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# Critical Review on Machine Learning in 5G Mobile Networks

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**Abstract:** The 5G wireless network standard was created through the 3rd Generation Partnership Project as the next big leap in wireless network technology. Offering several advantages over previous generations of wireless network technology 5G, promises to bring with it higher speeds, lower latency rates, better reliability, and much more. All these improvements offered by the Fifth-Generation network allowed for a variety of new applications that increased the complexity of maintaining the quality of service across the network due to their stringent and heterogeneous quality of service requirements, which must be met simultaneously. This increased complexity has motivated many researchers to propose innovative approaches in the literature, such as implementing network schedulers that can leverage different kinds of machine learning, network slicing, or combinations of several different techniques. This has motivated us to investigate the existing research regarding machine learning in network orchestration, to determine the most capable methods and algorithms to satisfy the quality-of-service requirements of the heterogeneous traffic flows across the 5G wireless network.

***Keywords:*** *5G, Network Slicing, QoS, Reinforcement Learning.*

## 1. Introduction

The development of 5G wireless network technology can be seen as a continuation of previous generations of wireless network technology standards, with many improvements to key network performance metrics such as speed, latency, reliability, and more [1]. Enabling a variety of new network applications like self-driving vehicles, mass IoT deployments, and high bandwidth applications like augmented reality and virtual reality [2]. Most of these applications can be classified into three classes of traffic, enhanced Mobile Broad Band (eMBB), Ultra Reliable Low Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) [3].

Autonomous vehicle applications are one example of URLLC, where high reliability and low latency, are key factors in maintaining quality of service (QoS). Augmented Reality and high-resolution video streaming are good examples of eMBB services, where throughput and high data rates are key factors in maintaining QoS for the user. High-density deployments of sensors or other Internet of Things (IoT) devices are a good example of mMTC applications, where the QoS is dependent on the network being able to support the high density of low-power devices. These network use cases i.e. (eMBB, URLLC, mMTC), have introduced heterogeneous QoS requirements, that need to coexist on the network [4].

This heterogeneous nature of the 5G wireless network increases the difficulty of resource management across the 5G network. Machine Learning ML and software-defined networking (SDN) are widely used to manage the increased complexity of the network QoS requirements [4] and in this paper, we discuss some of these solutions.

## 2. Problem Statement

Resource management across the 5G network has increased in complexity over previous network standards, due to the heterogeneous nature of the QoS requirements of the network traffic that coexist on the 5G network [3]. The existing network research has investigated a variety of methods to maintain QoS in 5G wireless networks, like using reinforcement learning (RL) enabled network schedulers [5] [6] and network slicing [7] in order to grant more flexible control over the network. Thus, we know we can improve the existing network deployments by deploying ML-enabled network schedulers and utilizing network virtualization and network slicing methods to better manage mobile network resources [8] [9].

But first, the most suitable ML algorithms need to be identified in order to deploy effective ML-based solutions into 5G networks. Relevant training datasets need to be created to utilize supervised or unsupervised machine learning and reinforcement learning (RL) algorithms require a suitable reward function to be deployed effectively into the 5G wireless network. In this work, we reviewed multiple research papers that used a variety of methods to create those necessary elements.

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## 3. 5G Network Usage

Use 5G wireless network usage is categorized into three main types: 1) eMBB, 2) URLLC 3) mMTC. Each with its own service requirements [10] [11], and each is discussed in the following sections.

A. eMBB

eMBB is defined by its high peak data rates and is one of the promises of the 5G network. The new radio (NR) will guarantee lower than 1 ms user-plane latency and downlink speeds of 10 to 20 Gb/s. A good example of eMBB usage is virtual reality and ultra-high-definition video streaming [2], [5].

B. URLLC

URLLC is defined by its ultra-reliability and responsiveness, with a delay not exceeding 1 ms at the cell edge, and high user equipment (UE) mobility. Good examples of URLLC usage are healthcare industry applications or self-driving vehicles.

C. mMTC

mMTC is defined by its high density of low-power devices which can exceed 100,000 devices per square kilometer. Those devices are expected to have battery lives of over 10 years. A good example of mMTC usage is IoT technology deployments like sensors [10].

The characteristics of these three 5G network use cases are summarized in Table 1.

**Table 1** Overview of 5G network use cases.

| | |
|---|---|
| **eMBB** | Support peak rates of 10 to 20 Gb/s.<br><br>User-experienced data rates, to be reached with a high degree of probability even in loaded network conditions.<br><br>**Low user-plane latency.** |
| **URLLC** | Delay not exceeding 1 ms even at the cell edge.<br><br>Offers very high UE mobility. |
| **mMTC** | Very high connection densities that far exceed 1,000,000 devices, per square kilometer. |

## 4. Machine Learning

Machine learning can be described as the process of allowing a machine to automatically learn meaningful relationships and patterns in data, through algorithms in a way similar to how humans learn [12]. Generally, ML is split into three main types: 1) Supervised learning, 2) Unsupervised learning 3) Reinforcement learning. The characteristics of these three types of ML algorithms are discussed in the following section.

A. Supervised Learning

In supervised learning the model is trained using a labeled training dataset, that can allow the algorithm to classify data or predict outcomes in real-world problems. While supervised learning is very effective when there is a large amount of labeled data available to be used for training. Its static nature and need for a training dataset make it a poor fit for a dynamic, QoS-aware, 5G network environment.

B. Unsupervised Learning

The unsupervised learning model also requires a training dataset like supervised learning. However, unlike supervised learning, the data used for training purposes is unlabeled, leaving the model to discover patterns in the data, without input from an external operator. This makes unsupervised learning more powerful in handling problems with datasets that have no obvious common patterns.

C. Reinforcement Learning

Unlike other types of ML, reinforcement learning (RL) does not need a training data set for the model to act. Reinforcement learning focuses on decision-making, operating based on a reward function that guides the algorithm to the desired outcome rather than using a training dataset, the algorithm relying on trial and error to maximize the reward function. RL is more suitable for dynamic models and is fit for use in the heterogeneous environment of 5G networks. The characteristics of these three types of ML are summarized in Table 2. The existing works that utilized the RL-based QoS provisioning schemes in the mobile network are discussed in the following section.

**Table 2** Overview of machine learning types

| **Supervised Learning** | **High accuracy if the training dataset is labeled correctly.** | **Requires a labeled training dataset. Cannot operate on new data on its own with training data.** |
|---|---|---|
| Unsupervised Learning | Capable of finding undiscovered patterns in large unlabeled datasets. | Requires human intervention and oversight for validation of results |
| Reinforcement Learning | Allows for automated decision-making. | Requires the researcher to be deeply familiar with the problem needed to be solved by the RL model in the first place, to create an effective reward function. |

## 5. Related Works

Resource management in wireless networks is an essential part of maintaining QoS for users. Many research works were carried out to develop new ways to optimize resource utilization across the mobile network. In the following section, we discuss several relevant research works in resource management for 5G wireless mobile networks.

The authors in [11] discussed the complexity of creating a scheduling algorithm capable of handling the new challenges that come with 5G wireless networks, then the authors proposed using a hybrid meta-heuristic model to obtain a weight function based on multiple attributes such as packet loss ratio and packet-delay budget, collected from the network. The authors classified network traffic in their simulation into one of three slices, i.e., (eMBB, mMTC, URLLC), using deep belief network and neural network techniques.

Then the authors compared several prominent resource scheduling techniques, i.e., proportional fair (PF), exponential EXP, and the LOG RULE, with their proposed method. In the author's conclusion their proposed method showed promising results in terms of throughput, packet loss, and fairness compared to the techniques stated above.

The authors in [5] proposed two network schedulers based on the advantage actor-critic RL algorithm, naming them D-A2C and CDPA-A2C, with the first part of each name referring to factors considered in their reward functions. Both network schedulers can be deployed to reconfigurable wireless networks to provide a great deal of autonomy in the way the network operates. Each of the proposed network schedulers used a different reward function. One of the schedulers (D-A2C) only considered the delay budget of a packet. The other scheduler (CDPA-A2C) considered the packet type, the channel quality, and the delay budget of each packet. To test the proposed solutions, the authors used packet delivery and general delay as the performance metrics in their simulations. Then the results of the two proposed schedulers were compared with more traditional network schedulers, i.e., proportional fair, and channel and QoS techniques. Both proposed network schedulers show improvements over the traditional network schedulers.

The authors in [13] proposed a hybrid machine learning network slicing algorithm that integrated the Glowworm Swarm and Deer Hunting algorithms. This proposed solution collected relevant data from packets across the network. Then the data collected is used to classify network slices into three main traffic types: eMBB, mMTC, and URLLC. However, further effort will be needed to improve the proposed solution to solve the more complex network scenarios.

The authors in [14] proposed a four-block framework that consisted of a Gatekeeper block, an Admission Controller block, a Forecast Aware Slice Scheduler, and an adaptive reinforcement learning based resource manager. The Gatekeeper block performs the classification. The Decision Maker block consists of two modules: an Admission Controller and a Forecast Aware Slice Scheduler. The Admission Controller processes requests across the network either granting or denying them. The accepted requests were then forwarded to the Forecast Aware Slice Scheduler. Lastly, an adaptive RL-enabled resource manager utilized an Actor-Critic model to receive denied resource allocation requests from the admission controller to decrease the chances of such instances. A network topology with only three UEs across the network is simulated in this work. More work is needed to evaluate the efficiency of the solution proposed under a scalable and overloaded network.

The authors in [7] investigated the saturation problem caused by huge numbers of mMTC in cellular networks and proposed a network architecture for 5G LTE networks to allow for improved coexistence of machine-to-machine (M2M) and human-to-machine traffic, each supported by different priority strategies to maintain the different QoS requirements for each traffic type. To accomplish that. The authors' method was built on an adaptive channel bandwidth selection that receives the data it requires for decision-making from aggregated M2M gateways. M2M gateways are described by the authors as clusters of sensors or other mMTC devices that send data using available narrowband or Wi-Fi to one device, which then in turn sends the collected data to the base station. M2M gateways are not an innovation but the particular process proposed by the authors is. As in conventional M2M gateways data, is collected from each device and automatically transmitted to the base station, but what the authors proposed is that the data sent by each M2M gateway is to be sorted by the base station into four memory buffer queues with different QoS requirements in real-time. The simulation results showed a 13% improvement in the efficiency of radio resource utilization. This paper mainly focused on resource utilization, disregarding other QoS metrics like packet delivery ratio.

The authors in [3] proposed a multi-agent reinforcement learning based method (MARL) for resource slicing to maintain the QoS of the various types of 5G network traffic. The authors named their proposed algorithm Correlated Q-learning based inter-slice resource block allocation (COQRA). In which each network slice (URLLC, eMBB) is treated as an intelligent agent and able to compete for network resources. Then a model-free COQRA algorithm is applied, to provide inter-slice resource distribution. The network resources of each slice are distributed among their users through a proportional fair algorithm (PF). Performance comparison was carried out through the Nash Q-learning algorithm and the priority PF algorithm. The proposed algorithm achieved superior throughput, latency and packet drop ratio, for URLLC and eMBB loads. However, this work did not evaluate performance metrics related to mMTC loads.

Table 3 summarized the most significant related works reported in this section.

**Table 3:** Summary of literature review.

| *NO.* | *Reference* | *Proposed Method* | *Limitation* |
|---|---|---|---|
| 1 | Combined Metric-Based Resource Scheduling for 5G Networks. [2021] | The authors proposed two schedulers, i.e. EXP and MLWDF-LOG. | The simulation scenarios only considered a single relatively low constant speed for all mobile users |
| 2 | Actor-Critic Learning Based QoS-Aware Scheduler for Reconfigurable Wireless Networks. [2021] | The authors proposed two schedulers D-A2C and, CDPA-A2C. Both use Advantage Actor-Critic reinforcement learning. D-A2C only considered the Delay Budget of each packet. CDPA-A2C considered the packet type, delay budget, and channel quality. | The authors only used packet delivery ratio and general delay as their performance metrics. In the simulation, only a fixed number of mobile UEs were considered. |
| 3 | Optimal 5G network slicing using machine learning and deep learning concepts. [2021] | The authors proposed a hybrid meta-heuristic model, which they labeled as GS-DHOA Glow-worm Swarm-based Deer Hunting Optimization Algorithm. That model consists of three main steps Data Collection optimal weighted feature extraction (OWFE), and Slicing Classification | The authors admit that the proposed model would need further improvements for implementation into more complex problems. |
| 4 | 5G network slices resource orchestration using Machine Learning techniques. [2021] | The authors designed a resource orchestration framework that consists of four main blocks. To implement those blocks the Authors proposed using machine learning techniques for classification. and used Regression Trees to predict slicing ratios. The authors also modeled admission control and scheduling as a type of optimization problem known as a knapsack. And used Deep RL for resource management. | The Authors limited the number of UEs in the simulation scenario to 3 for the sake of simplicity. |
| 5 | RAN Resource Slicing in 5G Using Multi-Agent Correlated Q-Learning. [2021] | The authors proposed a MARL-based resource allocation algorithm. That jointly optimized, URLLC and eMBB traffic. | The Authors did not consider massive Machine-Type communications (mMTC) optimization. |

## 6. Conclusion

It can be concluded that the 5G mobile network has enabled new network applications with heterogenous QoS requirements that co-exist on the same network. A new solution is needed to maintain QoS across the network, and machine learning is a promising way to achieve this objective. Reinforcement learning seems to be the most promising subset of machine learning to support the 5G mobile network. A combination of reinforcement learning, real-time network slicing, and network virtualization allows for the deployment of QoS-aware network schedulers that are dynamic and capable of adapting to the heterogeneous environment of 5G networks. Ensuring that all the heterogenous QoS requirements of the 5G network are being met.

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**Author contributions**

**Mohamed Mohsen Farouk:** Conceptualization, Literature Review, Writing. **Wai Leong Pang:** Guidance, Reviewing and Editing. **Gwo Chin Chung:** Reviewing and Editing, **Mardeni Roslee:** Reviewing and Editing.

**Conflicts of interest**

The authors declare no conflicts of interest.

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