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VISUAL IDENTIFICATION OF SOME REGULARITIES IN PACKET NETWORK TRAFFIC

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Modern heterogeneous packet networks generate network traffic with a complex structure. In this article, the object of study is a time series. The total number of User Datagram Protocol (UDP) packets has reached 250242. According to analysts, the growth trend of traffic, including real-time applications, will continue and the volume of data will grow, which may lead to the formation of packet queues when processed by network devices. In this case, there may be losses in case of long queues. To solve this problem, a power spectrum assessment was carried out. The AR maximum entropy estimator has been shown to be more sensitive than the auxiliary Fourier estimator.

Accounting for non-stationarity by spectral methods is possible only through estimation in a sliding time window. Nine diagrams of spectral-temporal analysis of the original series, its increments, and the mixed series of increments were obtained: with default parameters, with small and large windows. Diagrams related to the original series reflect the dynamics of changes in data transmission intensity in the network; they show higher temporal resolution, indicating the presence of high-frequency components (noise) and the presence of low-frequency components (trend). Diagrams with increments describe signals of periodic components; changing the length of the window did not reflect the presence of noise or trend signs. Diagrams with mixed increments show that frequency components are uniformly distributed. The uniqueness of this work lies in the real measured data, and a distinctive feature of the obtained results is the visual examination of the complex traffic structure, allowing for the resolution of the investigated problem. Practical application of the results obtained can be applied in Quality of Service (QoS) management, resource planning, and network performance optimization

Keywords: UDP, AR-estimation, moving window, packet intensity, long-term trend, high-frequency component

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1. Introduction

Modern multiservice networks, operating under the NGN/IMS (Next Generation Network/IP Multimedia Subsystem) concept, feature an optical transport core utilizing IP/MPLS technology. By the year 2022, this network reached the development level of a 4G optical network with DWDM HWT (Dense Wavelength Division Multiplexing) and ROADM (Reconfigurable Optical Add-Drop Multiplexer) technology, achieving a data transmission rate of 48*100 Gbps. This signifies the establishment of a fully digital, automated, and programmable world connecting people, machines, things, and locations in the Republic of Kazakhstan (RK). In 2023, the RK became a leader in internet speed within the EAEU and Central Asia, securing the 72nd position globally. Correspondingly, network traffic loads are growing and are expected to continue increasing. This leads to an uneven intensity in the arrival of packets to the servicing network devices [1]. The study of real network traffic in modern heterogeneous networks remains a pertinent task.

To handle the increasingly growing network traffic, it is necessary to conduct research on empirical data, as it allows for identifying the laws of packet intensity distribution. If previously it was a Poisson distribution, today it is already a Pareto distribution, and perhaps tomorrow it will be some other distribution. All this is very important for network devices to operate in accordance with QoS.

2. Literature Review and Problem Statement

In article [2], instead of numerical methods, a formula is developed for nonlinear compression of large-scale covariance matrices, based on the deep connection between nonlinearity and nonparametric estimation of the Hilbert transform of the sample spectral density. In this case, a kernel estimates of not the density itself (as done previously), but its Hilbert transform, is introduced. The authors of article [3] note that the definition of the Hilbert spectrum is described in terms of total energy and amplitude. However, there is a mismatch between the Hilbert spectrum and the traditional Fourier spectrum, which is defined through energy density. Corresponding difficulties hindered the transformation of Hilbert and Fourier spectral results. The authors of this article established a simple connection between them and obtained results of spectral analysis of Hilbert and Fourier spaces.

In work [4], tools for analyzing the singular spectrum (SSA) are considered. In this case, a one-dimensional series is divided into trends, periodic oscillations, other statistically significant components, and noise. Then the series is restored based on contributions from selected components with an estimation of the power spectra of the time series.

All the methods mentioned above have evolved into more modern methods today, such as estimating power spectra of time series using the AR estimation method, which is investigated in this article.

In article [5], a real-time monitoring method is proposed for satellite navigation. A spectral analysis using the least squares method is suggested, which can detect and classify changes in newly acquired data. Additionally, cross-wavelet analysis using the least squares method demonstrates temperature and precipitation to assess the results. The work is based on the classical least squares method or its modification, which simplifies it due to the low intensity of the time series.

The papers [6, 7] present the results of research on detecting seizure onset in electroencephalography (EEG) signals. This difficulty arises from the non-stereotypical nature of seizure activities and their inherent stochastic and non-stationary characteristics, just as in our time series. To effectively capture important characteristics from non-stationary EEG signals, a framework for joint spectral-temporal feature learning has been introduced. This involves the utilization of both continuous wavelet transform (CWT) and discrete wavelet transform (DWT) to extract spectral-temporal features and generate a time-frequency image.

The paper [8] presents traditional and some new methods of time series analysis, including spectral and wavelet analysis. In our opinion, the output data are not very informative, possibly due to the representativeness of the sample. Spectral-temporal diagrams depict time and frequency, but do not display signal power.

But there are still unresolved issues in these studies related to the time window, i. e. discrete transform. This approach more or less was used in [9]. In this paper was considered two approaches, namely convolutional sparse analysis and temporal spectral unmixing, are introduced within this framework to characterize distinct spatial structures and address the challenges posed by spectral variability. Additionally, a multiple change detection based on subpixel analysis is explored. Experiments conducted on three bitemporal hyperspectral imaging (HSI) datasets demonstrate the robustness of the proposed framework in capturing meaningful features and achieving high detection accuracy.

However, the multidimensional functions obtained contain redundant information and require substantial computational load.

Although there is a common belief that Fourier methods are poorly suited for processing non-stationary signals, the authors of the following paper [10] argue otherwise.

They introduce a novel and adaptive Fourier decomposition method (FDM) based on Fourier theory, showcasing its effectiveness in analyzing nonlinear and non-stationary time series. This FDM breaks down any dataset into a small set of 'Fourier intrinsic band functions' (FIBFs). The FDM offers a generalized Fourier expansion, incorporating variable amplitudes and frequencies of a time series through the Fourier method itself. To analyze multivariate nonlinear and non-stationary time series, they propose the concept of a zero-phase filter bank-based multivariate FDM (MFDM) utilizing the FDM. The proposed MFDM generates a finite number of band-limited multivariate FIBFs (MFIBFs), preserving intrinsic physical properties such as scale alignment, trend, and instantaneous frequency in multivariate data. These methods yield a time-frequency-energy (TFE) distribution, exposing the intrinsic structure of the data. This approach to revealing the internal structure of data is very similar to our study. It is also possible to use methods for deeper exploration of data structure. While these approaches find numerous practical applications, the outcomes of this paper were only moderately successful. The reason for this is that they do not consider the use of sliding windows.

In papers [11, 12], the authors made predictions for a time series with incomplete observations using the spectral-temporal metrics method (Missing Observation Prediction based on Spectral-Temporal Metrics, MOPSTM), yielding promising outcomes. The use of supervised random forest classification problems in this work using artificial gap filling of simulated datasets may not be applicable for measured empirical data like ours, there may be a loss of valid data. This narrows the scope of use of this approach.

The paper [13] addresses the shortcomings of the Fourier transform and proposes a multiplicative perspective on using trigonometric functions to quantify nonlinear interactions in any time series. The multidimensional spectral representation of a time series, which in this paper is called the Huang spectrum, identifies interactions between time-varying amplitude and frequency oscillatory components of different periods of the time series and explicitly quantifies the nonlinear interactions. The use of the proposed method does not give the expected results, since the series considered in this article is one-dimensional.

All this suggests that it is advisable to conduct a study on using discrete transformation, it allows to take a deeper look at the structure of the series and then use these facts for further research. Here a narrow time window, also the using wide windows very help us.

A narrow time window in spectral-temporal analysis can provide good temporal resolution and localization of rapid changes in the signal, specifically the high-frequency components. This is particularly useful for detecting high-frequency components in the signal. It also determines how well one can identify the moment in time when changes occur in the signal and «focus» on narrow time intervals, which is crucial for highlighting rapid transitions and short-term events.

All above suggests that research on time series related to real measured data is worthwhile.

3. The aim and objectives of the study

The aim of the study is to identify patterns of non-stationarity in time series data of network traffic using spectral-temporal analysis. Visual identification of non-stationarity patterns can contribute to the development of more accurate models explaining the behavior of the time series. Furthermore, understanding non-stationarity patterns can enhance the ability to forecast future changes in the time series. This can be crucial for decision-making and managing network resources or processes.

To achieve this aim, the following objectives are addressed:

– to construct a time series of UDP packet intensity;

– to perform differentiation of the time series;

– to conduct a power spectrum estimation of the original series;

– to generate three-dimensional diagrams of the distribution of spectral amplitudes for the original series, its shifts, and the shuffled series of increments.

4. Materials and methods of research

The object of the study is to empirical data of network traffic.

The subject of the study is the patterns of non-stationarity in time series data. As the network is heterogeneous, the structure of the series becomes more complex and variable, therefore the hypothesis of the study is that the series is non-stationary.

The original dataset was obtained using the Wireshark 2.2.10 analyzer program on the Bostandyk district line in Almaty city on April 7, 2017, from 14:00 to 19:00. The Wireshark output data was processed by a specially written program in the C# programming language to sort packets by individual protocols, namely TCP, UDP, MPEG, IGMP, ARP, DHCP, DNS (packet intervals). Additionally, the overall traffic is presented in a text document totaling 63 MB for further research.

In total, 278557 packets were read, covering various protocols, such as 158 Transmission Control Protocol (TCP) packets, 493 Address Resolution Protocol (ARP) packets, 25733 Moving Picture Experts Group (MPEG) packets, and 250242 User Datagram Protocol (UDP) packets, among others. Based on the collected data, a time series was constructed, specifically representing the packet intensity of the User Datagram Protocol. Simultaneously, their counting was performed every 10 seconds using the numerical-mathematical modeling package Matlab. Below is a segment of the measured network traffic:

278544 589.407462 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278545 589.407948 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278546 589.410029 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278547 589.410032 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278548 589.411109 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278549 589.412045 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278550 589.412680 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278551 589.414572 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278552 589.414575 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278553 589.417032 192.168.172.1 PTS_1380.644433333
MPEG_PES_audio-stream 1358 bytes;
278554 589.417037 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278555 589.417995 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278556 589.419081 192.168.172.20 239.2.2.52 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes;
278557 589.419924 192.168.172.1 239.2.1.4 UDP
Source_port:_bre Destination_port:_cisco-sccp
1358 bytes.

Early assumptions about the stationarity of the series may be unacceptable today due to the heterogeneous nature of the network. For this reason, this study employs the differentiation method for simplification, as well as the methods of AR maximum entropy estimation, Fourier estimation, sliding window, random data shuffling, and spectral-temporal analysis methods. Spectral-temporal analysis will aid in studying both the frequency and time characteristics of the signal. Joint spectral-temporal features are believed to contain sufficient and powerful feature information for working with network packets.

5. Research results based on an analysis of the distribution of spectral amplitudes in a time series to determine the main frequency components

5. 1. Visual analysis of the time series

The User Datagram Protocol (UDP) packets accounted for 89.95 % of the total 278557 packets. UDP is utilized for transmitting real-time traffic without ensuring packet delivery, making it crucial to analyze its structure. The measured UDP traffic dynamics series is shown in Fig. 1.

The time series contains 1800 levels. Visually, it is apparent that the graphic of the UDP protocol packet distribution has uneven intensity (the spread of observations increases and decreases over time). There are fluctuations in traffic intensity with significant variance, groupings in «bundles» in certain places, or sparse sections in other time intervals where there are few or no incoming packets. For a visual comparison of the presence of presumed non-stationary (trend) in the original series, differentiation has been performed, i. e., excluding the non-stationary component. This involves transitioning to a time series composed of differences between successive values of the series, i. e., the increments of the original time series.

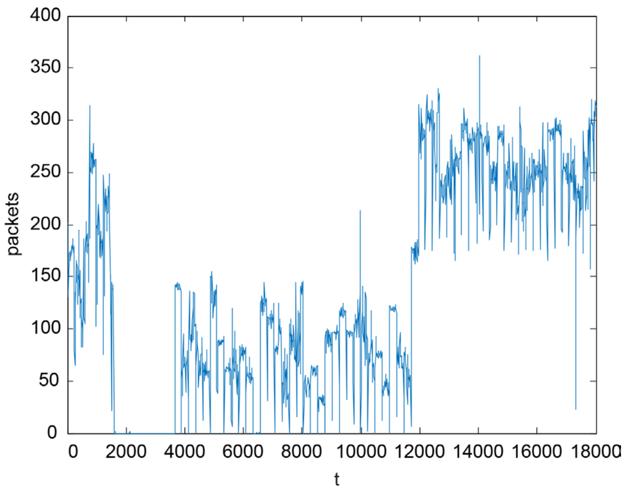


Fig. 1. UDP protocol packet arrival intensity

A visual analysis of the UDP packet intensity time series reveals that the original series exhibits uneven intensity. The dispersion of observations fluctuates over time, displaying traffic intensity pulsations with significant variance. There are clusters or «bursts» of intensity in certain periods, while other time intervals experience sparse sections with little to no incoming packets. Such behavior in the series can lead to network congestion or reduced performance.

5. 2. Performing time series differentiation

To visually compare the presence of presumed non-stationarity features (trend) in the original series, differentiation has been carried out, eliminating the non-stationary component. For this purpose, let's transit to a time series composed of the differences between successive values of the series, i. e., to the series of increments of the original time series (1).

To transform the original non-stationary series into a stationary one based on the mathematical expectation of the time series, differentiation is applied-taking the finite differences of the series values (with a dominance of low frequencies) using the formula:

$$Y(t) = X(t+1) - X(t). \qquad (1)$$

Fig. 2 displays the original series (in blue) and its increments (in red).

On the above figure, it can be observed that after the first differentiation of the time series, its visual pattern closely resembles a stationary series. The intensity appears relatively uniform, without traffic intensity pulsations, and lacks distinct clusters or «bursts». Therefore, first-order differentiation is deemed sufficient for further investigation.

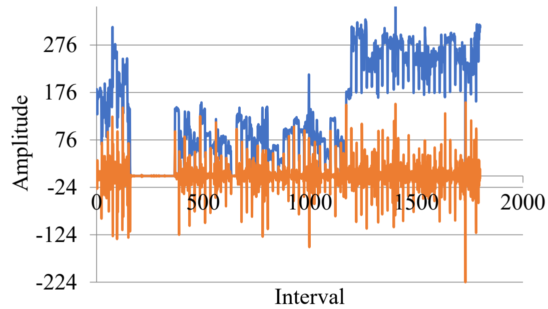


Fig. 2. The original series and its increments

Differentiation can be performed at various orders, including first, second, and beyond. In this study, first-order differentiation of the time series was applied. The process involved subtracting the previous value of the time series from the current one to eliminate the low-frequency component and stabilize the variance.

5. 3. Using the Auto-Regression (AR)-maximum entropy period estimation and an auxiliary «background» Fourier estimation in a double logarithmic scale

To proceed with further investigations, the file containing the UDP packet intensity time series data was selected in the «Spectra analyzer» program. Fig. 3 illustrates the program window with the chosen original file – UDP protocol packet intensity with a set polling interval of 10 seconds and an initial timestamp for the first measurement equal to 0. The series contains outliers, so it underwent winsorization.

In the Fig. 3, it is evident that the series appears smoother after the iterative removal of significant outliers. Power spectrum estimation of the original series data has been conducted in a double logarithmic scale, considering periods, as the «Freg» feature is not marked, as shown in Fig. 4.

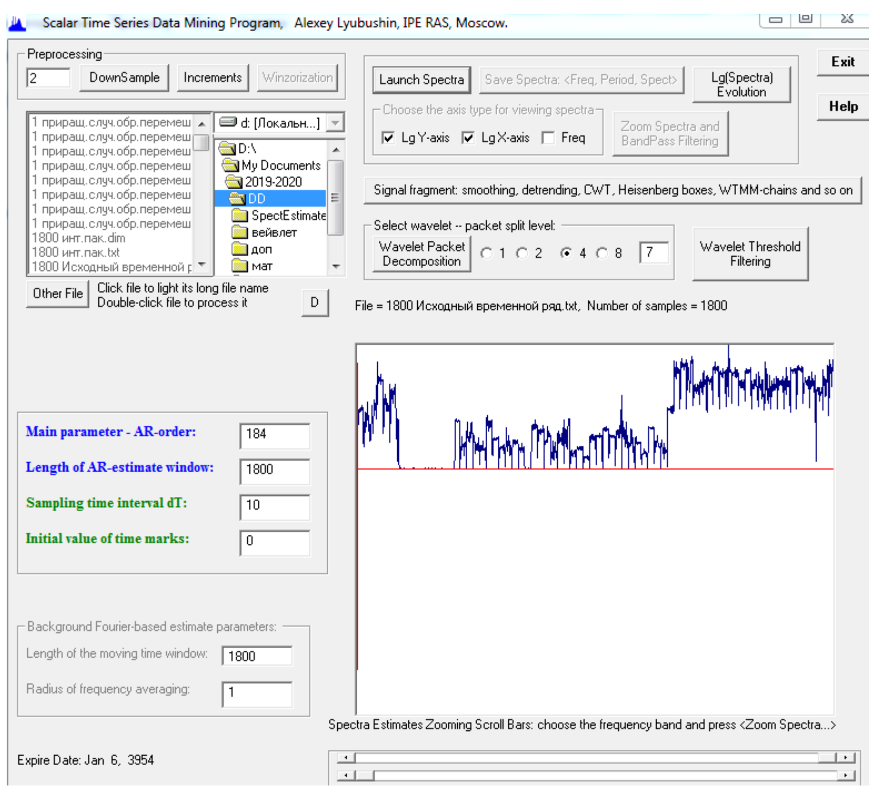


Fig. 3. The original series selected in the 'Spectra Analyzer'

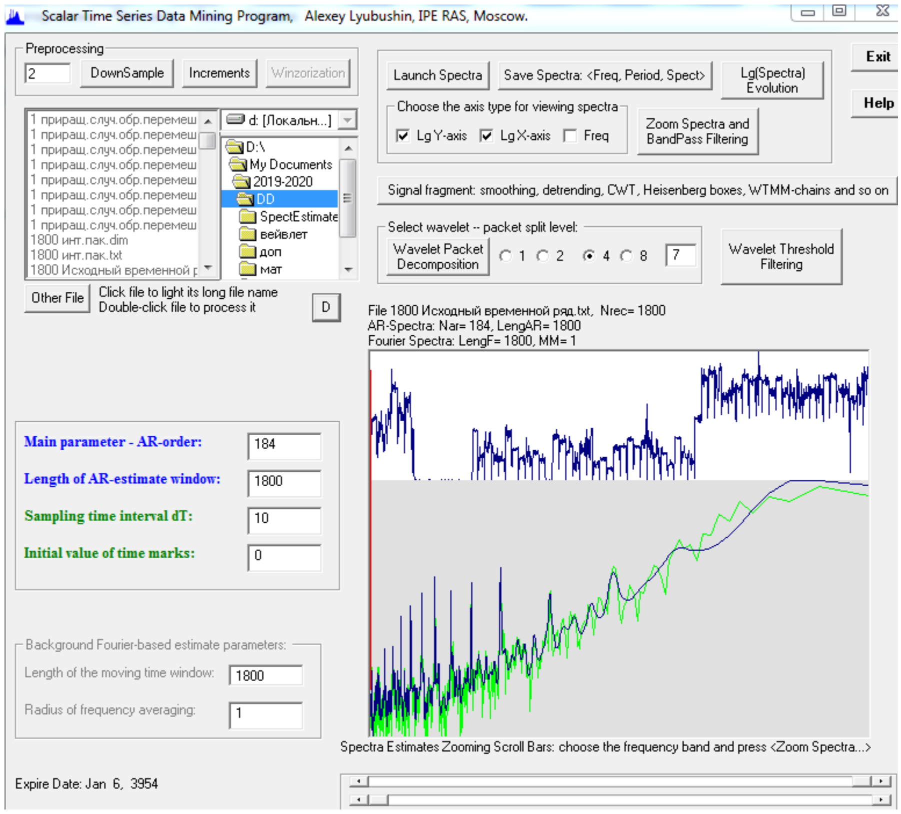


Fig. 4. Power spectrum estimation of the original series and background Fourier estimation

In the Fig. 4, there are two plots depicting power spectrum estimates of the original series: AR-maximum entropy period estimation (dark blue) and an auxiliary «background» Fourier estimation (light green on the monitor).

5. 4. Spectral amplitude distribution diagrams

Spectral-temporal analysis diagrams for non-stationary series are three-dimensional, where frequency is plotted on the vertical axis, time on the horizontal axis, and spectral power density (SPD) along the depth axis. In this process, a sliding time window spectral analysis procedure is employed, evaluating the evolution of the logarithm of power spectra in sliding time windows of a specified length. The output map is presented as a diagram of spectral amplitude distribution, where each column represents a Fourier amplitude spectrum calculated within the designated sliding time window. Darker areas on the diagrams (Fig. 5) correspond to higher amplitude spectra.

The above diagrams differ in the sizes of the areas colored in corresponding hues. In the first one, these areas are somewhat larger, and their quantity is smaller, creating an overall brighter image compared to the other two. This indicates the presence of low-frequency components (trend), harmonic components (signal), and high-frequency components (noise) in the first diagram. The more vivid colors specifically pertain to the latter two, suggesting the dominance of harmonic and high-frequency components. This is because the second diagram has almost no low-frequency components, and in the third diagram, both components were randomly distributed, forming a stochastic signal.

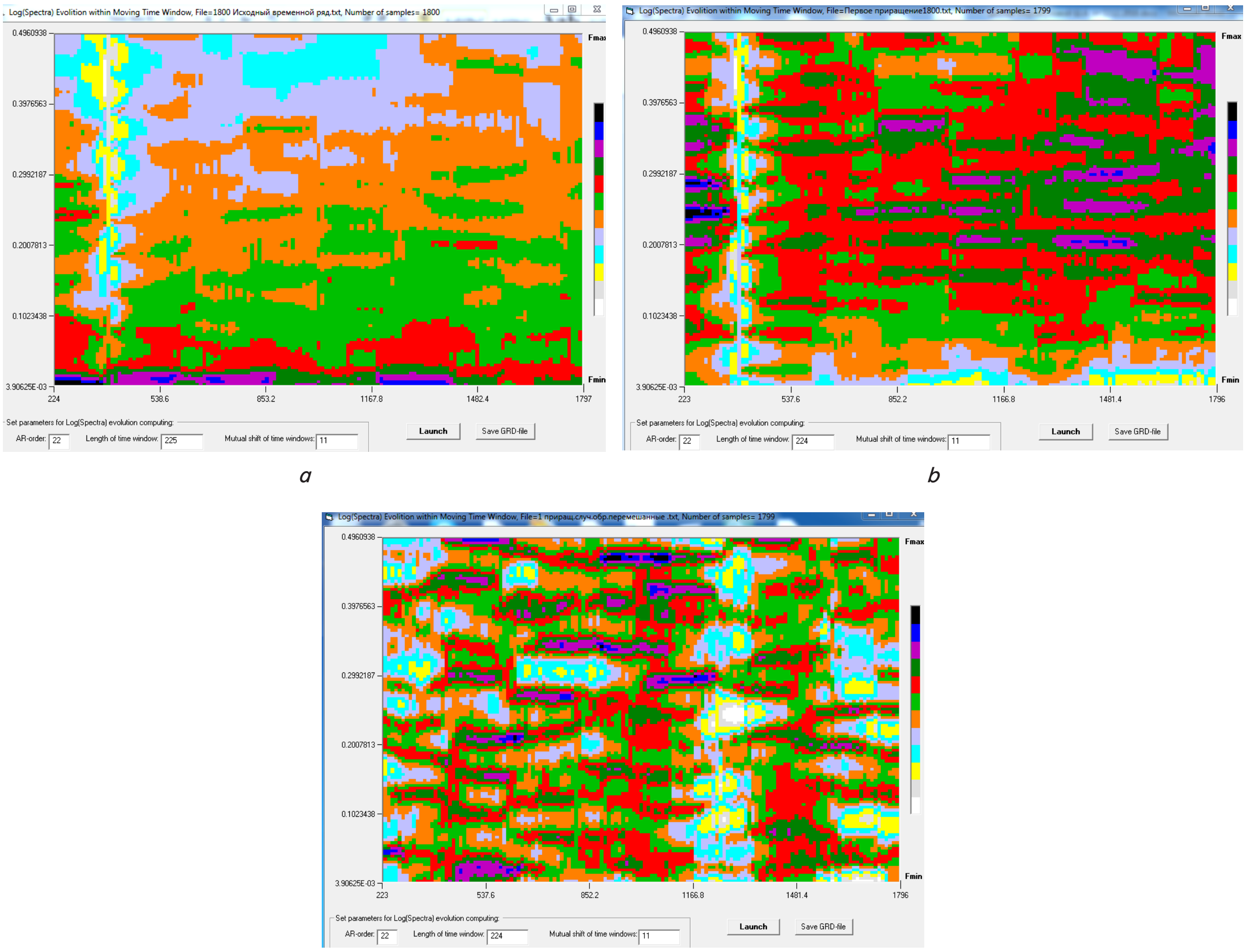
Decomposition of the original series into components using spectral methods is possible by adjusting the lengths of the sliding windows. The study involves examining the time series when selecting very short time windows. In Fig. 8–10, spectral-temporal analysis maps were obtained with very short selected time windows for the original series (AR-order=9, Length window=38, Mutual shift of time windows=11), for the increment series (AR-order=4, Length window=16, Mutual shift of time windows=11), and for the increment series shuffled in random order (AR-order=9, Length window=38, Mutual shift of time windows=11), respectively. The diagram presented in Fig. 6 has high temporal resolution, allowing for the detection of rapid changes in the signal, i. e., high-frequency components.

However, as the frequency resolution decreases in this case, the narrow window does not capture low-frequency components. This map describes fast changes in the signal. The diagram shown in Fig. 7 exhibits fewer changes in frequencies over time, indicating the presence of stable frequency characteristics in the series.

Clear and stable vertical frequency bands are visible on this map (Fig. 7).

In the diagram presented in Fig. 8, the frequency components have become more evenly distributed over time, and a random distribution of energy across frequencies is also visible. This map is colorful, and the vertical bands are less structured.

The spectral-temporal analysis diagrams shown in Fig. 6–8 were constructed using a very narrow analysis window, ranging from 0.9 % to 2.1 % of the series length. A narrow time window in spectral-temporal analysis can provide good temporal resolution and localization of rapid changes in the signal, i. e., high-frequency components. This is particularly useful for detecting high-frequency components in the signal and determining how well the moment of change in the signal can be identified, focusing on narrow time intervals, which is important for highlighting rapid transitions and short-term events.



a *b*

c

Fig. 5. Spectral-time analysis diagrams: *a* — diagram of the original series; *b* — diagram of the increment series; *c* — diagram of the shuffled increment series

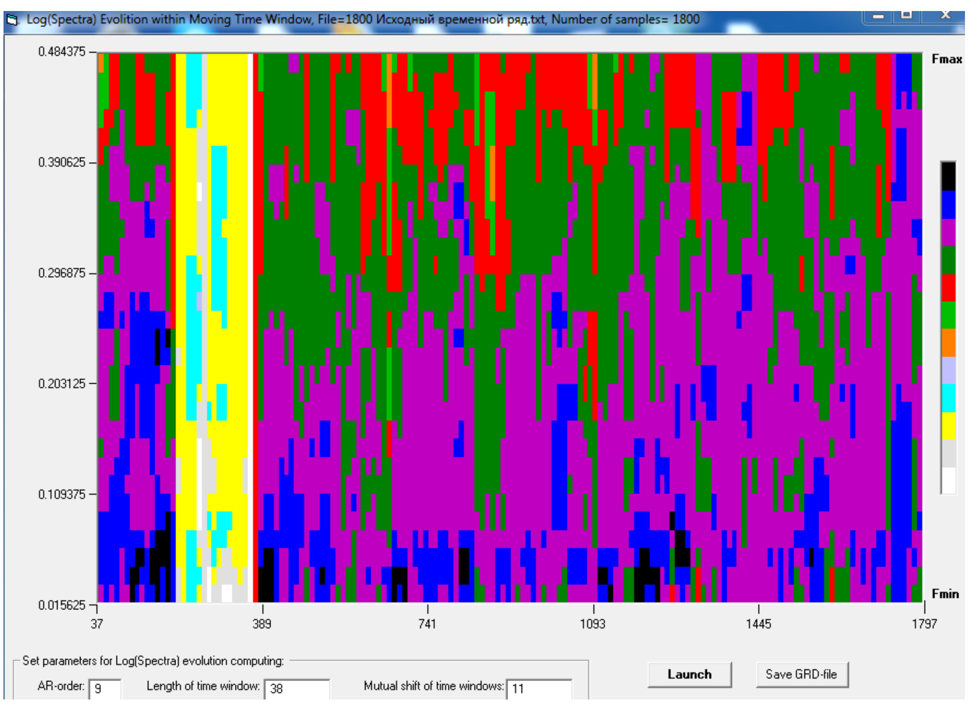


Fig. 6. Spectral-time analysis diagram of the original series

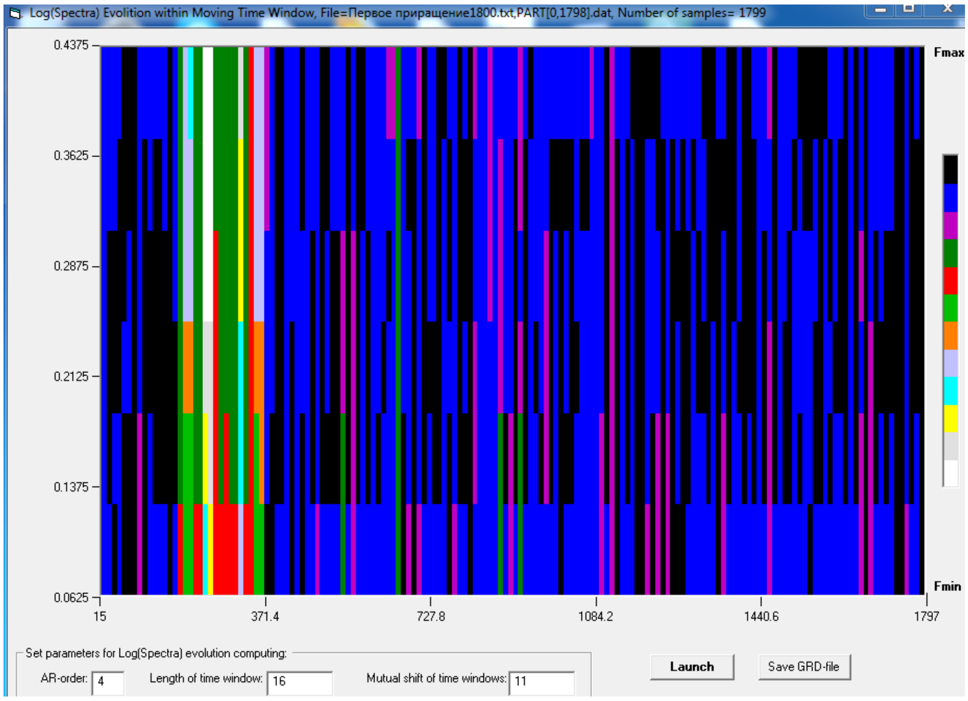


Fig. 7. Spectral-time analysis diagram of the increment series

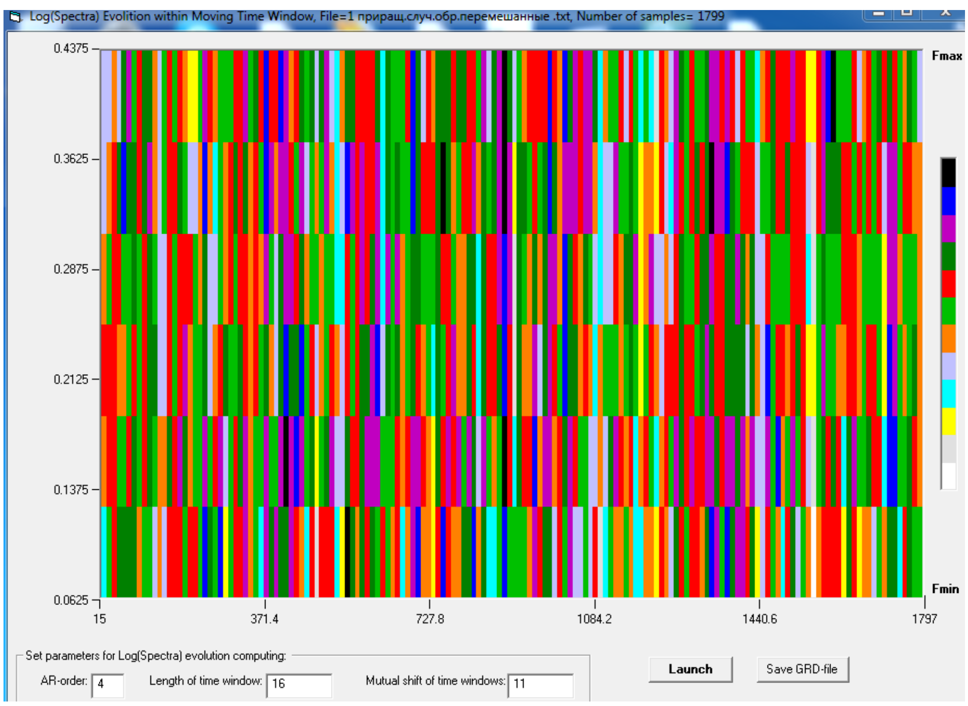


Fig. 8. Spectral-time analysis diagram of the shuffled increment series

From the perspective of the Heisenberg principle, which involves a trade-off between temporal and frequency resolution, a narrow time window leads to a reduction in frequency resolution, making it less accurate in determining frequency components, especially those that change slowly over time. Meanwhile, too short a window length increases purely statistical fluctuations in current spectrum estimates, making the diagram too noisy and less informative [14–16].

Investigation of the time series with the choice of long-time windows.

In Fig. 9–11, maps with selected large time windows (900) are obtained for the original time series (AR order=9, Length window=38, Mutual shift of time windows=11), the increment series (AR order=4, Length window=16, Mutual shift of time windows=11), and randomly shuffled values of the increment series (AR order=9, Length window=38, Mutual shift of time windows=11), respectively.

In the diagram presented in Fig. 9, the horizontal bands are more blurred over time, revealing general trends. This map is bright and has several frequencies with a predominance of low-frequency components.

In the diagram shown in Fig. 10, the frequency areas are clearly delineated without bright and very dark regions. This map highlighted the absence of trend and noise.

In the diagram presented in Fig. 11, the vertical bands are less structured, and the frequency components are relatively evenly distributed. This map exhibits a uniform distribution of energy across frequencies, independent of time. The diagrams shown above with wide windows provide better resolution of low-frequency signal components. A broader window offers a more accurate representation in the frequency domain, which is beneficial for detecting long-term trends, i. e., low-frequency components. These maps lack high-frequency harmonics and irregularities in the high-frequency spectrum.

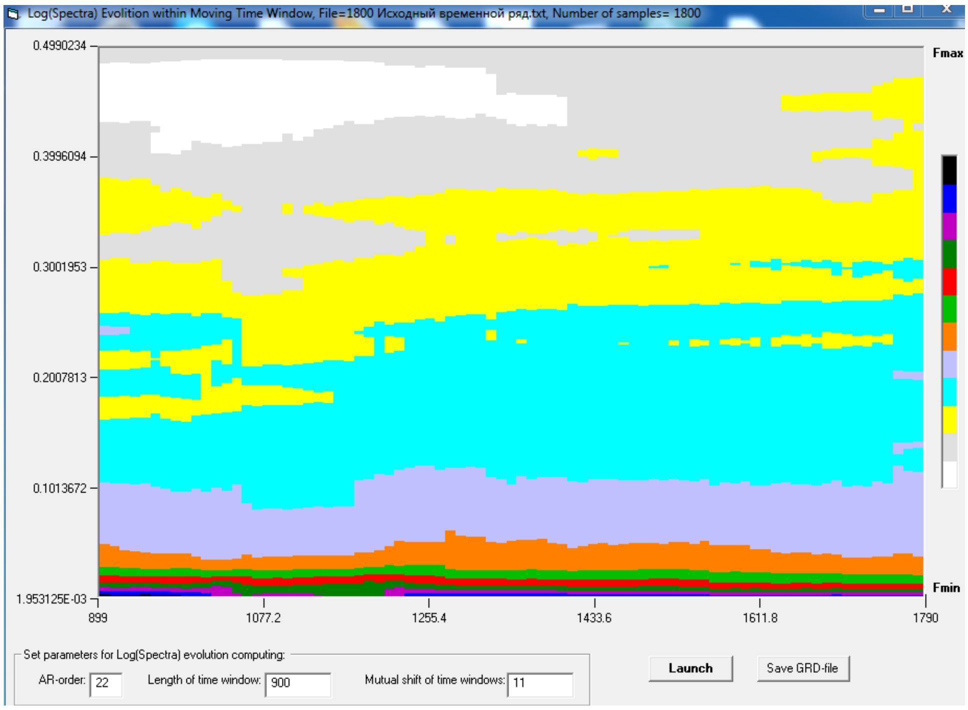


Fig. 9. Spectral-temporal analysis diagram of the original series

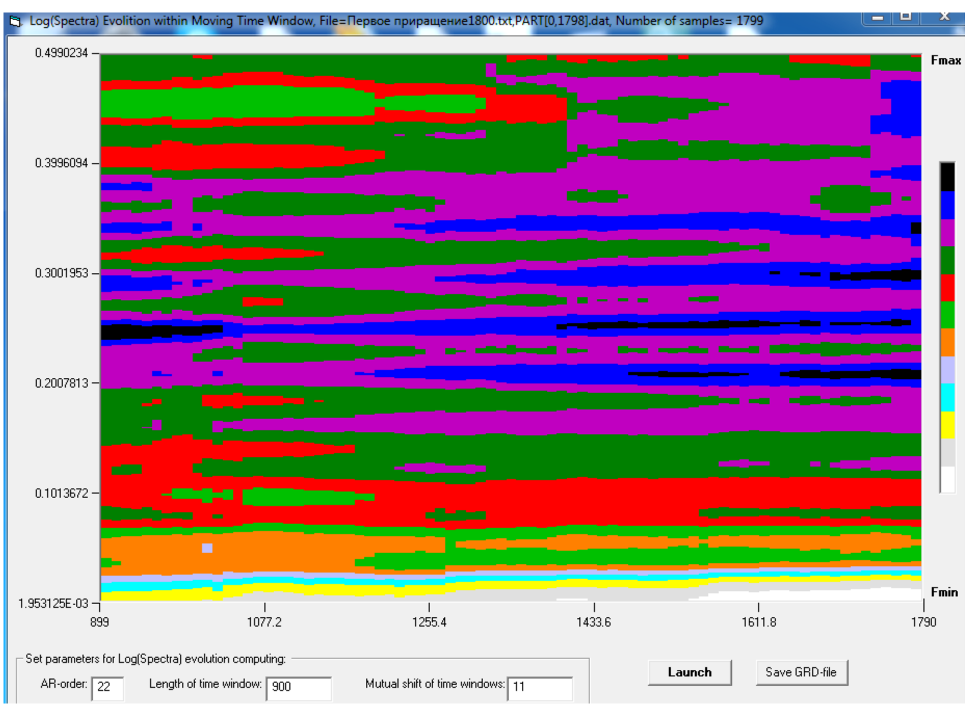


Fig. 10. Spectral-temporal analysis diagram of the first increment

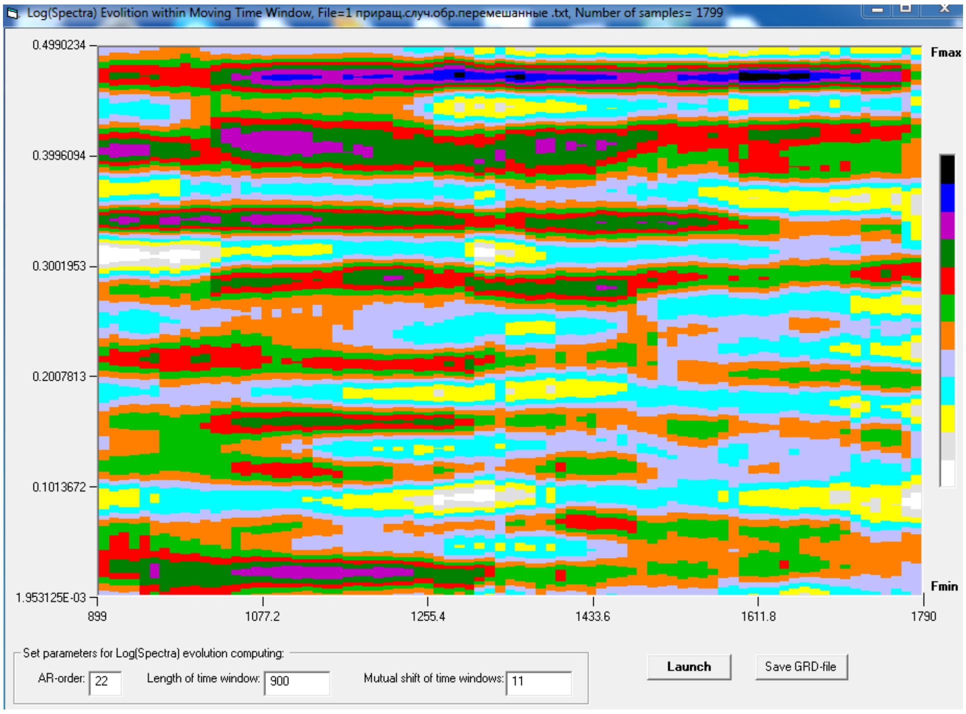


Fig. 11. Spectral-temporal analysis diagram of the shuffled increment series

6. Discussion of the results of identifying signs of non-stationarity using spectral-temporal analysis

In work describing SSA method [4], it decomposes a time series into linear combinations of its components without considering the time-varying frequency characteristics of the signal. Spectral-temporal analysis in this study breaks the signal into short segments, thanks to that the Fourier transform for each segment calculated. This allows analyzing changes in the frequency characteristics of the signal for each segment over time.

Unlike study using periodograms [5], which provides only spectral information, spectral-temporal analysis diagrams help analyze both frequency and time characteristics of the signal simultaneously, enabling a more comprehensive assessment of network traffic dynamics. This is made possible by the identification of patterns that might be overlooked when using only periodograms.

As for the methods in studies [6, 7] and present one, both methods provide tools for data analysis, but their applicability and scope depend on the type of data and specific research tasks. The advantage of spectral-temporal analysis lies in its ability to simultaneously analyze both frequency and time characteristics of the signal, thereby providing a more comprehensive understanding of the signal dynamics.

The authors of papers [11, 12] use the MOPSTM method for modeling artificial datasets with subsequent imputation of missing values. This approach may be limited in its applicability to measured empirical data, such as in the present study, as it can lead to the loss of actual data. In contrast, spectral-temporal analysis may offer a more versatile approach, as it can be applied directly to real data without the need for modeling or imputing missing values.

The results obtained in this work are explained by the following data:

– the visually expressed complex structure of the time series, presented in Fig. 1, could influence the obtained results of its further study of its spectral characteristics. Spectral-temporal analysis performed decomposition and allowed the slow, periodic and high-frequency components to be highlighted. The study of dynamic traffic characteristics becomes relevant when assessing the performance of a high-speed network;

– the performed first-order differentiation proved that the structure of the series is multicomponent, highlighting the displacement from the series (Fig. 2), which, unlike the original one, had a uniform intensity, there were no clusters of packets in certain places or, on the contrary, discharged areas. This helped to see and notice features and changes in intensity that were not very obvious in the original series;

– study of increments and its mixing. The results of studying the structure of increments and randomly mixed increments help to see and understand the presence/absence of random components in the structure of the original series and allow to identify certain patterns;

– uneven traffic intensity affects the dynamics of the time series, and this can be seen visually by constructing the time series. And the features of this intensity were highlighted using window management in the Spectra analyzer program. Using spectral-temporal analysis, it was discovered that the original series is non-stationary. This non-stationary series contains a trend, as evidenced by Fig. 9, in which several low-frequency components seem to be stratified and stretched over a large time interval. This non-stationary series contains periodic fluctuations in the signal data and these periodic fluctuations are clearly visible in Fig. 5, which are represented as vertical bars at high frequencies. Basically, in all spectral-temporal analysis figures there are large or small fractions associated with windowed possibilities, but they still dominate and the color intensity or brightness shows the extent of the presence of these frequencies at different points in time. This non-stationary series also contains noise components that can be seen using spectral-temporal analysis using very small windows (Fig. 6) and that its offset shown in Fig. 7 becomes noisy and uninformative;

– factors and reasons that can explain the observed changes in the intensity and structure of the time series are packet data transmission, integration and convergence evolutions in the network, as well as an increase in the number of consumers of telecommunications network services.

The limitations inherent in this study focus on the visual representation of the measured series. For an analytical description, there are many other studies, such as fractal analysis, the theory of deterministic chaos, and others.

The development of this research method is the decomposition of the original series into an infinite sum of periodic functions, each with a different frequency. Spectral methods typically cover a class of algorithms that represent matrices using linear algebraic methods, involving the eigenvalues of matrix vectors, such as the Hankel matrix.

Further research will be devoted to wavelet analysis with Gaussian kernel smoothing, involving the construction of Morlet diagrams, Heisenberg boxes, and skeletons. These methods are powerful tools for analyzing temporal data and signals that can be utilized in various scientific and engineering fields to identify patterns, structures, and characteristics in the data.

7. Conclusions

1. The choice of real measured data, specifically the UDP packets, is justified by the fact that functioning packet networks for real-time applications employ traffic classification with a prioritization mechanism. Investigating the increasing dominance of real-time traffic serves as a test for the operational network to further develop this issue. Out of the measured 278,557 packets, the share of UDP packets was 89.84 %.

2. First-order differencing stabilized the series variance, removed the trend, and made the original series more stationary. This calls for further and more in-depth analysis of the time series.

3. The Fourier spectral estimation of the original series demonstrated a relatively weak sensitivity to extracting periodic components in the series and is primarily used for constructing two-dimensional periodograms compared to the AR maximum entropy estimation. The latter is adapted to capture nonlinearity and correlation in the data, forming three-dimensional diagrams.

4. Three-dimensional diagrams of spectral amplitude distribution visually revealed that the investigated series is non-stationary. Spectral-temporal analysis diagrams with the following parameters for the original time series (AR-order=22, Length window=225, Mutual shift of time windows=11), for the increment series (AR-order=22, Length window=224, Mutual shift of time windows=11), and for the randomly shuffled increment series (AR-order=22, Length window=224, Mutual shift of time windows=11) visually confirmed that the real series exhibits signs of non-stationarity, the increment series is stationary, and the shuffled series is purely random. Additionally, the obtained diagrams identified noise, signal, and trend in the series.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has associated data in a data repository.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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