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Exploring AI-Based Adaptive Resource Management in 5G Networks

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***Abstract*—Resource allocation is a key challenge for gNB scheduler in 5G networks, for distributing limited resources to end devices. The scheduler's goal is to optimize transmission quality and quality of service for applications like real-time communication, video streaming, IoT, and autonomous driving. Traditional scheduling algorithms struggle to cope with the dynamic and heterogeneous demands of 5G networks, which result from the increasing number of connected devices, network traffic and application requirements. We propose Artificial Intelligence techniques for gNB scheduler and enable intelligent and adaptive resource allocation. By utilizing AI, the scheduler learn from network data, adapt to changing conditions, and optimize resource utilization and transmission quality for different applications. Our approach involves implementing three AI techniques: Performance comparisons between AI-based and classical scheduling algorithms are conducted using metrics such as network throughput, latency, packet loss, resource usage, and user satisfaction. The proposed AI-based scheduling algorithms have the potential to improve network performance, reduce congestion, conserve resources, and enhance the user experience in 5G networks.**

***Index Terms*—5G, gNB, Artificial Intelligence, LSTM, Deep Reinforcement Learning, Online Learning, Machine Learning**

I. Introduction

We deployed a 5G standalone (SA) network, which consists of only 5G components [1], unlike the common 5G networks that rely on 4G components. The SA network enables us to conduct further research, such as demonstrating High Throughput and Ultra-Reliable Low-Latency Communications [2]. However, a major challenge in 5G networks is to optimize the complex configuration options and resource allocation. Previous approaches without AI [3], [4] have addressed this challenge, but they may not be flexible enough to cope with the dynamic and heterogeneous demands of 5G networks.

Various solutions with AI have already been developed. Some approaches support resource allocation with Deep Reinforcement Learning to optimize beamforming, power control and interference coordination [5]. Alternative solutions perform optimized and fast real-time resource slicing with deep-dueling neural networks [6]. Figure 1 illustrates an overview of AI in a 5G network.

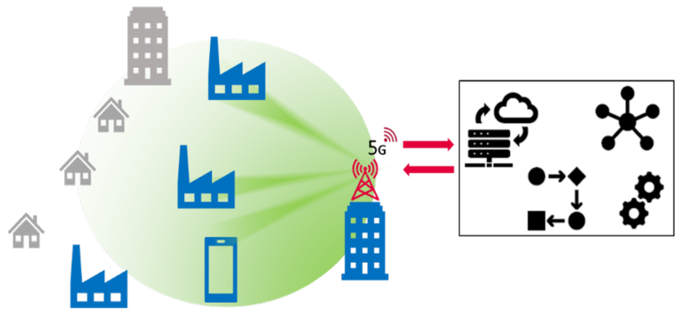

Fig. 1. AI implementation into 5g network

II. AI Based Optimization of the gNB scheduler

In 5G networks, a gNB scheduler is usually controlled by rules and algorithms defined by standardization organizations e.g. 3rd Generation Partnership Project (3GPP). These rules and algorithms define how resources are distributed to end devices based on quality of service (QoS) requirements, priorities, channel status, and network utilization [7].

However, the increasing complexity of 5G and the various applications limit the control with rule-based and classical algorithms. In summary, there is no standard configuration of the gNB scheduler that fits best for all environments. For this reason, artificial intelligence algorithms gain more importance in future. Our goal is the development of a scheduler that adopts to changes in the environment. Additionally, it evolves over time, i.e. enable continuous learning. The following three aspects represent optimization approaches for AI:

Resource Optimization: Deep Reinforcement Learning is an AI technique that combines reinforcement learning and deep neural networks [8]. Figure 2 shows the basic operation of a Deep Reinforcement Learning algorithm.

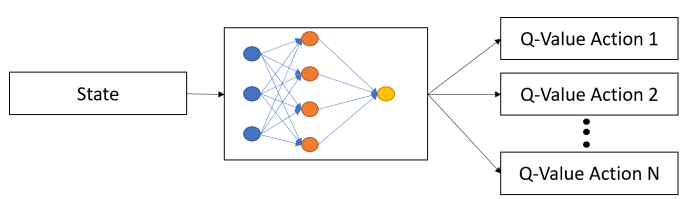

Fig. 2. Deep Reinforcement Learning

In the context of the gNB scheduler, Deep Reinforcement Learning optimizes the allocation of network resources, such as future slices. The scheduler learns by trial and error, combined with feedback on its decisions, and adjusts its resource allocation strategy accordingly.

Real-time Adaptation: Online Learning is a machine learning approach where the model learns and adapts in real-time as new data becomes available [9]. In the case of the gNB scheduler, online learning enables the scheduler to adapt and adjust its decisions based on changing network conditions. The scheduler continuously receives and processes real-time data on network parameters such as traffic load, signal quality, and interference levels. It optimizes resource allocation, user or service prioritization and network performance by updating its decision-making process to network conditions. For example, it dynamically allocates bandwidth based on traffic demands, prioritizes critical services during congestion, and adjusts transmission policies for improved network efficiency.

Network Faults: The second and third layer leverages Long Short-Term Memory models, a type of time series models, to detect or predict network faults, supporting the gNB Scheduler. Time series data represent a sequence of observations collected over time, such as network performance metrics. LSTM models are a type of recurrent neural network (RNN) that can capture dependencies and patterns in time series data [10]. By training an LSTM model on historical network data, the gNB Scheduler can detect anomalies or predict potential network failures. This allows proactive actions, such as traffic rerouting, resource reallocation or maintenance triggering, to prevent disruptions and maintain network stability and reliability.

III. Evaluation Concept

To evaluate the AI algorithms in 5G networks, a comprehensive experimental evaluation is conducted. The following methodology is used to evaluate the performance and effectiveness of the implemented AI algorithms:

- Data collection: Real data is collected from the 5G SA network, including network performance metrics, congestion levels, resource utilization, and user experience. This data forms the basis for evaluating the AI algorithms.
- Test Scenarios: Different scenarios are designed to evaluate the performance of the AI algorithms. The scenarios include different network conditions, traffic loads, and QoS requirements to simulate real-world operation.
- Performance metrics: Several metrics are compared for effectiveness of the AI algorithms. These metrics include network performance indicators such as throughput, latency, and packet loss, as well as congestion levels, resource utilization, and user satisfaction.
- Comparative analysis: The results of the AI-enabled gNB scheduler are compared to the performance of the classical algorithms. This comparative analysis provides insights into the improvements achieved by the AI algorithms in terms of network performance, congestion reduction, resource efficiency, and user experience.
- Statistical analysis: Statistical methods are applied to analyze the collected data and draw meaningful conclusions. The significance of the differences between the AI algorithms and the traditional algorithms will be evaluated using appropriate statistical tests.

Through rigorous experimental evaluation, this study aims to provide quantitative evaluation of the AI algorithms on the performance of the gNB scheduler in 5G networks. Analysis of the results based on various metrics provides valuable insights into the effectiveness and benefits of using AI techniques in resource management and transmission optimization.

IV. Conclusion and Future Work

We demonstrated how AI algorithms support a gNB scheduler and why this is increasingly important. We also presented the steps for implementing and evaluating such algorithms. Our future work involves implementing the AI algorithms in our 5G SA network's gNB scheduler and conducting an extensive evaluation. Moreover, we plan to deploy other AI algorithms for autonomous network management, such as learning, fault detection and recovery, self-optimization, efficiency, and scalability.

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