INTELLIGENT COGNITIVE ENGINE FOR 5G NETWORK QUALITY OF SERVICE MANAGEMENT

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ABSTRACT

5G-New scenario transparency in communication between various types of networks that are interconnected is expected in radio multimedia. A prevalent issue across all these diverse platforms is the equitable distribution of the restricted network resource among rival apps. A transcendent measure of how equitably properties are distributed to end-users is called Quality of Service (QoS). It is derived from subscriber satisfaction levels and depends on how quickly the network responds to possible infractions of established regulatory guidelines. There are discussion on the perspective of 5G network trust in terms of QoS management, demand formulation, xMBB, M-MTC, and U-MTC. There is a proposed architecture that controls access in the 5G network's data plane. A new cognitive engine for artificial intelligence that is built on memory is put forth. The idea is to translate the probabilistic sign of a set of variables related to resource distribution to the end-user for multi-service improvement.

KEYWORDS

Deep Reinforcement Learning, Memory-Based Artificial Intelligence, 5G Quality of Service, Machine Learning.

1. INTRODUCTION

The core principles of “Quality of Service (QoS)” in 5G networks differ significantly from those in existing 4G/LTE networks. The advent of “5G-NR (new radio)” technology promises significantly faster data speeds for all IP-based services. In addition to successfully standardizing the models and guiding principles of service quality management at the network level, 3GPP has developed the most recent generations of mobile networks and added new features to their networks. When QoS management principles are applied at the network level, more mobile applications that regulate QoS according to service quality standards should be developed, and Bearer services should create the essential high-level data interchange [17]. New forms of QoS management that can make use of QoS network model management have been

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deployed in 4G networks that are based on QoS model management at the network level.

Certain outdated software need to be updated in certain situations. On the other hand, there are terminals that employ QoS terminal model management. It indicates that for a few years, two QoS management approaches coexisted in mobile terminals. Two QoS management models are employed in this scenario, and Figure 1 illustrates how these models have evolved. With the proliferation of smart phones and other connected devices, users are increasingly demanding higher data throughput from their networks, a demand that 5G aims to meet. One of the key features of 5G is its emphasis on integrating various sub-technologies such as "massive machine-type communication (mMTC)", "ultra-Reliable Low Latency Communications (uRLLC)", and "enhanced mobile broadband (eMBB)". This integration is designed to support a wider range of services compared to current networks [1]. Anticipated to become over twelve stretches more rapidly as compared to the 4G/LTE, 5G-NR as designed is projected to accommodate about a thousand fold increases in diverse traffic compared to existing networks.

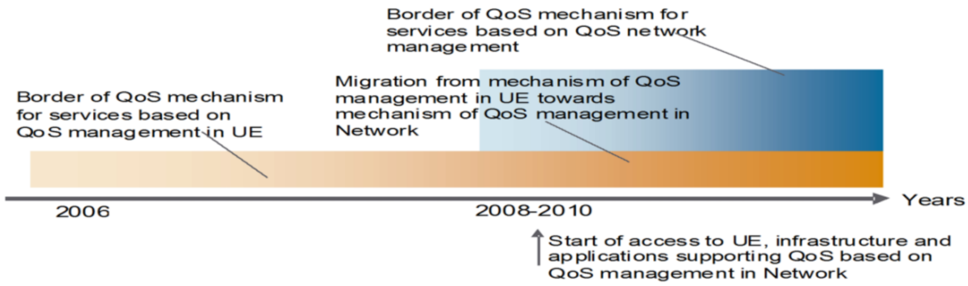

Figure 1: Two QoS management models in Mobile networks [adapted from 3GPP]

1.1. 5G Network Quality Of Service

The 5G network's exceptional spectrum efficiency and incredibly low end-to-end latency are two of its main features [2]. This means that the 5G network must be completely aware of QoSpriority "(QoS-aware)" when sending high-speed data streams, such as audio and video packages.

Social media of today is pushing the need for networks that can self-optimize and self-heal. Large amounts of data that result from these mechanisms and the related computational complexities have proven to be too much fortraditional analytical QoS regulating procedures to handle. In this context, extensive global research is presently being conducted to discover new artificial intelligence (AI) and machine learning (ML)-centered 5G system QoS governance and evaluation resolutions. There is practically at all times a contract flanked by the internet supplier and those who subscribe to them in any communication network [3].

Consumers and regulators, who supply both the market demand for communication services and the efficacy of operators' network infrastructure, are two important players in the telecommunications market whose trust should be taken into account when implementing a systematic approach to the trusted communication network. Figure 2 illustrates how the criteria of regulators and customers for a trustworthy mobile communication network may diverge or coincide. Table 1 displays the key elements influencing the subscriber's and the regulator's trustworthiness in declining order of significance [18].

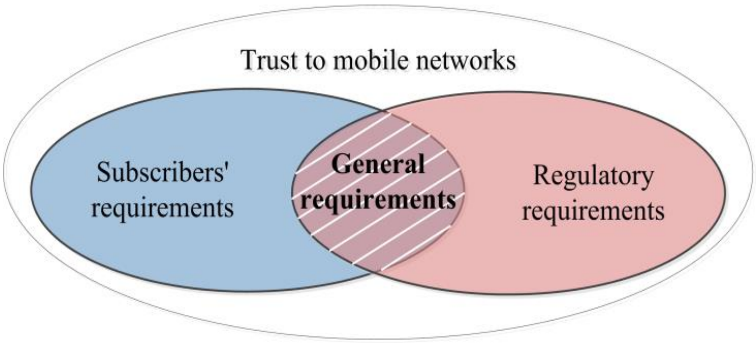

Figure 2: Domains of trust to mobile networks [adapted from QoS-aware]

1.2. Subscriber Comfort Experience (Sce)

Figure 3 illustrates the three categories into which 5G network quality metrics can be categorized: Network Performance (NP), Quality of Service, and Quality of Experience (QoE). While QoE metrics are subjective and determined by individuals based on their own experiences, NP and QoS are objective indicators that may be assessed using specialized analyzers. Lower trust in 5G networks among regulators and business-to-business (B2B) and business-to-government (B2G) clients will be the main result of the decline in QoS and NP, but lower trust in the mass market will be the result of the decline in QoE [19].

For the purpose of discarding, violating packets are identified using call drop probability. Prioritizing allows the network to impose a set of rules on the subscriber that define the quality of service (QoS), which in turn leads to the subscriber comfort experience (SCE). The primary challenge in implementing 5G networks, given its anticipated speed and granularity, is not only determining how to fulfill service level agreements (SLAs) but also enhancing subscriber connection experiences [4]. The impact of providing quality to the subscriber, including packet loss probability, end-to-end delay, and the implications of bandwidth variance, is contingent upon the available bandwidth.

Thus, among the queries that need to be addressed in a conceptual framework are the following: how does enhancing 5G's QoS improve the experience of its subscribers? Which machine learning approach achieves the optimal level of monitoring that is adaptive for “key performance indicators (KPI)” of 5G network while preventing measurement interference? Which simulation tools are necessary to get the best possible End-to- End QoS design? What remain as the optimal outcomes that could be shown on a console to assist a 5G network supplier in effectively managing the net system?

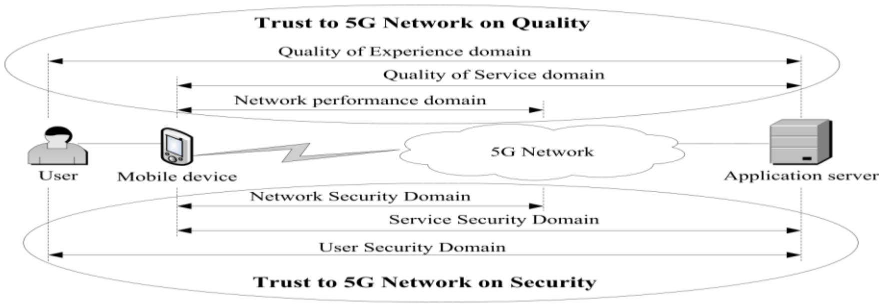

Figure 3. Quality and security levels of trust to mobile network [adapted from 5GNQ]

2. Conceptual Framework for 5G

Conceptual Framework for 5G Machine Learning's five cutting-edge technologies are the foundation of the 5G- NR network's conceptual architecture and are regarded as its essential building pieces [5]. These include beam- forming, enormous multiple-in/multiple-out, femtocells, millimeter wave, and full-duplex technology.

Integrating many performance measures in both virtual and real-world scenarios is the primary objective of the 5G network. Therefore, a net system slicing architecture that is anticipated to span several managerial and functional domains provides the foundation for end-to-end performance. These domains include the operation & management control planes, the mobile suppliers contact/carriage networks, and the cloud-centric core. Autonomic cognitive networks that are self-critical and self-organizing are necessary to handle a high number of service slices due to the complexity of integration [6].

These networks should have built-in performance designs. Every service slice caters to a certain vertical or use case. For this reason, machine learning (ML) techniques are being proposed by standards bodies and organizations like the IEEE and the 5GPPP designed for the "network enhancement and monitoring of Service Level Agreements (SLA)". "Network failures, design, accounting, presentation, performance, safety and security (FCAPS)" are the proposed factors that determine SLA in 5G-NR. The slanted quality of service, or console practice, which 5G network subscribers are required to get is governed by FCAPS collectively [7].

3. Proposed Processes of Machine Learning (ML) for 5G-FCAPS

Three service levels, referred to as portfolios, have been proposed to ease the process of machine learning (ML) for 5G-FCAPS monitoring, control and administration.

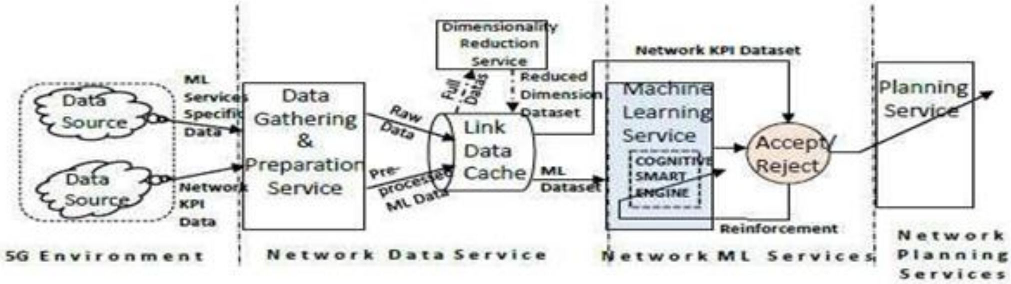

Figure 4: Concept of Machine Learning for 5G Quality of Service [adapted from 5GPPP]

4. Discussion

Figure 4 illustrates distinct tiers of services, comprising "Layer-1 Data services", "Layer-2 Machine Learning services", and "Layer-3 Planning services". Network operators can select multiple service slices from these tiers based on their prioritized needs, including data bandwidth availability. Operationally, Layer-1 takes care of any necessary pre-processing of the incident data related to 5G traffic. The ML receives its predictive learning functionalities from Layer-2. The machine learner's taught preventative or predictive action policy is then implemented by the "Layer-3 Planning services".

Figure 1 also illustrates the main idea of our research, which is the subject of our study. Artificial intelligence is used by a proposed "Cognitive Smart Engine (CSE)" to acquire the 5G event traffic flow dissemination arrangements or dataset. The information gathered from the built model is applied to monitor the arrival of any data packs at a 5G system access plug, or femtocell [8].

The idea expands on our created intelligent deep neural network model to examine the performance supervision components of FCAPS (i.e., "QoS parameters"). It has been demonstrated that the memory-based ML model can accomplish quick, autonomous, self-critical network access control. It is utilized to enhance the network's "Subscriber Comfort Experience (SCE)" and stems from the innate deep reinforcement learning characteristics of a "probabilistic random access memory neural network (pRAM-NN)" [9], [10], [11], [12], [13]. As illustrated in Fig. 1, this concept is dubbed as the "cognitive smart engine (CSE)" for ease of use.

5. CONCLUSION

The link capacity between an IP switch core and inter-working units (IWU) is measured in bits per second, or channel capacity. The "variable bit rate (VBR)" data packs inter-arrival procedure is combined with white "Gaussian noise n(t)" with constant energy spectrum to produce the initial simulation approach. This suggests noise that is not associated. As a result, throughout the simulation process, packetization error behavior as shown by actual statistical data sources is mimicked [14]. The memory-centered deep fortification neural net system adaptive moderator certifies that the noisy packets do not violate the quality of service before sending them to the channel buffer [15], [16].

Here, the QoS prioritizing is set as a dynamic signal threshold by the Accept/Reject method. Contingent on the condition of the link cache, packets found to be in violation, determined by whether the packet loss/dropping probability signal is activated or not, will either be discarded immediately or stored for the future transmission. We simulate with the upper tier of the 5G network with an "integrated design environment (IDE)" that we built internally. The open-source tools MATLAB/Simulink, NeuralWare, and Python are used to model the machine learning techniques for artificial neural networks. This stage of the design involves creating and testing a prototype dashboard.

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