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INTEGRATION OF MACHINE LEARNING-BASED PREDICTION AND DYNAMIC QOS OPTIMIZATION INTO ADAPTIVE VONR SCHEDULING IN 5G STANDALONE NETWORKS: A SIMULATION-BASED APPROACH

The rapid development of fifth-generation networks in the Standalone (5G SA) variant puts forward new requirements for the implementation of voice services, in particular Voice over New Radio (VoNR), which are critically dependent on stable quality of service (QoS) indicators. Traditional radio resource scheduling algorithms, such as Round Robin and Proportional Fairness, are based mainly on instantaneous channel characteristics (SNR, CQI), without taking into account historical quality metrics such as jitter, delay, or packet loss, which leads to unstable operation of voice services in a variable radio environment. This is especially relevant for 5G SA, where there is no dependency on LTE infrastructure and all responsibility for QoS is placed on the new architecture.

The paper proposes a simulation-based approach to building an adaptive scheduler for VoNR that combines the prediction of modulation parameters using machine learning algorithms with dynamic optimization of MCS, QCI, and power consumption. Based on a decision tree ensemble model, the optimal modulation is estimated based on the current SNR value and the aggregated QoS performance of previous intervals. The simulation architecture implemented in MATLAB provides for modeling radio channel changes using Markov chains with three discrete states (Good, Average, Bad), which allows to reproduce realistic scenarios of mobile network operation. The adaptive scheduler integrates several levels of decision-making: ML model forecast, heuristic correction in favorable radio conditions, and dynamic class of service (QCI) control, which ensures that transmission parameters are matched to current and predicted channel conditions. The power consumption is also taken into account as a full-fledged QoS metric, which reduces the load on user equipment at high signal levels. A comparative analysis of three schedulers (Round Robin, Proportional Fairness, Adaptive) is carried out according to the key indicators: delay, jitter, packet loss, power consumption, throughput, and MOS.

The results of the study confirm that the adaptive ML scheduler demonstrates significantly better voice connection quality, especially in unstable radio channel conditions. The proposed approach minimizes losses and delays, stabilizes the MOS, and improves the power efficiency of the system without compromising the quality of service. Thus, the integration of machine learning into the decision-making loop for VoNR in 5G SA is a promising area that can be expanded by implementing multi-user scenarios, more complex ML models, and practical testing in real network infrastructure.

Key words: *VoNR, 5G Standalone, QoS, adaptive scheduling, machine learning, modulation, SNR, CQI, QCI, MCS, Round Robin, Proportional Fairness, Adaptive, ML scheduler, simulation modeling, MATLAB, Markov chains, MOS, power consumption, jitter, delay, packet loss.*

Formulation of the problem. The appearance of the 5G Standalone (SA) architecture has opened up opportunities for the full implementation of new types of services, among which VoNR (Voice over New Radio) connections play a key role. As opposed to transitional solutions, such as VoLTE or EPS fallback, the implementation of voice services in a fully independent 5G network requires solving a number of new challenges, including dynamic management of radio resources in a variable channel environment, ensuring a stable quality of service (QoS), and optimizing latency, loss, and power consumption.

In traditional scheduling schemes, such as Round Robin or Proportional Fairness, decisions about modulation parameters or class of service (QCI) are made primarily based on instantaneous channel characteristics, with little regard for historical trends or service context. This limits the system's ability to respond effectively to the dynamics of the network environment, which is especially critical for voice connections that are sensitive to jitter, loss, and latency. In 5G SA-type networks, these limitations become even more critical, as the system must independently provide a full service stack without relying on LTE infrastructure. In addition, promising approaches to resource management involve the integration of intelligent mechanisms, such as machine learning, but their real-time application to voice traffic is still not well studied. This creates the necessity to develop adaptive schedulers capable of predicting changes in radio conditions and QoS parameters, changing modulation and MCS in accordance with the foreseen conditions, and reducing power consumption without compromising service quality. Solving these problems is a key step towards stable and efficient VoNR implementation in real 5G Standalone networks.

Analysis of recent research and publications. Ensuring quality of service (QoS) for voice services in fifth-generation (5G) mobile networks, in particular in the Standalone architecture, is the subject of active research in the scientific community. Particular attention is paid to the challenges associated with radio channel instability, including changes in signal-to-noise ratio (SNR), the impact of latency, jitter, packet loss, and the need to adapt modulation in real time. Works [1, 5] consider the importance of a guaranteed level of QoS for voice connections in VoNR networks and justify the necessity of adaptive radio resource management. Researchers in [7, 8] draw attention to the potential of machine learning in managing service parameters, in particular, the ability to predict modulation and CQI to improve the resilience of voice traffic to channel changes. Paper [13] proposes an ML-based scheduling approach that demonstrates the potential to reduce delays, but its adaptability is limited by the lack of integration with quality of service (QCI) and power management. In [3, 14], an overview of the QoS subsystem in the 5G architecture is provided, including QCI, MCS, CQI, and resource assignment mechanisms. At the same time, these works focus mainly on stationary traffic or lack the time aspect of radio channel changes, which limits the relevance of the approaches to real-world scenarios.

Some studies [9, 11] cover radio channel modeling using stochastic models, in particular Markov chains, but they are rarely combined with intelligent schedulers or do not cover the full set of QoS metrics critical for VoNR. Some publications [2, 12] offer separate heuristics for changing modulation when SNR changes, but without reference to the historical behavior of service parameters or machine learning.

A general review of published works leads to the conclusion that existing studies do not offer a comprehensive model that simultaneously takes into account QoS dynamics, modulation prediction, MCS and QCI adaptation, power consumption, and stochastic channel variability. This integration is the subject of this paper.

The purpose of this study is to investigate the possibilities of integrating predictive machine learning models into the process of adaptive radio resource planning for voice services in 5G Standalone networks. The main focus is on modeling and evaluating the effectiveness of an intelligent scheduler that changes modulation, MCS, QCI, and power consumption in accordance with dynamic radio conditions and quality of service (QoS) parameters. The work is aimed at building a full-fledged simulation model using stochastic approaches to radio channel modeling and implementing an ML module as an element of decision-making. The study involves a comparative analysis of traditional and adaptive schedulers to determine their ability to provide a stable voice connection under variable SNR conditions. This approach allows us to identify the advantages of adaptive architecture, reduce terminal power consumption, and improve user experience. In addition, the study provides a basis for further developments in the area of implementing intelligent schedulers in real telecommunications environments.

Summary of the main research material. In modern fifth-generation (5G) mobile networks, in particular in the Standalone (SA) variant, the provision of voice services via Voice over New Radio (VoNR) technology is a priority area of development for both operators and network equipment manufacturers. The main challenge of implementing VoNR is to ensure a guaranteed level of quality of service (QoS) in a changing radio channel, which is especially typical for mobile scenarios with dynamically changing signal-to-noise ratio (SNR), interference, signal fading and other factors inherent in the frequency bands in which NR operates. Traditional approaches to radio resource allocation in mobile communications systems are usually focused on fixed Channel Quality Indicator (CQI) thresholds, which are directly related to the choice of Modulation and Coding Scheme (MCS). In such models, which are used in standard schedulers, the level of service for voice traffic is determined purely by the current channel state, without taking into account the historical behaviour of QoS parameters such as latency, jitter, packet loss, or power consumption. This creates significant risks for voice quality, as short-term channel degradations can lead to excessive degradation of end-user perceived parameters, such as MOS (Mean Opinion Score). In the case of voice services, such instability leads to signal distortion, dialogue breaks, lag, and other undesirable effects [1]. In addition, standard scheduling schemes are not optimised for power consumption, which is a critical factor in mobile terminals and IoT devices that may also use voice services in 5G.

In response to these challenges, this study modelled and implemented a new type of scheduler that dynamically adapts the transmission parameters of voice traffic depending on both instantaneous and aggregated QoS characteristics. The approach is based on the use of machine learning to predict the optimal modulation based on a combination of factors, and combining this prediction with heuristic logic that takes into account the physical parameters of the radio channel, service history, and current SNR level. Additionally, the MCS and QCI adaptation system is implemented, which allows not only to select the optimal modulation, but also to ensure the appropriate quality of service in accordance with the service category. In order to reproduce realistic scenarios of the adaptive scheduler, a full-fledged MATLAB simulation model was built, including the time generation of radio conditions, the use of a Markov model for the transition between radio channel states (Good, Average, Bad), the calculation of the full range of QoS metrics and the accounting of power consumption at each moment. This approach allows for comparisons between scheduling algorithms with simple resource allocation without QoS (Round Robin), QoS-oriented scheduling algorithms (Proportional Fairness), and the new ML-adaptive approach under the same network environment (Adaptive).

Thus, the proposed problem statement provides for a transition from static and isolated modulation adaptation mechanisms to a comprehensive and integrated approach, in which the decision to change transmission parameters is based on a multifactorial analysis of the QoS history, the current channel state, and the forecast model. A special feature of the approach is the inclusion of power consumption as a QoS indicator, which significantly extends the application scope of the scheduler in energy-sensitive scenarios.

Despite significant progress in the implementation of voice services in fifth-generation mobile networks, in particular, based on the VoNR architecture, there is still no single effective approach to managing radio interface resources that would ensure stable voice quality in a variable radio channel. Most implemented systems are based on fixed or linear-adaptive algorithms that rely exclusively on instantaneous CQI or SNR values. This ignores time dependencies, cumulative dynamics of QoS parameters, as well as factors associated with changes in the network environment, such as latency instability, increasing losses or accumulated jitter.

In addition, modern schedulers usually do not take into account the historical behaviour of traffic and are unable to identify situations where the quality of service deteriorates gradually rather than instantly. Such scenarios are especially critical for voice services. The user's perceived quality is not a linear function of just one parameter. Instead, it is formed as an integral effect of delays, losses, and jitter accumulated over several seconds. This necessitates the creation of a planning mechanism that is capable of multidimensional channel state estimation and adaptation of the relevant transmission parameters based on a combination of instantaneous and average QoS values.

An extra problem that needs to be solved is the lack of the ability of the scheduler to perform a coordinated adaptation of several parameters at once – modulation, coding scheme (MCS), class of service (QCI), and terminal power consumption mode – based on a holistic predictive analysis. In most practical implementations, there is fragmentation: for example, adaptation is performed only for MCS, while the choice of QCI or power mode remains static, or vice versa – the type of service is fixedly linked to the class of service without taking into account the actual state of the network. This limits the effectiveness of such solutions in real time. From a technical point of view, an important component of the problem is the lack of models that simultaneously take into account the variability of the radio channel over time, the dependence between successive QoS measurements, the stochastic nature of losses and latency, and the nonlinear dependence of MOS on input factors. Creating a simulation environment that reproduces such characteristics is a difficult but necessary condition for reliable testing of any next-generation scheduler. Thus, the study aims to address the identified problems by building an integrated model that allows:

– to combine the prediction of service parameters using machine learning with classical resource planning schemes;

– to take into account the time dynamics and historical values of QoS metrics (latency, jitter, losses) when making decisions on the choice of modulation and coding scheme (MCS);

– to perform automated selection of class of service (QCI) based on predicted radio conditions and service requirements;

– to dynamically adjust the power consumption of the terminal in accordance with the channel conditions and the selected modulation, which minimises power consumption without degradation of voice quality;

– to ensure the maintenance of a high average voice quality score (MOS) by adapting key transmission parameters in real time;

– to simulate smooth changes in channel conditions using a stochastic model of transitions between states (Markov chain), which approximates the modelling conditions to real-world scenarios.

Elements of scientific novelty.

The architecture for modelling and adaptive scheduling of voice services in a 5G SA network proposed in this study forms a number of significant scientific and technical innovations that distinguish it from existing approaches. The main elements of scientific novelty are both the simulation architecture itself and the introduction of innovative data-driven decision-making mechanisms. First of all, an original model of an adaptive resource scheduler was developed that combines analytical mechanisms for determining modulation with predictive algorithms based on machine learning methods. The peculiarity of the implementation is that the model takes into account not only the current SNR value but also the aggregated values of QoS metrics for previous periods of time when making decisions. This allows to take into account the inertia in the behaviour of the network channel and identify trends of deterioration or improvement of service that are not available for classical instant schedulers.

Another key contribution is the integration of modulation type prediction (16-QAM, 64-QAM, 256-QAM) using an ML model based on four parameters: SNR, Latency, Jitter and Packet Loss. The use of an ensemble of models based on a decision tree allowed us to achieve high accuracy while maintaining the interpretability of decisions. In addition, the adaptive scheduler implements the logic of heuristic correction of ML-model solutions based on SNR thresholds, which avoids unjustified modulation reductions in favourable radio conditions.

For the first time, the dynamic interdependence between the predicted modulation, the chosen coding scheme (MCS) and the class of service (QCI) is implemented. In classical implementations, such parameters are fixed or statically set based on the traffic profile, while in the proposed model it changes according to the predicted channel conditions. Thus, the scheduler is able to automatically lower the priority of service in unfavourable conditions, or, conversely, increase the class of service when the QoS improves, which allows for more efficient use of resources and increased stability of voice traffic service.

It is worth noting the extension of the standard QoS model by including power consumption as a full-fledged metric for voice traffic. The model reduces power consumption at high SNR values and selects efficient modulation, which is relevant both for reducing the load on terminals and improving the efficiency of the network infrastructure as a whole.

Another element of scientific novelty is the construction of a time simulation using a Markov chain to model the smooth transition between the three states of the radio channel (Good, Average, Bad). Such a model allows reproducing signal quality fluctuations over time with greater accuracy than using independent Gaussian noise or fixed scenarios. This, in turn, ensures higher simulation reliability and allows us to evaluate the behavior of schedulers in realistic variable channel conditions. In addition, a new weighting formula for calculating MOS was proposed that takes into account the influence of three key factors – latency, loss, and jitter – with experimentally validated weighting factors. This approach makes it possible to simulate not only the technical efficiency of transmission, but also the subjective quality of voice perception by the user.

Overall, this study has created a holistic simulation platform for testing adaptive voice service scheduling algorithms in 5G SA that combines ML methods, simulation modeling, and engineering principles of modulation adaptation, providing a high degree of reliability and practical value of the results.

Simulation architecture in MATLAB.

To reproduce the behavior of an adaptive voice packet transmission scheduler in a 5G SA network, taking into account radio channel dynamics, variability of QoS metrics, and the impact of machine learning, a full-fledged simulation model was implemented in MATLAB. The model structure includes several interconnected components: a dynamic SNR(t) generator, a stochastic model of radio channel states, a transmission planning subsystem with options for implementing various algorithms (Round Robin, Proportional Fairness, Adaptive), a QoS evaluation module, and a mechanism for integrating with the ML model [2]. The simulation takes place in the time dimension with a fixed step, which ensures that the input parameters change at each moment of time. The presented implementation uses a simulation horizon of 100 seconds with a sampling interval of 1 second (Fig. 1). For each moment of time t, a signal-to-noise ratio (SNR) value is generated that models the variability of radio conditions in a real environment. For this purpose, a combined model is used, which includes a sinusoidal component (simulating periodic changes in conditions due to mobility) and additive Gaussian noise, which models random disturbances. Additionally, SNR values are limited to a physically acceptable range (5–35 dB), which prevents the generation of unrealistic extremes.

After generating the SNR(t) value, each of the schedulers performs the corresponding voice traffic transmission scheduling procedure. In the case of classical approaches (Round Robin, Proportional Fairness), the algorithm uses fixed thresholds to determine the modulation and MCS, depending on the CQI, which is derived from the SNR value using a piecewise linear relationship. In the case of an adaptive scheduler, on the contrary, the input vector consists of the current SNR value and the aggregated values of QoS indicators for the previous three time intervals (latency, jitter, loss), after which it goes through a normalization procedure and is fed to the input of a machine model built on the basis of an ensemble of decision trees. The output of the machine model integrated into the adaptive scheduler is a categorical variable that determines the appropriate level of modulation in the current radio service conditions. The decision is based on four key input parameters: the current SNR value and the averaged values of latency, jitter, and packet loss over the last three simulation intervals. This approach allows taking into account not only the instantaneous state of the radio channel, but also the effects of inertial degradation or stabilization of the quality of service. However, given the potential errors of ML forecasting in conditions close to the limit values or when observing non-standard combinations of parameters, the model implements a heuristic procedure for adjusting the output. In particular, in cases where the SNR level exceeds 22 dB, the predicted modulation is checked for feasibility in terms of using the available radio resource. If the predictive model makes a decision in favor of a lower modulation (e.g., 16-QAM), which potentially limits the bandwidth in a high-quality channel, a forced uprate to 64-QAM is performed. Similarly, when the SNR is above 26 dB, an automatic transition to 256-QAM is allowed, even in the case of an indecisive forecast. This heuristic allows balancing between the caution of the ML model and the aggressive use of favorable conditions, which, in turn, ensures an increase in spectral efficiency without a significant increase in losses or a decrease in MOS [2]. The use of heuristic correction is especially justified in cases of short-term improvement of transmission conditions, since machine models that operate on average QoS values may demonstrate an inertial delay in response, which requires proactive intervention at the level of scheduler logic.

For each transmission session in the simulation, a network state is generated based on a Markov chain with three states (Good, Average, Bad), each of which has fixed parameters of latency, jitter, losses, and power consumption (Fig. 2). The transition matrix is designed to mimic the inertia of the channels: a state is highly likely to persist, but there

```
% Генерація динамічного SNR(t)
snrBase = 20;  % початковий рівень SNR
snrVec = snrBase + 5 * sin(2 * pi * timeVec / 50) + normrnd(0, 1, size(timeVec)); % шум + хвилі
```

Fig. 1. A snippet of the code for generating the dynamic signal SNR(t) in MATLAB. The value is formed on the basis of the baseline, sinusoidal variation, and normal noise, which together model periodic changes and random fluctuations in the radio channel

```
% Визначення наступного стану за допомогою Марковської моделі
currentState = find(mnrnd(1, transitionMatrix(currentState, :)));
```

Fig. 2. A fragment of the implementation of a stochastic transition between network states based on a Markov chain. For the currentState, the next state is selected according to the corresponding row in the transitionMatrix by the multivariate binomial distribution method

are also non-zero chances of transitioning to a neighboring state (for example, from Good to Average or vice versa), which corresponds to the behavior of a mobile user moving through coverage cells or changing the orientation of the device.

The QoS analysis module calculates the main metrics for each scheduler: average latency, average jitter, Packet loss rate, throughput, round trip delay (RTD), and average power consumption [3]. Based on these metrics, an integral quality indicator is calculated – MOS (Mean Opinion Score), which is modified to meet the requirements for voice services: the formula takes into account the weighted impact of latency, loss and jitter, with thresholds that meet current ITU-T recommendations.

The simulation results are accumulated in the data structure for each scheduler separately, which allows for a full-fledged comparative analysis of the performance of Round Robin, Proportional Fairness, and the proposed ML-based adaptive solution. In the final part of the simulation, a set of visualizations (graphs) is generated that demonstrate the dynamics of QoS metrics over time, as well as the behavior of parameters that directly depend on the scheduler – modulation, MCS, CQI, QCI. The resulting simulation is suitable for multifactorial analysis of schedulers' behavior under various radio channel conditions. Its structure allows to trace the impact of scheduling algorithms on key voice traffic quality indicators, including latency, jitter, losses, power consumption, and MOS, with high resolution, and ensures the reliability of conclusions about the effectiveness of the implemented adaptive mechanisms.

Description of schedulers.

The simulation model implements three types of schedulers that differ in their decision-making logic for selecting modulation, Modulation and Coding Scheme (MCS), and service quality for voice traffic [4]. The choice of these three algorithms is driven by the need to compare the proposed solution with basic and common strategies used in mobile communication systems.

The first type – Round Robin – is a basic scheduler that implements the simple principle of uniform distribution of radio resources among users without taking into account any quality of service parameters. In the implementation of this simulation, modulation and MCS are set according to fixed CQI thresholds that directly depend on the current SNR value. For example, if $CQI < 7$, 16-QAM is assigned, if $7 \leq CQI < 12$, 64-QAM is assigned, and if $CQI \geq 12$, 256-QAM is assigned. This scheme provides technical fairness, but completely ignores changes in latency, loss, or jitter, making it unsuitable for QoS-critical scenarios, such as voice traffic [2].

The second scheduler, Proportional Fairness (PF), is a QoS-oriented scheduling algorithm that attempts to balance efficiency and fairness based on the ratio of current to average user throughput. Modulation is determined based on CQI, but with a more flexible consideration of channel conditions. Although PF does not directly take into account latency or loss, it responds to the overall radio channel condition and is able to partially adapt to unstable conditions. However, its adaptation is not QoS-directed in the narrow sense – the scheduler does not adjust transmission parameters to ensure stable MOS or minimize jitter [5].

The third proposed scheduler, Adaptive, integrates a machine learning algorithm, heuristic logic, and a power adaptation mechanism. Unlike previous solutions, it is based not only on instantaneous channel parameters but also on the history of QoS metrics, including average latency, jitter, and percentage of losses. The input vector is fed to an ML model that determines the most appropriate modulation for the current conditions. Additionally, heuristic rules are implemented to increase modulation at high SNR regardless of the ML prediction, ensuring more aggressive resource utilization in favorable conditions [2].

In addition to modulation adaptation, the scheduler dynamically selects the appropriate Modulation and Coding Scheme (MCS) and binds it to the QoS Class Identifier (QCI) to ensure compliance with voice traffic service standards (e.g., QCI = 1 or QCI = 5) [6]. The model also provides a mechanism for reducing latency and losses by adjusting transmission parameters, which allows achieving higher MOS values compared to the baseline schemes. Thus, the proposed adaptive scheduler implements a multilevel decision-making strategy: ML-based forecasting, heuristic correction, dynamic assignment of transmission parameters, and power consumption optimization. This ensures flexibility, resistance to unstable channels, and improved QoS compared to traditional designs. Table 1 shows the comparative characteristics of the implemented schedulers.

Fig. 3 shows the change in modulation (16-QAM, 64-QAM, 256-QAM) over time for each of the three implemented schedulers. The Round Robin scheduler demonstrates a fixed modulation selection logic based solely on the current CQI value. As a result,

Table 1

Comparative characteristics of the implemented schedulers

Scheduler	Main control parameter	Modulation dialing logic	Reaction to QoS metrics	QCI adaptation	Power consumption
Round Robin	CQI	Fixed thresholds	None	Static	Static
Proportional Fairness	CQI + Throughput ratio	Dynamic thresholds	None	Static	Static
Adaptive (ML)	SNR + QoS + ML	Forecast + heuristics	Includes 3 previous ones	Dynamic	Adaptive

the graph shows a relatively stable distribution of modulations, without a flexible response to changes in transmission conditions. While Proportional Fairness utilizes CQI and incorporates the ratio between current and average throughput to enable partial modulation adaptation, it does not consider QoS metrics such as latency or loss. By comparison, the proposed adaptive scheduler performs more dynamic modulation changes during the simulation. This is due to the fact that the modulation selection decision is based not only on SNR, but also on aggregated QoS metrics and machine model predictions. In combination with additional heuristic conditions, the adaptive scheduler is able to switch to higher modulation schemes in favorable radio conditions, even if the model predicted a more conservative value [7].

Thus, the graph clearly demonstrates that the adaptive design responds more sensitively to variations in the network environment than basic algorithms, which is a crucial advantage for QoS-sensitive traffic such as VoNR.

Machine Learning model integration for adaptive scheduling.

This study presents a machine learning model designed to support the development of an adaptive scheduler that accounts for the current channel state and QoS parameters by predicting the optimal modulation level (16-QAM, 64-QAM, or 256-QAM) under varying network conditions. The model is built on the basis of a training dataset generated by preliminary modeling of system behavior in different radio conditions and QoS parameters. A total of 2000 synthetic examples were collected, each containing input values: SNR, Latency, Jitter, and Packet Loss. These parameters act as a feature vector.

The training set contains a total of 2000 examples evenly distributed among the three main modulation classes: 16-QAM, 64-QAM, and 256-QAM. Table 2 summarizes the main statistical characteristics of

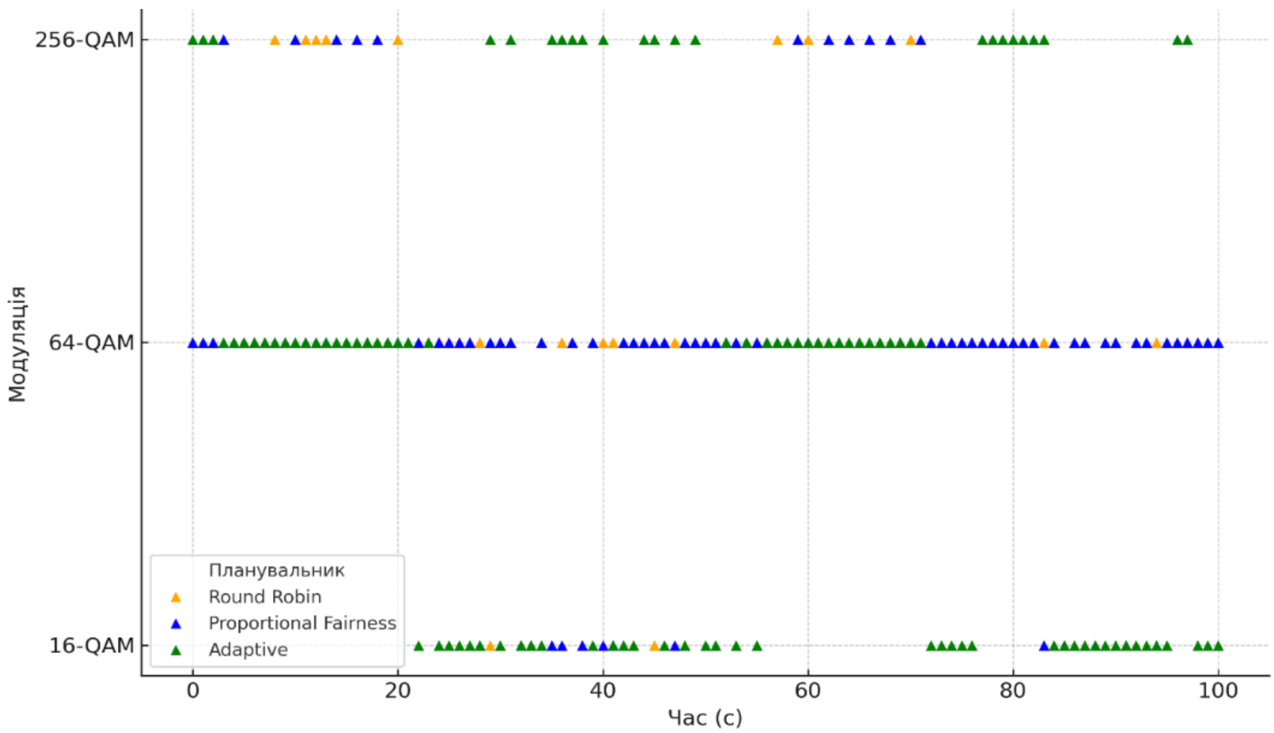

Fig. 3. Modulation change (16-QAM, 64-QAM, 256-QAM) over time for three schedulers

Table 2

Input Feature Statistics – VoNR ML Training Set

	Average	Average deviation	Min	25%	Median	75%	Max
SNR	19.959	8.766	5.097	12.141	20.221	27.52	34.992
CQI	7.883	4.296	1.0	4.0	8.0	12.0	15.0
MCS	19.127	5.556	10.0	14.0	19.0	24.0	28.0
Latency	9.012	3.087	3.415	6.46	8.926	11.489	14.997
Jitter	1.366	0.583	0.349	0.863	1.358	1.845	2.499
Loss	1.61	0.913	0.078	0.858	1.59	2.34	3.499
Throughput	154.02	53.02	60.02	108.275	153.568	197.578	264.306
MOS	4.04	0.235	3.603	3.847	4.033	4.234	4.5
Power	1.039	0.429	0.3	0.665	1.041	1.399	1.798

the parameters used as input features, including average, minimum, and maximum values. The data encompasses a representative range of VoNR conditions and contains sufficient variability to enable the training of a machine learning model with high generalizability.

The target variable is represented as a categorical class – a type of modulation encoded in the form of three numerical labels. Before starting training, the input data were normalized to a single scale space, which avoids the overwhelming influence of individual parameters on the training process. To increase the reliability of the model, the sample was divided into training (80%) and test (20%) parts using stratified hold-out. As a basic classifier, an ensemble model of the Bagged Trees (Bootstrap Aggregation) type was chosen, which combines several decision trees into a stable model with high generalizability. The implementation used 200 trees, each of which is trained on a random subset of the training data. The depth of the tree is limited by setting the MaxNumSplits parameter to prevent overtraining [9]. This choice is due to the model's suitability for integration into a simulation environment, where it demonstrates a sufficient level of classification ability to predict modulation in a variable radio channel (Fig. 4). Although the absolute value of accuracy on the test set is limited, it is sufficient to support real-time decision-making in combination with heuristic rules and dynamic QoS context.

Fig. 5 shows the results of testing the model in the form of a mixing matrix. As can be seen from the graph, the model demonstrates the largest number of correct classifications for the 256-QAM class, but at the same time, there is a systemic bias – the model tends to assign higher modulation schemes even when the true value is lower. This is due to the peculiarities of the training set and the sensitivity of SNR as a feature. Such behavior is typical for models relying on aggregated QoS metrics without access to extended historical data. To address this, additional heuristic constraints were introduced during integration into the simulator to promote decision stability and mitigate potential losses. Thus, even with imperfect classification accuracy, the model is effectively used as a preliminary estimator in the adaptive scheduler loop.

After the training procedure, the model was saved as a .mat file and integrated into the general simulator as part of the adaptive scheduler. During the simulation process, at each step, the adaptive scheduler generates a vector of input parameters (SNR, average latency, jitter, and losses for the previous three time intervals), normalizes it, and feeds it to the model input. The resulting predicted modulation value is used as a key parameter for further selection of MCS, QCI, and power consumption [10]. To increase the reliability of the decisions made, as well as to avoid underestimation of predictions in favorable channel conditions,

```
% Навчання моделі на тренувальних даних
t = templateTree('MaxNumSplits', 20);  % контроль складності дерев
modulationTree = fitcensemble(X_train, y_train, ...
    'Method', 'Bag', ...
    'NumLearningCycles', 200, ...
    'Learners', t, ...
    'Prior', 'uniform');
```

Fig. 4. Implementation of training a classification model of the Bagged Trees type in MATLAB using 200 decision trees and a depth limit (MaxNumSplits)

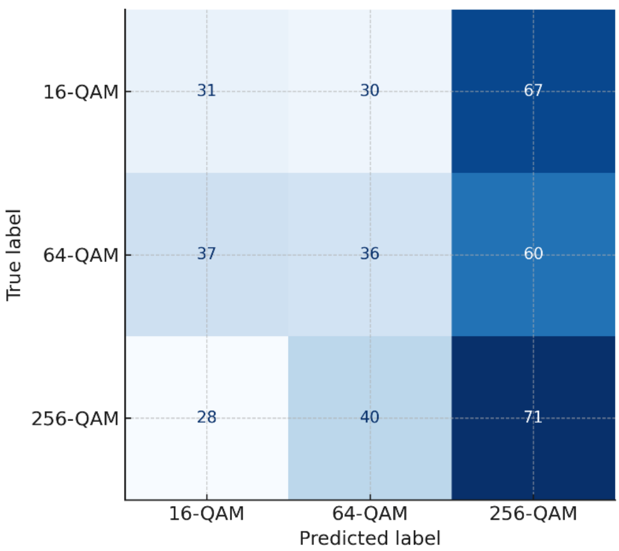

Fig. 5. Mixing matrix for predicting the type of modulation (16-QAM, 64-QAM, 256-QAM). The predominant prediction of the 256-QAM class is observed, which is compensated by heuristic constraints in the adaptive scheduler

an additional heuristic correction module is implemented: at SNR > 22 dB, the system allows increasing the predicted modulation by one level, and at SNR > 26 dB – assigning 256-QAM regardless of the model's prediction, if it does not contradict QoS indicators. This approach allows balancing between the caution of the ML solution and the efficient use of resources in a high-quality radio channel. Thus, the implemented module is not limited to forecasting, but acts as an adaptive decision-making subsystem integrated into the radio resource management loop in a variable radio environment.

Markov model of channel states.

A stochastic model based on Markov chains with discrete states was used to model changes in the radio environment in real time. This approach allows to realistically reproduce the behavior of the radio channel in conditions of user mobility, changes in network load, and stochastic fluctuations caused by interference and multipath signal propagation [11]. In contrast to sinusoidal or static SNR variation models, the Markov model incorporates the channel's probabilistic inertia, providing a better approximation of realistic behavior in 5G Standalone networks.

Table 3 shows the state transition matrix. Thus, three states are used in the simulation: Good, Average, and Bad, each of which is characterized by fixed parameters of latency, jitter, loss probability, and power consumption. For example, in the Good state, the latency is ~5 ms, the loss probability is 3%, and the jitter is 0.5 ms. In the Bad state, these parameters increase according to the worse quality of the channel. This division provides sufficient variability to assess the impact of radio conditions on QoS parameters [11].

Table 3

Transition Probabilities Between Radio Channel States in the Markov Model

Current state	Good	Average	Bad
Good	0.80	0.15	0.05
Average	0.30	0.50	0.20
Bad	0.10	0.30	0.60

This matrix is constructed to reflect a high probability of maintaining the current state with a simultaneous non-zero probability of transitioning to an adjacent state. This way, the simulation takes into account both the short-term stability of transmission conditions and possible sudden degradations or improvements, for example, when the user changes position, moves between cells, or encounters interference. The next state is selected at each time point t using a multivariate binomial distribution (multinomial sampling) implemented in MATLAB using the mnrnd function (Fig. 6). This guarantees that the actual transitions correspond to the specified matrix and allows creating realistic patterns of radio channel behavior.

The simulation also accounts for the terminal's power consumption, which varies depending on the channel state: poorer transmission conditions require higher power levels to maintain connectivity.

```
        for i = 1:numPackets
            % Визначення наступного стану за допомогою Марковської моделі
            currentState = find(mnrnd(1, transitionMatrix(currentState, :)));

            % Моделювання затримки, джитера, втрат та енергоспоживання
            currentDelay = max(0, stateDelays(currentState) + normrnd(0, stateJitter(currentState))); % Плавніші затримки
            currentJitter = abs(normrnd(stateJitter(currentState), 0.5)); % Джитер
            currentPower = statePowerConsumption(currentState); % Енергоспоживання
            currentRoundTripDelay = currentDelay * 2; % Затримка кругового шляху
```

Fig. 6. Implementation of the selection of the next channel state based on probabilities from the transition matrix using the mnrnd() function in MATLAB

For each of the three states (Good, Average, Bad), the corresponding power consumption values are set (0.5, 1.0, and 1.5 W, respectively). These values were selected based on analytical models and publications that indicate the typical range of power consumption of user equipment (UE) in VoNR mode – usually in the range of 0.5–1.5 W, depending on signal strength, modulation, and transmitter activity. To summarize, the model allows not only to analyze QoS indicators, but also to evaluate the power efficiency of different schedulers in the dynamics [12].

Simulation of changes in channel states in the time dimension allows tracking not only instantaneous QoS values, but also cumulative effects such as accumulated latency, loss variability, or power consumption, which are critical when serving voice traffic with strict requirements for connection stability [13]. Thus, the stochastic model of channel states is the basic element of the simulation environment that the adaptive scheduler relies on when making decisions.

Measurable Quality of Service (QoS) metrics.

The simulation model evaluates all key QoS metrics that are critical for the operation of voice services in 5th generation networks. The indicators are calculated in the time dimension with a fixed interval of 1 second. This approach allows tracking the change of QoS indicators in dynamics and comparing the effectiveness of different schedulers in realistic conditions. Fig. 7 shows the change in the integral MOS (Mean Opinion Score), which assesses the subjective quality of a voice connection based on latency, loss, and jitter. All schedulers demonstrate a waveform that corresponds to the sinusoidal nature of SNR changes in the simulation. The most pronounced fluctuations are observed for Round Robin and Proportional Fairness, which do not have built-in mechanisms for smoothing or taking into account historical QoS indicators. The Adaptive Scheduler, although it demonstrates a similar fluctuation rhythm, provides a higher MOS level almost throughout the entire interval. This indicates that even when conditions are variable, it provides a more effective response to channel degradation. The reason for the sinusoidality is that SNR(t) itself has a wave nature, and the ML model does not work on the basis of perfectly inert smoothing, but with a delay of one or two steps – due to the aggregation of QoS metrics. In other words, adaptation does not stop the oscillations completely, but reduces their amplitude and improves the overall quality level.

Latency is one of the most critical parameters for voice traffic. The graph shows that Round Robin and Proportional Fairness demonstrate a relatively stable but high average latency (~9–10 ms), which almost does not change in response to channel degradation (Fig. 8). In the case of Round Robin, this is the result of a complete lack of adaptation, and in PF, it is a consequence of limited sensitivity to QoS [15]. The adaptive scheduler, on the contrary, responds to changes in the channel state. Its graph shows lower latency values in high SNR conditions, but also fluctuates with the same frequency as SNR(t). This indicates two things:

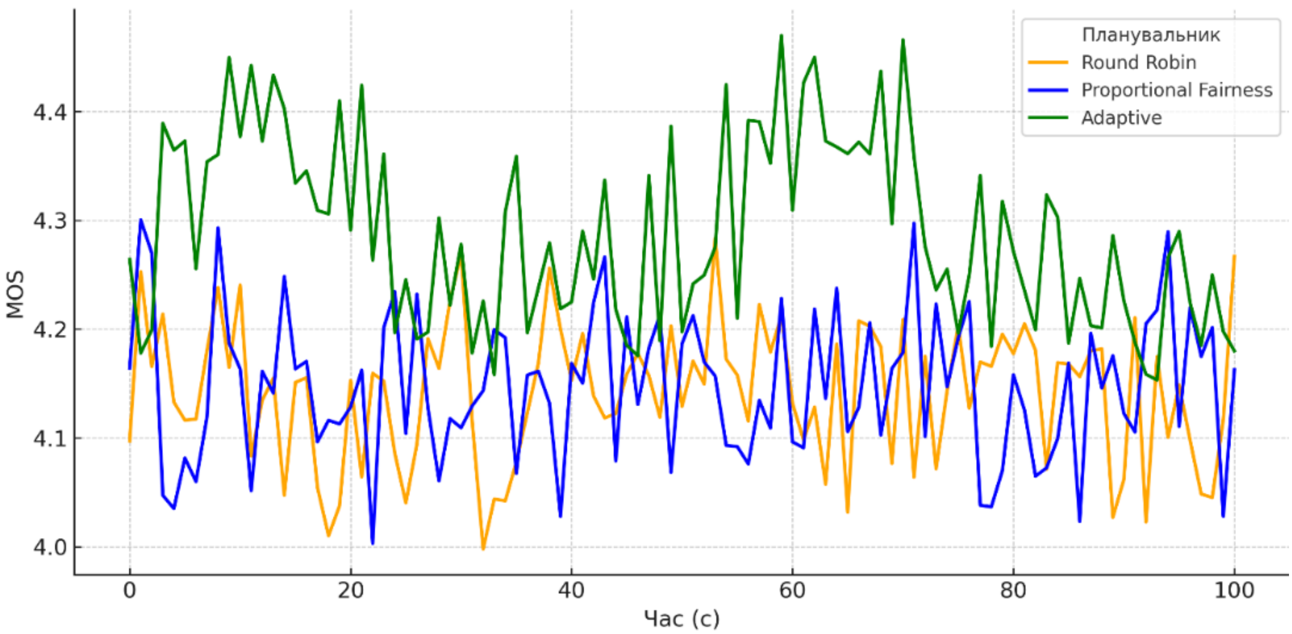

Fig. 7. MOS dynamics over time

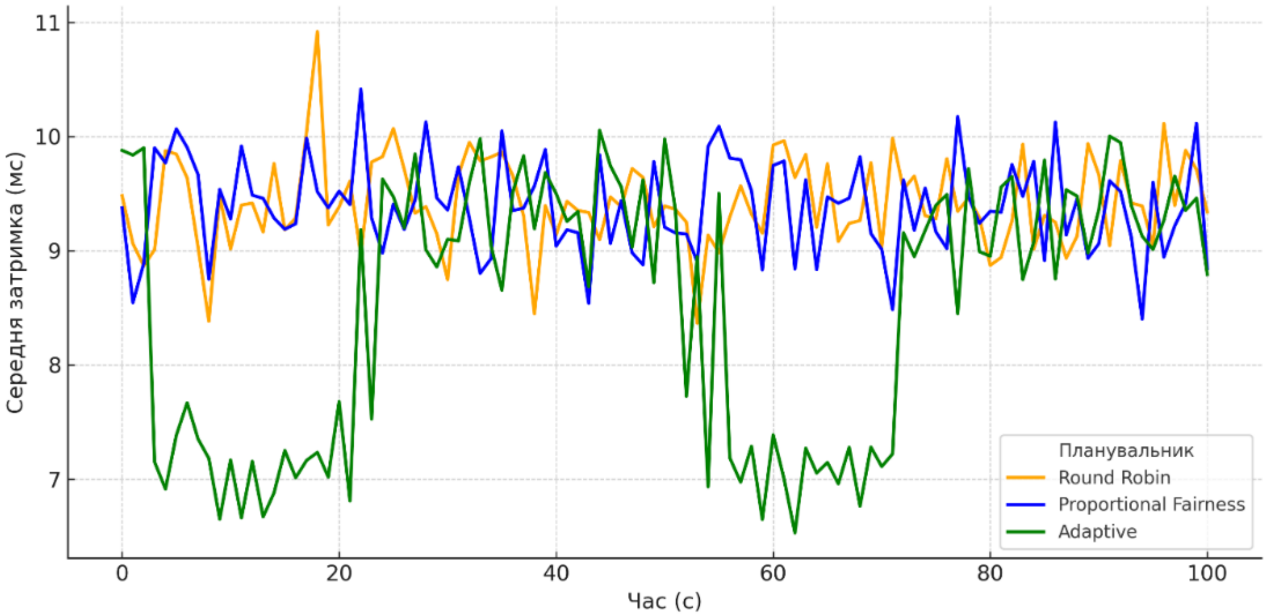

Fig. 8. Average latency

1) The scheduler changes modulation and transmission parameters in response to signal phases.

2) Latency fluctuations are not a sign of instability, but the result of active adaptation to changing radio conditions, which provides local minima when the channel improves.

Thus, even in the presence of a wave structure, the adaptive scheduler demonstrates higher efficiency and flexibility, allowing to avoid delay in critical phases.

Packet loss is a key metric for voice services, especially in the context of 5G SA, where the lack of real-time HARQ compensation means that losses directly affect voice quality [16]. Fig. 9 shows that Round Robin demonstrates regular loss peaks synchronized with a decrease in SNR – which is fully consistent with the absence of any adaptation mechanism. Proportional Fairness partially smooths out these spikes by better managing resource allocation, but it also does not take active action when the channel quality decreases.

The adaptive scheduler demonstrates a much lower level of packet loss throughout the entire

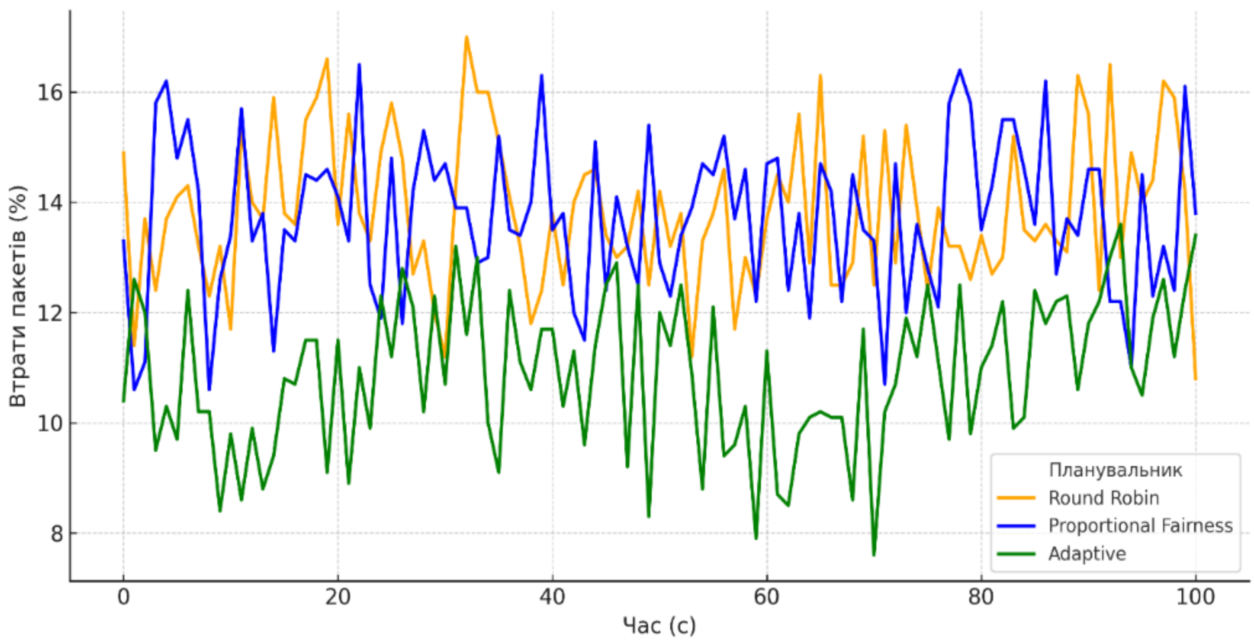

Fig. 9. Dynamics of packet loss (%)

simulation period. This is explained by its ability to change the modulation and MCS parameters to less aggressive ones in a timely manner as soon as a tendency to degrade the quality of service is detected [17]. Although the model does not always manage to completely avoid peak losses – in particular, due to the limited accuracy of machine forecasting and the latency caused by smoothing historical data – the adaptive scheduler effectively reduces the amplitude of loss fluctuations. The periodic structure of the graph is preserved in this case as well, due to the sinusoidal nature of the input SNR, but the oscillation pattern for Adaptive has a much lower amplitude. This indicates not passive imitation of radio conditions, but active adaptation to their changes in real time using both current and historical QoS metrics.

Jitter is another critical QoS metric for VoNR, as instability in packet delivery time causes noticeable audio distortion [2]. Fig. 10 shows that jitter in basic schedulers (especially in PF) is periodic in nature with an amplitude correlated to the low SNR phases. These schedulers fail to mitigate jitter fluctuations because they do not account for the QoS implications of modulation changes.

The adaptive scheduler demonstrates much better behavior: although waviness is present (due to the nature of SNR(t)), the jitter amplitude is much smaller and the transient phases are less pronounced. This indicates:

– less aggressive modulation selection under unstable QoS conditions;

– successful response to short-term degradation by taking into account previous values (latency, loss, jitter);

– adjusting transmission without drastic changes.

Reducing jitter fluctuations has a positive effect on the overall MOS, which is consistent with the previous analysis (Fig. 7).

Fig. 11 shows the change in power consumption over time for the three implemented schedulers. As can be seen from the graph, the basic Round Robin and Proportional Fairness algorithms do not have any mechanisms for dynamically reducing power consumption – they generate consistently higher values regardless of changes in radio channel conditions [2]. Their power profile remains at around 0.84–0.86 W with noticeable peaks. In contrast, the adaptive scheduler implements a heuristic to reduce power consumption in favorable conditions, in particular when combining high SNR and using highly efficient modulation (256-QAM). This reduces the transmit power at the user equipment (UE) during favorable radio conditions without sacrificing QoS. As a result, the average power consumption of Adaptive during the simulation is the lowest among all implemented schedulers (in the range of 0.80–0.83 W), and the nature of its change is more smooth.

Thus, Adaptive demonstrates not only higher quality of service, but also power efficiency, which is especially important for user devices with limited power resources.

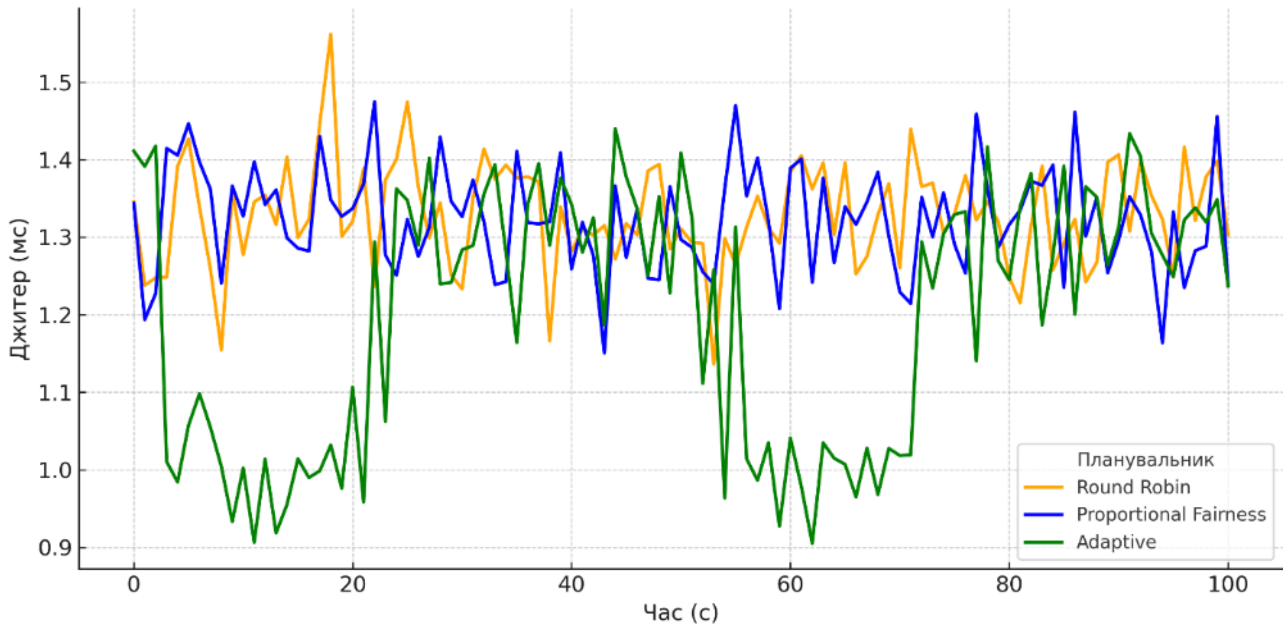

Fig. 10. Jitter

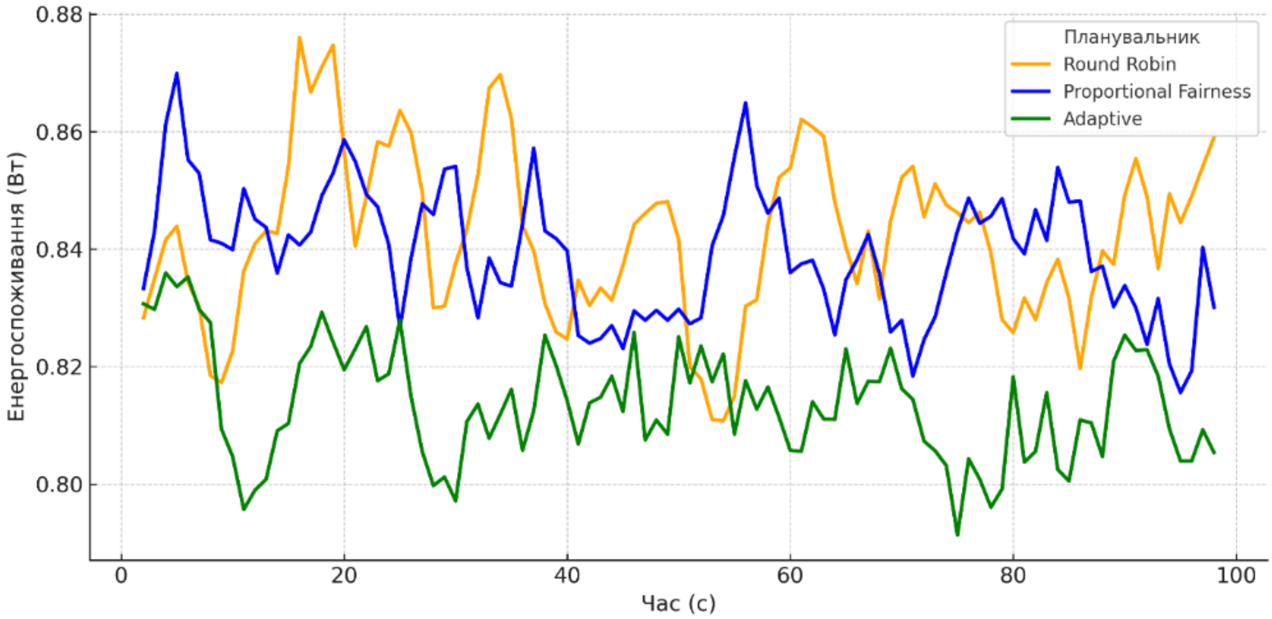

Fig. 11. Power consumption of 5G voice services over time depending on the scheduler

Conclusions. This paper presents a simulation study of an adaptive voice service scheduler in a 5G SA network that combines machine learning techniques with dynamic QoS optimization. The proposed architecture integrates ML-prediction of appropriate modulation based on current and historical QoS metrics, and implements heuristic rules for transmission adaptation and power control. The MATLAB simulations enabled a comparative evaluation of three schedulers (Round Robin, Proportional Fairness, and Adaptive) in a dynamic radio environment modeled using a Markov-based approach. The results demonstrate the advantages of the adaptive design in reducing latency, jitter, and packet loss, improving the Mean Opinion Score (MOS), and lowering power consumption under favorable transmission conditions.

Thus, integrating the ML model into the radio resource management process enhances the flexibility and adaptability of the VoNR system in 5G Standalone networks, representing a promising direction for further research and practical deployment. Future work may extend this approach by incorporating more advanced forecasting models, supporting multi-user scenarios, and enabling implementation on software-defined radio (SDR) platforms.

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Ветошко І.П., Кравчук С.О. ІНТЕГРАЦІЯ ПРОГНОЗУВАННЯ НА ОСНОВІ МАШИННОГО НАВЧАННЯ ТА ДИНАМІЧНОЇ ОПТИМІЗАЦІЇ QOS В АДАПТИВНЕ ПЛАНУВАННЯ VONR У МЕРЕЖІ 5G STANDALONE: СИМУЛЯЦІЙНИЙ ПІДХІД

Стрімкий розвиток мереж п'ятого покоління у варіанті Standalone (*5G SA*) *висуває нові вимоги до реалізації голосових сервісів, зокрема Voice over New Radio* (*VoNR*), *які є критично залежними від стабільних показників якості обслуговування* (*QoS*). *Традиційні алгоритми планування радіоресурсів, такі як Round Robin та Proportional Fairness, базуються переважно на миттєвих характеристиках каналу* (*SNR, CQI*), *не враховуючи історичні метрики якості, такі як джитер, затримка або втрати пакетів, що призводить до нестабільної роботи голосових сервісів у змінному радіосередовищі. Особливо це актуально для 5G SA, де немає залежності від LTE-інфраструктури, і вся відповідальність за забезпечення QoS покладається на нову архітектуру.*

У статті запропоновано симуляційний підхід до побудови адаптивного планувальника для VoNR, який поєднує прогнозування параметрів модуляції за допомогою алгоритмів машинного навчання з динамічною оптимізацією MCS, QCI та енергоспоживання. На основі моделі ансамблю дерев рішень здійснюється оцінка оптимальної модуляції залежно від поточного значення SNR та агрегованих QoS-показників попередніх інтервалів. У симуляційній архітектурі, реалізованій у MATLAB, передбачено моделювання змін радіоканалу за допомогою ланцюгів Маркова з трьома дискретними станами (*Good, Average, Bad*), *що дозволяє відтворити реалістичні сценарії функціонування мобільної мережі. Адаптивний планувальник інтегрує декілька рівнів прийняття рішень: прогноз ML-моделі, евристичну корекцію у сприятливих радіоумовах та динамічне керування класами обслуговування* (*QCI*), *що забезпечує узгодження параметрів передачі з поточними та прогнозованими умовами каналу. Також враховується енергоспоживання як повноцінна QoS-метрика, що дозволяє знижувати навантаження на користувацьке обладнання при високих рівнях сигналу. Проведено порівняльний аналіз трьох планувальників* (*Round Robin, Proportional Fairness, Adaptive*) *за ключовими показниками: затримка, джитер, втрати пакетів, енергоспоживання, пропускна здатність та MOS.*

Результати дослідження підтверджують, що адаптивний ML-планувальник демонструє істотно кращі показники якості голосового з'єднання, особливо в умовах нестабільного радіоканалу. Запропонований підхід дозволяє мінімізувати втрати та затримки, стабілізувати MOS та підвищити енергоефективність системи без зниження якості сервісу. Таким чином, інтеграція машинного навчання в контур прийняття рішень для VoNR у 5G SA є перспективним напрямом, що може бути розширений шляхом реалізації мультикористувацьких сценаріїв, складніших ML-моделей та практичної апробації в умовах реальної мережевої інфраструктури.

Ключові слова: *VoNR, 5G Standalone, QoS, адаптивне планування, машинне навчання, модуляція, SNR, CQI, QCI, MCS, Round Robin, Proportional Fairness, Adaptive, ML-планувальник, симуляційне моделювання, MATLAB, ланцюги Маркова, MOS, енергоспоживання, jitter, затримка, втрати пакетів.*