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Machine Learning for QoE Management in Future Wireless Networks

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Abstract

The growth in volume and heterogeneity of accessible services in future wireless networks (FWNs), imposes pressure to communication service providers (CSPs) to expand their capacity for network performance monitoring and evaluation, in particular in terms of the performance as it is perceived by end-users. The quality of experience (QoE)-aware design model allows to understand and analyze the operation of networks and services from the end-user's perspective. In addition, network measurements based on QoE constitute a key source of knowledge for the overall functionality and management of the network. In this respect, the implementation of artificial intelligence (AI) and machine learning (ML) in QoE management, increases the accuracy of modeling procedures, improves the monitoring process efficiency, and develops innovative optimization and control methodologies.

1 Introduction

QoE in wireless networks is a metric used to define the end-user's evaluation of the performance of the communication services and reflects the true level of user satisfaction, taking into consideration subjective aspects associated with the impact of the overall experience. The general principle of QoE-awareness in network design should be implicitly supported in all layers of the functional architecture and should take into account the subjective nature of the perceived experience, given that 5G networks are presumed to be inherently user-centered.

The QoE concept has the capacity of becoming one of the key leading frameworks for mobile network quality control. Directly related to the end-user's subjective experience, QoE enables a deeper, more holistic view of the variables that affect the network's functionality, supplementing traditional notions based on technical metrics such as quality of service (QoS) [1].

Although QoE is dependent on QoS, conventional network planning and management methods that rely exclusively on the optimization of a network's key performance indicators (KPIs) to improve service quality are insufficient to meet the widely divergent requirements of FWNs. ML-based network configuration and optimization contrariwise, has the potential to maximize the overall network QoE while meeting the service requirements and network capacity [2].

In this paper, state-of-the-art outcomes are examined and new approaches and challenges relevant to the ML-aided management of QoE in FWNs are discussed. In the light of growing changes, such as the transition to virtualized and softwarized networks, the deployment of the network slicing concept and the gradual growth of the emerging 5G usage scenarios, the evaluation of ML solutions in QoE management is examined.

2 Machine Learning Methodologies

ML refers to the field of computer science that allows algorithms the ability to directly extract models from data without needing to program them directly, drawing inferences and predictions from input samples [3]. ML methods are divided into three broad classes, based on whether a learning signal or feedback is available to a learning system, i) in supervised learning (SL), where examples of inputs and their desired outputs are provided to the algorithm, ii) in unsupervised learning (UL), where no labels are provided to the algorithm, leaving the pattern embodied in the input data to be discovered on its own and iii) in reinforcement learning (RL), where training data in the form of rewards and punishments are presented only as feedback on the performance of the algorithm in a dynamic environment [4].

3 QoE Modeling

One of the crucial stages in the QoE management is QoE modeling, since the model's output will determine the consistency and precision of the next steps in the management procedure. These models take common influencing factors into consideration and aim to predict the end-user's overall satisfaction [5]. Identifying the requirements of the network services and the influence of disruptions on the perceived quality of the end-user, requires the development of models for particular applications, and mappings that link measurable parameters with QoE values [6].

3.1 Factors that Influence QoE

QoE is a qualitative indicator of the level of the end-user's satisfaction with mobile services and applications. Under certain scenarios and environments, users interact with mobile services that substantially impact the degree of the experienced satisfaction [7]. According to the Qualinet white paper [8], a QoE influence factor is prescribed as any feature of a user, system, service, application, or context whose factual state or setting can affect the user's experience quality. These influencing factors can be classified as human-related, system-related and context-related [9]. Additionally, a content-related influencing factor category was added for video streaming applications [10].

3.2 QoE Metrics and Evaluation Methodologies

Most of the work on QoE to date has focused on subjective measurement methodologies and QoE is generally interpreted in terms of user perception and satisfaction. Users usually rate a number of perceived quality aspects on a scale, such as a mean opinion score (MOS) and report their ability to run a service and their level of satisfaction through survey methods such as interviews, focus groups and questionnaires [11]. However, exploiting objective tests and consistent estimation models, QoE can also be objectively estimated. It is possible to measure or approximate the objective parameters effecting the end-user’s experience through various quantifying estimation models, including testing in intrusive mode, non-intrusive mode or planning mode [12].

Unlike KPIs that only provide network-specific output statistics, QoE metrics are based on key quality indicators (KQIs), a series of metrics which offer service quality information at the application level [13]. The subjective QoE metrics are frequently used in practice, but their limitation consists in that their evaluation is time consuming and laborious and cannot be used for real-time operation monitoring [14]. The limitations of subjective metrics have increased the need to implement objective models that measure or predict the quality perceived by the end-users [15].

3.3 QoS/QoE Mapping

The concept of QoS/QoE mapping is based upon computing of the values of QoE from a set of measurable input parameters. The objective parameters of QoS refer to the degree of service adequacy and include network performance KPIs such as delay, throughput, packet loss, and jitter. QoE can be derived from these metrics using a QoS/QoE mapping process where appropriate mathematical functions are applied. However, the QoE influencing factors additionally include subjective user-centric parameters that cannot be measured directly from the network, but can influence the end-user’s overall experience [16]. Taking into consideration not only the QoS metrics but also the user’s influencing factors, the QoE values can be indirectly predicted with a high degree of accuracy, by employing ML algorithms in order to map these parameters with estimated values of QoE [17].

3.4 QoE Prediction

Although the metrics of QoS and QoE are very distinct, they share a high degree of correlation. Therefore, determining the association between user-oriented and network-oriented parameters is of paramount importance [18]. The techniques of QoE estimation allow the translation of application, system and network related requirements into QoE metrics [19]. A theoretical and methodological framework is supported by ML as to evaluate the QoE-QoS relationship, which provides a series of methods to construct a correlation model to automatically predict the QoE value. The main learning types that match the modeling of this relationship include i) deductive and inductive learning, ii) supervised, semi-supervised and unsupervised learning, iii) offline and online learning, iv) batch and incremental learning and v) passive and active learning [20].

4 QoE Monitoring

QoE monitoring is one of the most critical procedures performed by CSPs to ensure the highest possible experienced quality for their clients in a quality engineering environment. The measured values are used to gain insight into the actual state of the network, as well as to manage traffic and provide feedback for billing and security actions. Consequently, it must be guaranteed that the acquired data is accurate in order to provide the CSPs with a fair representation view of the service quality experienced by the end-users [21].

4.1 User-centric Monitoring

Applications that operate on client devices may have access to device capabilities and context information, such as location, user activity patterns and metrics at the application level. This data can be used to monitor QoE for end-users at the application layer, while monitoring can be performed per-service, per-user, and per-content [22].

4.2 Network-centric Monitoring

Although user-centric logs have access to application-level metrics, most CSPs do not currently have access to customers device probes and therefore depend on in-network probe measurements. Usually, probes are dispersed around different sections of the service delivery chain and capture data about the functionality of network paths and links. To gain perspective into approximated QoE, this data needs to be applied to application-specific QoS-to-QoE models [22].

5 QoE Optimization

QoE management's primary objective is to overseer QoE through optimization and control methodologies. In terms of maximizing the satisfaction of end-users and optimally exploiting the finite system resources, such processes provide improved operational efficiency with constant and adaptive service delivery control. From the mobile network operator's (MNO) perspective, the aim is to retain satisfied end-users in a way to reduce customer churn, whilst allocating the available radio and network resources effectively [23].

5.1 Network Softwarization

The implementation of network softwarization is enabled by software-defined networking (SDN) and network function virtualization (NFV) technologies. Using these technologies, network softwarization can provide the programmability, flexibility and modularity that is essential to FWNs. Network softwarization refers to the aspects of designing, implementing, architecting, deploying and operating the network physical infrastructure by intergrading and allowing full use of software capabilities. A softwarized network is able to provide the required flexibility and adaptability and moreover, to assure the development of automated network reconfiguration by applying self-management and automation functionality processes [24].

5.2 Traffic Management

Traffic engineering (TE) is a fundamental networking issue, considering a range of network flows with source and destination nodes, so as to find a way to forward data traffic to maximize a utility function. For TE challenges such as traffic management and resource allocation in the complex communication environment of 5G networks [25], ML's role is to monitor the network traffic and determine the best resource allocation policy, providing an end-to-end (E2E) orchestration functionality that includes service classification and prioritization for guaranteeing adequate levels of QoS [26].

5.3 Resource Allocation in Network Slicing

In the emerging network slicing framework, the QoS requirements of services offered in various slices will be differentiated, based on the type of communication (e.g., enhanced mobile broadband (eMBB), massive machine type communications (mMTC) or ultra-reliable low latency communications (uRLLC)) each slice supports, thus making critical the development of a dynamic resource allocation mechanism that will monitor the performance and resource utilization of all network slices, and accordingly dispense network resources in order to address the various QoS requirements [27]. ML-based resource allocation mechanisms will introduce intelligence in the decision process for the appropriate distribution of available resources to the network slices, so that each of them will be in a position to satisfy its required level of QoS independently of changes in network conditions [28].

6 Conclusions

Meeting the end-users' service quality expectations and requirements in the user-centric FWNs, entails efficient QoE management. This paper has outlined state-of-the-art outcomes and pointed out the key aspects and challenges of research activity with respect to embedding AI and ML-based approaches in QoE management. ML solutions have been examined concerning QoE management mechanisms, including QoE modeling, monitoring and optimization, in the light of growing FWNs innovations, such as the utilization of virtualized and softwarized networks, the implementation of network slicing and the development of novel 5G usage scenarios.

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