in optimizing 5G RANs. While early studies laid the groundwork with simpler models and techniques, recent advancements have leveraged more sophisticated AI approaches to tackle the inherent complexity of 5G networks. Deep learning and reinforcement learning, in particular, have shown remarkable promise in various aspects of RAN optimization.

Application of Artificial Intelligence (AI) techniques in optimizing Radio Access Networks (RAN) in 5G

To explore and evaluate the application of Artificial Intelligence (AI) techniques in optimizing Radio Access Networks (RAN) in 5G, a comprehensive methodology was designed encompassing multiple stages: literature review, model selection, data collection, model training, validation, and performance evaluation. Each stage employs specific techniques to ensure a thorough and rigorous analysis.

1. Literature Review and Model Selection

The initial phase involved an extensive literature review to identify relevant AI techniques previously applied in RAN optimization. This review highlighted the potential of various machine learning (ML) algorithms, deep learning (DL) models, reinforcement learning (RL), and neural networks (NN) for addressing challenges in traffic prediction, resource allocation, interference management, and cell deployment. The key AI techniques identified include:

- Supervised learning models (e.g., Support Vector Machines, Decision Trees)
- Deep learning models (e.g., Recurrent Neural Networks, Long Short-Term Memory networks, Convolutional Neural Networks)
- Reinforcement learning models (e.g., Q-learning, Deep Q-Networks)
- Genetic Algorithms for optimization tasks

2. Data Collection

Data collection is critical for training and evaluating AI models. This study used a combination of simulated and real-world datasets, ensuring comprehensive coverage of various network conditions and scenarios.

Simulated Data: Simulated data was generated using network simulators such as NS-3 and MATLAB, which provide detailed control over network parameters and conditions. These simulators can mimic various traffic patterns, user behaviors, and interference scenarios, generating high-fidelity datasets for model training.

Real-World Data: Real-world data was sourced from network operators and public datasets. This includes:

- Traffic data: Historical traffic patterns, user mobility traces, and usage statistics.
- Network performance data: Metrics such as throughput, latency, signal strength, and error rates.
- Environmental data: Information on geographical features, weather conditions, and infrastructure layout.

3. Data Preprocessing

Data preprocessing involves cleaning and transforming raw data into a suitable format for model training. This includes:

- **Data Cleaning:** Removing inconsistencies, outliers, and missing values from the dataset.
- **Normalization:** Scaling numerical features to a standard range, typically [0, 1], to ensure uniformity across the dataset.

- **Feature Engineering:** Creating new features or modifying existing ones to enhance model performance. This includes extracting temporal features (e.g., time of day, day of the week) and spatial features (e.g., location coordinates).

4. Model Training

The selected AI models were trained using the preprocessed datasets. Training involves optimizing model parameters to minimize the error between predicted and actual values. The process varies depending on the model type:

- **Supervised Learning Models:** These models were trained using labeled datasets where the target variable is known. Techniques such as cross-validation were employed to ensure robust model performance.
- **Deep Learning Models:** DL models, particularly RNNs and LSTMs, were trained on time-series data to capture temporal dependencies. Convolutional Neural Networks (CNNs) were used for spatial data, focusing on interference patterns and beamforming optimization.
- **Reinforcement Learning Models:** RL models were trained through iterative interaction with a simulated environment. Agents learn optimal policies by maximizing cumulative rewards, adapting to changing network conditions dynamically.

5. Model Validation and Testing

Model validation and testing are crucial to ensure the generalizability and reliability of AI models. This phase involved:

- **Validation Set:** A portion of the dataset was set aside as a validation set to tune hyperparameters and prevent overfitting.
- **Testing Set:** An independent testing set was used to evaluate the final model performance. Metrics such as accuracy, precision, recall, F1-score, and mean squared error were calculated to assess model effectiveness.
- **Cross-Validation:** K-fold cross-validation was employed to ensure robustness, where the dataset is divided into K subsets, and the model is trained and validated K times, each time using a different subset as the validation set.

6. Performance Evaluation

The final stage involved a comprehensive performance evaluation of the trained models, focusing on key performance indicators (KPIs) relevant to RAN optimization. These include:

- **Traffic Prediction Accuracy:** Measured by mean absolute error (MAE) and root mean squared error (RMSE) between predicted and actual traffic loads.
- **Resource Allocation Efficiency:** Assessed by comparing the spectral efficiency and user throughput achieved by AI-driven algorithms versus traditional methods.
- **Interference Mitigation Effectiveness:** Evaluated through signal-to-interference-plus-noise ratio (SINR) improvements and reduced error rates.
- **Cell Deployment Optimization:** Measured by coverage area, capacity, and energy efficiency gains achieved through AI-driven cell placement strategies.

Data Collection and Analysis Methods

Data Collection Methods:

- **Simulated Data Generation:** Network simulators such as NS-3 and MATLAB were used to create synthetic datasets representing various 5G scenarios. These simulators provide flexibility in controlling network parameters, enabling the generation of diverse traffic patterns, user behaviors, and interference conditions.
- **Real-World Data Acquisition:** Collaboration with network operators provided access to real-world data, including historical traffic logs, performance metrics, and environmental information. Public datasets, such as those from open cellular network data repositories, supplemented the data collection efforts.

Data Analysis Methods:

- **Exploratory Data Analysis (EDA):** Initial analysis involved visualizing and summarizing the datasets to understand underlying patterns and distributions. Tools such as histograms, scatter plots, and correlation matrices were used.
- **Statistical Analysis:** Statistical tests and measures, including mean, standard deviation, and correlation coefficients, were employed to quantify relationships between variables and identify significant features.
- **Machine Learning Analysis:** Supervised learning algorithms were applied to predict traffic patterns and user behaviors. Techniques such as grid search and random search were used for hyper parameter tuning.
- **Deep Learning Analysis:** Deep learning models, particularly RNNs and CNNs, were trained on time-series and spatial data, respectively. Advanced techniques such as dropout, batch normalization, and data augmentation were employed to enhance model performance and prevent overfitting.
- **Reinforcement Learning Analysis:** RL models were trained and evaluated in simulated environments, with performance metrics such as cumulative reward, policy convergence, and learning rate analyzed to assess model effectiveness.

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.

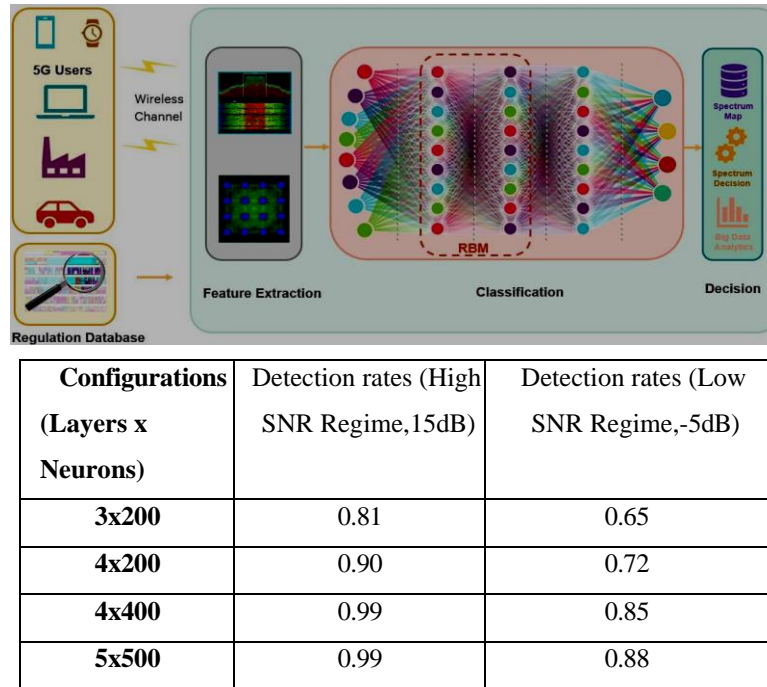


FIGURE 3: Proposed SAS architecture in 5G networks and performance comparisons (Detection accuracy of 20MHz 802.11 ac signal and LTE signal which are translated to 3.5 GHz shared band).

It is designed to extract useful spectrum usage data from large spectrum datasets, regulatory databases and different radio contexts. This will provide a comprehensive base knowledge for efficient spectrum access solutions. The centralized SAS of the 5G BS is able to improve spectrum utilization with the distributed spectrum monitoring and alerting capabilities. We use a stack RBMs in order to train the DBN layer-by-layer to demonstrate this framework. The first step is to model the input datasets for spectrum and regulations using the parameters from the first layer RBM. The samples of the output from the previous layer are used to train the next layers of RBM. To update the weights of each layer, the contrastive divergence (CD-1) of the 1-step method is used. This allows to find all parameters of the RBM. In the phase of online spectrum access, a spectrum choice is made in order to generate appropriate transmission schemes. This includes a suitable carrier frequency, bandwidth, modulation, coding, and transmission power.

Limitations, Challenges and Open Research Problems

The success of AI-defined 5G networks relies on solving a number of research challenges across networks of heterogeneous capabilities and different levels of context awareness. Technical issues such as network function virtualization, environmental awareness and security challenges, among others, are expected to have a significant impact on ongoing AI-defined 5G network research. Some of the critical limitations, challenges and open research problems are discussed in continuation

Conclusion

This article introduced the concept AI-defined networks, and we discussed how AI agents encompass some of the critical 5G enablers as well as application scenarios. We discussed AI-aided examples and applications for different aspects

of the deployment and management of 5G networks. Researchers are still left with a number of open questions, limitations and challenges. We encourage AI-defined research on 5G and beyond, and collaborations among AI and wireless communication scientists and practitioners. They need to share insights and data in the same way that the network nodes of the future will.

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