INTELLIGENT MACHINE-LEARNING-BASED METHODS FOR QUALITY OF SERVICE ASSURANCE IN TELECOMMUNICATION NETWORKS

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Abstract: *This paper systematizes intelligent methods for ensuring Quality of Service (QoS) in modern telecommunication networks. In contrast to a survey-level description of the application areas of artificial intelligence (AI), the emphasis is placed on specific classes of machine learning (ML) methods and their role in the transition from reactive to proactive network management: failure prediction and predictive maintenance, anomaly detection, network resource optimization and network slicing, as well as the formation of self-optimizing and autonomous networks. AI-based approaches to QoS/SLA management are reviewed, and the key challenges are outlined — data quality and privacy, model interpretability, and integration with existing management systems. It is concluded that intelligent methods are a necessary condition for ensuring sustainable quality of service in 5G and next-generation networks.*

Keywords: *artificial intelligence, machine learning, quality of service, QoS, SLA, failure prediction, anomaly detection, network slicing, self-optimizing networks, 5G.*

Introduction

The growth of traffic volumes, the proliferation of services with stringent latency requirements, and the deployment of 5G networks substantially raise the requirements for Quality of Service (QoS) in telecommunication networks. Traditional quality management methods based on static thresholds and manual monitoring increasingly prove insufficient under dynamically changing load and growing infrastructure complexity. Under these conditions, artificial intelligence (AI) and machine learning (ML) methods become a key tool for ensuring quality, enabling the transition from reactive fault remediation to their proactive prediction and prevention [1].

For the telecommunications industry of Uzbekistan, this task acquires practical significance in the context of implementing the “Digital Uzbekistan 2030” strategy, which envisages the modernization of the network infrastructure of the national telecommunications operator and the transition to a customer-oriented service delivery model. At the same time, in practice the parameters of Service Level Agreements (SLAs) are often established on the basis of declarative rather than actually measured network characteristics, which reduces the validity of the operator’s commitments to the customer.

This work pursues two objectives. First, to systematize intelligent methods of quality-of-service assurance by classes of tasks addressed — drawing on a systematic survey of ML applications in the field of information and communication technologies [1], which highlights such directions as network optimization, resource allocation, anomaly detection, and security assurance. Second, to propose an SLA formation model in which the target parameters are derived from the measured characteristics of real traffic using machine learning methods.

1. Failure Prediction and Predictive Maintenance

One of the most significant areas of AI application is the prediction of network equipment failures. ML algorithms analyze historical event logs, key performance indicators (KPIs), and incident records, identifying patterns preceding failures and predicting their occurrence before the actual outage. This reduces downtime, improves service reliability, and lowers operating costs.

In [2], an intelligent model for predicting QoS violations is proposed based on a modified particle swarm optimization algorithm using the parameters of response time, availability, and transmission rate, demonstrating a prediction accuracy of 94%. Such approaches underlie predictive maintenance, in which repair and preventive work is planned on the basis of a forecast of equipment condition rather than after a failure occurs. In the context of the model proposed in this work, the same measurable indicators — delay, jitter, and packet loss — form a common data layer on which both failure prediction and the justification of SLA parameters can be built.

2. Anomaly Detection and Network Security

Anomaly detection in network traffic is an important component of quality and security assurance. Recent studies demonstrate the high effectiveness of both supervised and unsupervised methods. In [3], for the detection of network anomalies, an autoencoder based on Long Short-Term Memory (LSTM) networks is applied, effectively identifying deviations in traffic time series. Study [4] shows that deep learning models substantially improve the accuracy of threat detection compared with traditional methods.

A systematic review of anomaly detection methods in Network Functions Virtualization (NFV) environments [5] classifies ML approaches and emphasizes their role in ensuring the reliability of virtualized infrastructure. The applied study [6] demonstrates that a Random Forest model achieves an anomaly classification accuracy of 94.3%, while the use of SHAP values improves the interpretability of decisions — a critically important property for operation in real networks. As applied to the proposed model, anomaly detection methods make it possible to monitor compliance with the measurement-based SLA parameters, treating their violation as a deviation from the agreed traffic profile.

3. Resource Optimization and Network Slicing

In 5G architectures, network slicing is regarded as a key mechanism for guaranteeing differentiated QoS for heterogeneous applications. ML methods are applied to forecast slice load and to intelligently allocate resources. A survey of machine learning methods for network slicing [7] systematizes approaches to predicting resource demand and ensuring Service Level Agreements (SLAs), noting that under conditions of limited spectral resources excessive over-provisioning is unacceptable.

In [8], a hybrid deep-learning-based slicing scheme is proposed to ensure SLAs in mobility scenarios, predicting the resource requirements of slices. A review of slice admission control methods based on deep reinforcement learning [9] details the balancing between accepting new requests and maintaining SLAs for previously admitted slices. A comprehensive review of the advances and challenges of 5G network slicing [10] emphasizes the role of ML models in predicting congestion and failures for the proactive maintenance of QoS. The classification of traffic profiles underlying the proposed model is methodologically close to the slice allocation task: SLA parameters differentiated by service classes can serve as input requirements for network resource allocation.

4. Self-Optimizing and Autonomous Networks

A logical development of intelligent quality management is the emergence of Self-Organizing Networks (SON) and autonomous networks. The review [11] examines the evolution of hybrid SON, standardization trends, and an architectural vision for 6G networks, in which self-configuration, self-optimization, and self-healing functions are implemented on the basis of AI. Such networks adapt to changing conditions, minimizing operator intervention and maintaining stable quality of service.

A promising direction is the application of large generative models in telecommunications. In [12], the opportunities and challenges of using generative AI for network management tasks are analyzed, while study [13] examines the standardization of generative-AI-based architectures for Radio Access Networks (RAN). These approaches open the way toward intelligent control loops capable of interpreting high-level objectives and autonomously translating them into configuration decisions. The proposed model can be regarded as an element of such a transition: SLA parameters automatically derived from measurements can serve as input data for self-optimizing control loops, although for the national operator full-scale autonomy appears to be a more distant prospect.

5. Proposed Model for SLA Formation Based on Traffic Measurement and Machine Learning

Intelligent methods are directly integrated into service-level management processes. A review of intent-driven service management approaches [14] describes the autonomous translation of declarative user requirements into configuration policies, which reduces the number of errors and SLA violations. Study [15] highlights the problem of operational efficiency in maintaining SLAs in AI-enabled service chains, while a comprehensive review of service level agreements [16] systematizes the SLA lifecycle and emphasizes the insufficient formalization of quality of service based on actually observed characteristics.

Developing this direction further, an SLA formation model is proposed based on the empirical analysis of real network traffic. In the first stage, the key quality indicators — delay, jitter, and packet loss — are measured, and the specifics of the traffic are determined by service types and load nature. Thus, the target values of the indicators are derived not from a priori assumptions but from the observed behavior of the network.

In the second stage, to automate the processing of measurement results, the use of machine learning methods is proposed: classification and clustering of traffic profiles make it possible to automatically identify homogeneous service classes and to derive differentiated SLA parameters for each of them. Thus, the process of setting target indicator values shifts from expert judgment to a reproducible, data-driven procedure, which is consistent with the general trend toward intelligent quality management.

The resulting values provide the operator with an objective, measured basis for forming contracts with customers: instead of declarative figures, the agreement incorporates SLA parameters confirmed by actual measurements. The contract structure includes a separate SLA section based on actually observed quality indicators, which increases the validity of the operator's commitments and the transparency of relations with the customer.

At the current stage, the proposed model is conceptual in nature. Its experimental verification on real traffic, the selection and accuracy evaluation of traffic-profile classification algorithms, and its integration into the operator's contractual practice are the subject of further research.

6. Challenges and Limitations

Despite the proven effectiveness of intelligent methods, their application — including within the framework of the proposed model — is associated with a number of limitations that are especially significant in the conditions of a national telecommunications operator in an emerging market.

First, a key limitation is the availability and quality of data. The proposed model relies on measurements of real traffic and training on labeled profiles; however, collecting representative data requires a deployed QoS monitoring system, and the formation of training datasets involves organizational and technical costs. In addition, the processing of user traffic raises questions of data protection and privacy.

Second, a tangible barrier is the shortage of specialists combining competencies in telecommunications and machine learning, as well as the need to revise the operator's organizational contracting processes in order to transition to SLAs based on measurements rather than on declarative values.

Third, many machine learning models remain weakly interpretable, which limits trust in automatically derived SLA parameters; improving interpretability, for example through SHAP values, is an active research direction [6]. Finally, the integration of intelligent components with existing network management systems requires standardized interfaces and coordinated architectural solutions [11]

Conclusion

The systematization carried out shows that intelligent machine-learning-based methods cover the full cycle of quality-of-service assurance in telecommunication networks — from failure prediction and anomaly detection to resource optimization, network slicing, and autonomous management. In this context, an SLA formation model is proposed in which the agreement parameters are derived from the measured characteristics of real traffic (delay, jitter, packet loss) with automatic classification of traffic profiles using machine learning methods. This approach ensures the validity of the operator’s commitments and transparency for the customer. Further research should be directed toward the experimental verification of the model on real traffic, the evaluation of the accuracy of classification algorithms, and its extension through the analysis of SIP signaling protocol indicators within the framework of the dissertation research.

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