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COMPARATIVE EVALUATION OF ROUND ROBIN, PROPORTIONAL FAIRNESS AND ML-DRIVEN ADAPTIVE SCHEDULING FOR VONR IN 5G SA

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This paper presents a comparative evaluation of three scheduling algorithms—Round Robin, Proportional Fairness, and a Machine Learning–driven Adaptive Scheduler—for Voice over New Radio (VoNR) transmission in 5G Standalone networks. The study aims to assess how machine learning integration and heuristic modulation control can enhance the quality of service (QoS), user experience (MOS), and power efficiency of voice traffic under dynamic radio conditions. A MATLAB-based time-domain simulation was developed, incorporating a Markov model of radio channel states (Good, Average, Bad) and a machine learning model based on an ensemble of decision trees. The Adaptive Scheduler utilizes historical QoS parameters (latency, jitter, packet loss) together with SNR-based predictions to select the optimal modulation and MCS level, supported by heuristic corrections in favorable conditions. Comparative results demonstrate that the ML-based scheduler provides more stable QoS, higher MOS, and better adaptation to channel variability than classical approaches, confirming its potential for improving real-time VoNR performance in 5G Standalone environments.

Key words: *5G Standalone (5G SA); Voice over New Radio (VoNR); adaptive scheduling; machine learning; MATLAB simulation; Markov channel model; modulation and coding scheme (MCS); quality of service (QoS); mean opinion score (MOS); power consumption; Round Robin; Proportional Fairness; heuristic modulation control; radio resource management.*

Summary of the main research material

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.

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 [1]. 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.

```
% 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.

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 [1]. 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 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.

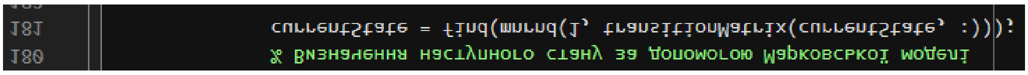

Fig. 2. A fragment of the implementation of a stochastic transition between network states based on a Markov chain.

For the currentState, the next state is selected according to the corresponding row in the transitionMatrix by the multivariate binomial distribution method.

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 [2]. 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 [3]. 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 [1].

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 [4].

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 [1].

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) [5]. 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.

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

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, 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 [6].

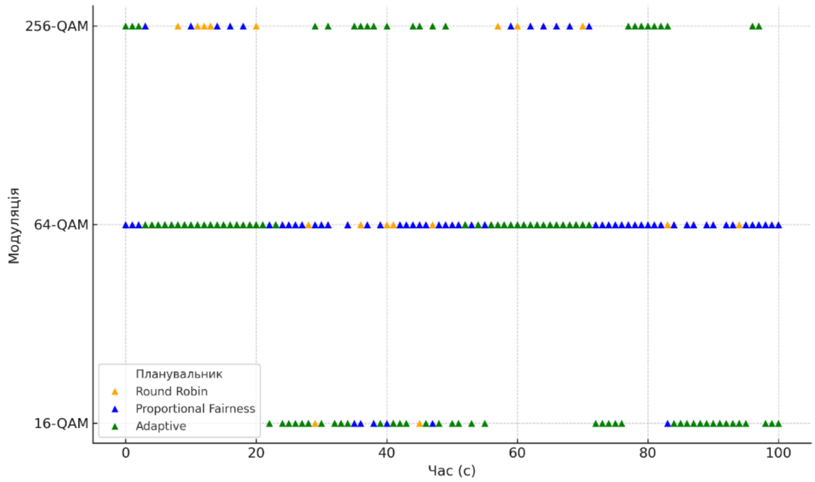

Fig. 3. Modulation change (16-QAM, 64-QAM, 256-QAM) over time for three schedulers.

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.

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 [7]. 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 2 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 [7]. 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 [8].

Table 2 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. 4). This guarantees that the actual transitions correspond to the specified matrix and allows creating realistic patterns of radio channel behavior.

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

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 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 [9].

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 [10]. Thus, the stochastic model of channel states is the basic element of the simulation environment that the adaptive scheduler relies on when making decisions.

Conclusions.

This study presented a comparative evaluation of three scheduling algorithms—Round Robin, Proportional Fairness, and a Machine Learning–driven Adaptive Scheduler—for Voice over New Radio (VoNR) transmission in 5G Standalone (SA) networks. The simulation environment developed in MATLAB modeled time-varying radio conditions using a Markov chain with three discrete channel states (Good, Average, Bad) and included a comprehensive QoS and MOS evaluation framework. The analysis demonstrated that traditional schedulers such as Round Robin and Proportional Fairness, while maintaining fairness or throughput balance, are not capable of sustaining stable voice quality under fluctuating radio conditions. In contrast, the proposed Adaptive Scheduler, which combines a machine learning model based on decision tree ensembles with heuristic modulation control, achieved significantly better adaptability and robustness. By incorporating short-term QoS history (latency, jitter, loss) and instantaneous SNR into its decision process, the

Adaptive Scheduler dynamically selected modulation and coding schemes (MCS) and adjusted QoS Class Identifiers (QCI) according to real-time network dynamics.

The results showed that the ML-driven adaptive design consistently improved MOS, reduced packet loss and jitter, and optimized power consumption compared to the baseline approaches. The integration of heuristic modulation elevation under high SNR further enhanced spectral efficiency without noticeable degradation in service quality. Overall, the conducted research confirms that applying machine learning and probabilistic modeling in 5G SA scheduling provides tangible improvements for QoS-sensitive services such as VoNR. The proposed simulation framework and findings can serve as a foundation for further development of intelligent schedulers capable of real-time adaptation in next-generation wireless systems.

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