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INTELLIGENT COMPUTER NETWORK TRAFFIC FORECASTING SYSTEM BASED ON SYNPHASE DATA PROCESSING

The article considers the problem of increasing the efficiency of computer network management by forecasting their traffic using intelligent data processing methods. The feasibility of using new generation stochastic models, in particular periodically correlated stochastic processes (PCSP), which allow simultaneously taking into account the random nature of traffic formation and its daily cyclicity, is substantiated. Unlike classical models (Poisson, Markov, ARIMA, fractal), which are limited in reproducing complex patterns, the PCSP-based approach provides a more adequate description of real processes in telecommunication systems.

The architecture of an intelligent forecasting system is proposed, the core of which is synphase data processing algorithms. The implemented procedures include parametric covariance estimation, spectral analysis of centered signals using the Fourier transform, and averaging of correlation components to reduce the influence of noise components. This ensures high accuracy of reproducing network load variability and forming stable forecasts even under conditions of stochastic deviations.

Experimental testing was conducted based on data from the Internet provider UFONet (Ternopil). It was found that the system correctly identifies critical peak intervals (1.8–2.1 TB in the evening) and periods of minimum load (0.5–0.7 TB at night). Additionally, an automatic load level classification module was implemented, which translates numerical forecasts into a categorical form (“minimum”, “average”, “critical”). Such a mechanism allows operators and providers to carry out proactive resource management, reduce the risks of overloads and plan maintenance in the least active time intervals.

The practical significance of the results obtained lies in creating a decision support tool for network infrastructure administrators, which increases the stability of the system and the quality of service provision to users. The scientific novelty of the work is determined by the synthesis of PCSP methods and synphase analysis in a single intelligent forecasting system. Prospects for further research are related to the integration of the developed system with machine learning algorithms and the expansion of its application to multi-level computer networks of the next generations.

Key words: *computer networks, intelligent system, traffic forecasting, synphase processing, periodically correlated random process, MATLAB.*

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ІНТЕЛЕКТУАЛЬНА СИСТЕМА ПРОГНОЗУВАННЯ ТРАФІКУ КОМП'ЮТЕРНИХ МЕРЕЖ НА ОСНОВІ СИНФАЗНОЇ ОБРОБКИ ДАНИХ

У статті розглянуто проблему підвищення ефективності управління комп'ютерними мережами шляхом прогнозування їхнього трафіку з використанням інтелектуальних методів обробки даних. Обґрунтовано доцільність застосування стохастичних моделей нового покоління, зокрема періодично корельованих випадкових процесів (ПКВП), що дозволяють одночасно врахувати випадкову природу формування трафіку та його добову циклічність. На відміну від класичних моделей (Пуассонівських, Марковських, ARIMA, фрактальних), які обмежені у відтворенні комплексних закономірностей, підхід на основі ПКВП забезпечує більш адекватний опис реальних процесів у телекомунікаційних системах.

Запропоновано архітектуру інтелектуальної системи прогнозування, ядром якої є алгоритми синфазної обробки даних. Реалізовані процедури включають оцінювання параметричної коваріації, спектральний аналіз центрованих сигналів за допомогою перетворення Фур'є та усереднення кореляційних компонент для зниження впливу шумових складових. Це забезпечує високу точність відтворення варіативності мережевого навантаження та формування стійких прогнозів навіть за умов стохастичних відхилень.

Експериментальна апробація проведена на основі даних інтернет-провайдера UFONet (м. Тернопіль). Встановлено, що система коректно ідентифікує критичні пікові інтервали (1,8–2,1 ТБ у вечірні години) та періоди мінімального навантаження (0,5–0,7 ТБ уночі). Додатково реалізовано модуль автоматичної класифікації рівнів навантаження, який переводить числові прогнози у категоріальну форму («мінімальне», «середнє», «критичне»). Такий механізм дозволяє операторам і провайдерам здійснювати проактивне управління ресурсами, зменшувати ризики перевантажень та планувати технічне обслуговування у найменш активні часові інтервали.

Практичне значення отриманих результатів полягає у створенні інструменту підтримки прийняття рішень для адміністраторів мережевої інфраструктури, що підвищує стабільність роботи системи та якість надання послуг користувачам. Наукова новизна роботи визначається синтезом методів ПКВП і синфазного аналізу в єдиній інтелектуальній системі прогнозування. Перспективи подальших досліджень пов'язані з інтеграцією розробленої системи з алгоритмами машинного навчання та розширенням її застосування на багаторівневі комп'ютерні мережі наступних поколінь.

Ключові слова: *комп'ютерні мережі, інтелектуальна система, прогнозування трафіку, синфазна обробка, періодично корельований випадковий процес, MATLAB.*

Statement of the problem

The intensive development of information technologies and digital services leads to an unprecedented increase in the load on computer networks. Millions of users generate large amounts of data every day in the form of multimedia content, streaming services, and transactional operations, which forms a highly dynamic and stochastic nature of network traffic. In the face of such challenges, the creation of intelligent forecasting systems that are able not only to monitor the current state of the network, but also to predict its future load in order to avoid overloads and ensure the high-quality functioning of the infrastructure becomes especially relevant.

Analysis of recent research and publications

Intelligent forecasting systems combine mathematical traffic models (from classical stochastic to modern hybrid and fractal), forecasting algorithms (autoregressive, Markov, machine learning, neural networks), software complexes with an interactive interface and network integration tools.

Over the past decades, a number of models have been proposed in world science to describe network traffic, in particular, the Poisson model [1], Markov models [2–3], ON–OFF models [4] describe the alternation of active and passive states; convenient for multimedia, but do not reproduce long-term correlation, modulated Markov (MMF, IPP) [5], autoregressive models (AR, ARIMA) [6], fractal models [7–8], TES models [9], models based on machine learning [10–11], hybrid models [12].

All traditional models have value in their classes of problems, but an intelligent forecasting system requires a model that simultaneously takes into account stochasticity, correlation, and periodicity (existing models do not provide this).

Formulation of the research objective

The most promising approach in this context is the approach based on periodically correlated stochastic processes (PCSPs) [13], which reflect the cyclical nature of daily fluctuations, phase variability and stochastic nature of traffic. The combination of this model with synphase analysis [14] of data opens up the possibility of creating a new generation of intelligent systems capable of predicting network load with high accuracy and generating recommendations for optimizing equipment operation.

Thus, the task of developing an intelligent computer network traffic forecasting system that combines a mathematical model of the PCSP, an algorithmic core of synphase processing, and software for practical use by providers and network administrators is relevant.

Presentation of the main research material

To substantiate the structure of the traffic load model, which is the core of the synphase analysis method and intelligent forecasting system, empirical data obtained from the Internet provider UFONet in Ternopil was used. Visualization of the dynamics of network traffic registered during a seven-day period (01–07.07.2024) in the residential complex “Park Complex” is shown in Fig. 1.

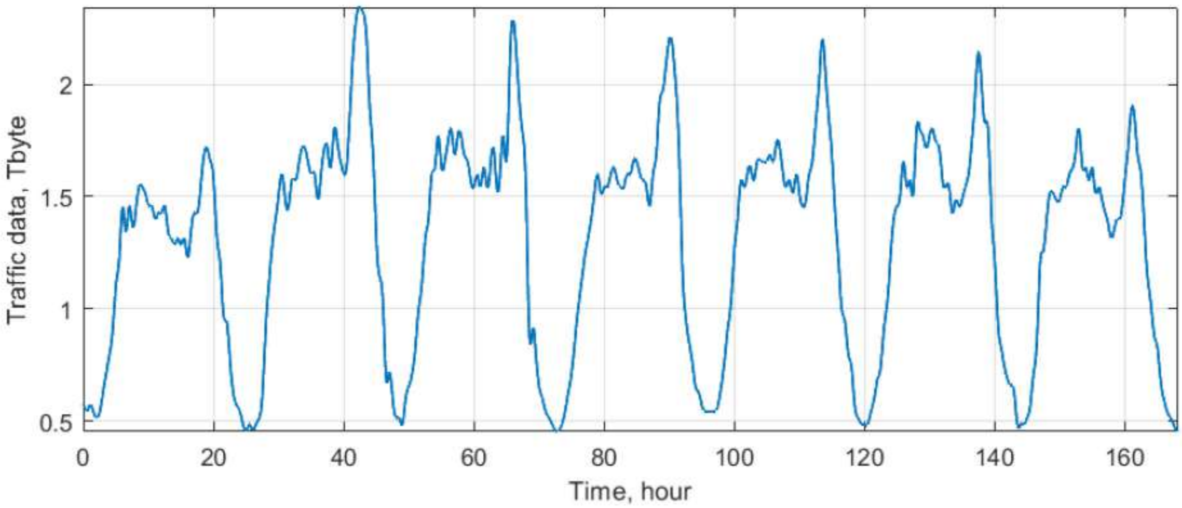

Fig. 1. Traffic data of the residential complex “Park Complex”

The graph (Fig. 1) of network traffic shows two key characteristics – variability and periodicity. Variability is manifested in fluctuations in traffic volumes from 0.5 to 2 TB, uneven load within cycles, and regular deviations from the average level of 1.2–1.7 TB. Periodicity reflects daily cyclicality: traffic peaks are repeated daily, the lowest values occur at night, and the highest values during the day and evening, which indicates the rhythmic nature of the load.

Therefore, the traffic in Fig. 1 has a pronounced variability and stable daily periodicity, which allows predicting the nature of loads and planning network resources taking into account recurring cycles.

The presence of significant variability (stochasticity) of traffic characteristics (Fig. 1) makes it impossible to apply a deterministic approach to its mathematical description. Under such conditions, it is advisable to use a stochastic approach, which provides adequate modeling of the processes of traffic load formation. Based on this approach, methods and intelligent forecasting systems are created that can take into account the specifics of real data.

The stochastic representation of traffic load opens up the possibility of building flexible and adaptive models. They reflect both the temporal periodicity of the signal and its amplitude instability, characteristic of real electronic communication systems.

A model of network traffic behavior, presented in the form of a PCSP, which takes into account the daily cyclicality and stochastic nature of traffic:

$$\xi(t)=\sum_{k\in Z}\xi_k(t)e^{-\frac{j2\pi k}{T}},\quad t\in R,\tag{1}$$

where $\xi_k(t)$ – stochastic component of traffic load; $e^{-\frac{j2\pi k}{T}}$ – periodic component of load traffic, $T = 24$ hour.

The stochastic traffic load model (1) reflects not only its real nature, but also forms the basis for the development of intelligent forecasting methods aimed at practical application in computer network control systems.

The PCSP methods implement three fundamental algorithms for processing network traffic data: synphase, component, and filter. The synphase approach is key for an intelligent forecasting system, as it analyzes the dynamics more deeply, first determining the covariance of the data, and then isolating the frequency components through the Fourier transform. In contrast, the component and filter methods estimate the covariance directly in the frequency domain. Synphase processing in an intelligent traffic forecasting system is based on the assumption that the informative characteristics of the network load can be represented as functions with recurring time-dependent features that are formed in the structure of correlation components:

$$\hat{B}_k(u)=\frac{1}{T}\sum_{k\in Z}\hat{b}_\xi(t,u)e^{-\frac{j2\pi k}{T}},\tag{2}$$

where $\hat{b}_\xi(t,u)$ – parametric covariance; T – period of traffic load data corresponding to the duration of the day; u – time shift.

Correlation components (2) allow the intelligent system to distinguish characteristic features of network traffic, which significantly increases the accuracy of predicting its load and provides effective support for computer network management processes.

The procedure of averaging components (2) is a necessary step to increase the stability and reliability of the forecast according to the expression:

$$M_u\left\{\hat{B}_k(u)\right\}=\frac{1}{U}\sum_{k\in Z}\hat{B}_k(u).\tag{3}$$

Averaging $M_u\left\{\hat{B}_k(u)\right\}$ filters out noise fluctuations, allowing the intelligent system to generate generalized recommendations based on stable long-term traffic patterns. For the provider, this means focusing on strategic resource planning and improving the reliability of infrastructure management, while 3D visualization $\hat{B}_k(u)$ is designed for in-depth analysis of current and short-term processes.

The averaged synphase 3D components $M_u\left\{\hat{B}_k(u)\right\}$ are shown in Fig. 2.

Based on the analysis of averaged traffic data, it was found that the average load during the working period is about 1.4 TB per day, with deviations ranging from 0.5 TB during the night hours to over 2 TB in the evening. The variability is approximately ±0.6 TB from the average, which emphasizes the high stochasticity of the process.

The averaged correlation components allowed us to determine the time intervals with the highest load. In particular, peak values are predicted to occur in the period 19:00–23:00, when the load increases to 1.8–2.1 TB, while the minimum values are recorded in the period 03:00–06:00, when the traffic decreases to 0.5–0.7 TB. Averaging the results confirmed the repeatability of such dynamics throughout the entire weekly cycle, which gives grounds to consider it a stable characteristic of network behavior.

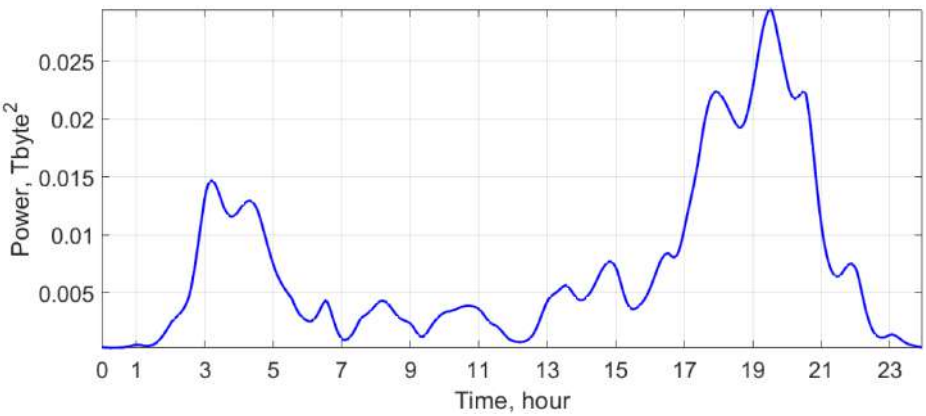

Fig. 2. Averaged synphase 3D components of computer network traffic load data

For an intelligent system, this means that forecasting has not only a qualitative but also a quantitative basis. The system is able to warn about possible overload at specific times of the day and provide the operator with recommendations, for example, about the need to reserve additional resources for evening periods or optimize maintenance during hours of minimum load. Thus, the combination of 3D visualization and averaged results with numerical characteristics creates a comprehensive picture that simultaneously reflects the instantaneous dynamics of the process and its long-term patterns.

An additional functional element of the intelligent system is the module for automatic detection of peak intervals. Its task is to generate time stamps with classification of the predicted load into categories:

– "critical load" – a traffic level exceeding a threshold value (for example, over 1.8–2.0 TB), when there is a risk of overloading network equipment;

– "average load" – the operating traffic range (1.0–1.7 TB), which corresponds to the normal functioning of the network;

– "minimum load" – time intervals with the lowest user activity (up to 0.7 TB), when it is possible to perform preventive work.

The module's operating algorithm is based on the results of synphase forecasting: after calculating synphase components and building a traffic forecast, the system automatically determines the intervals of exceeding the set thresholds and assigns the appropriate category.

It is assumed that the intelligent system generates predicted traffic values in the form of a time sequence:

$$X(u)=\left\{M_1\left\{\widehat{B}_k(1)\right\}_1, M_2\left\{\widehat{B}_k(2)\right\}, \ldots, M_u\left\{\widehat{B}_k(u)\right\}\right\}, \quad u\in[0,U], \tag{3}$$

where $M_u\left\{\widehat{B}_k(u)\right\}$ – predicted load at time u.

We define three load ranges based on threshold values:

$$\Omega=\begin{cases} \min\ load, & 0\le M_u\left\{\widehat{B}_k(u)\right\}<\theta 1 \\ average\ load, & \theta 1\le M_u\left\{\widehat{B}_k(u)\right\}<\theta 2, \\ \max\ load, & M_u\left\{\widehat{B}_k(u)\right\}\ge\theta 2 \end{cases} \tag{4}$$

where θ1 і θ2 – adaptive threshold levels determined taking into account the statistics of the forecast data, $\theta 1 = \mu - \sigma 1$ та $\theta 2 = \mu + \sigma$, where μ – average value, σ – standard deviation.

The thresholds θ1 and θ2 define the interval of statistically normal fluctuations of the traffic signal around the mean μ, which allows to automatically separate typical states from anomalous ones. Thus, the system moves from simple forecasting to intelligent decision support.

Fig. 3 shows the result of the automatic peak interval detection module, which is an additional functional element of the intelligent traffic forecasting system.

The intelligent system automatically calculated the thresholds θ1 and θ2:

– lower threshold $\theta 1 \approx 0.009$ – "low load" limit, corresponding to periods of lowest user activity;

– upper threshold $\theta 2 \approx 0.015$ – "critical load" limit, exceeding which may cause network equipment to be overloaded.

The graph in Fig. 3 shows two main peak segments where the amplitude exceeds θ2: the first – approximately between 3.14 and 3.28 hours, the second – from 17.29 to 20.52 hours. In these intervals, the system records the "critical load" and generates the corresponding time stamps for the operator.

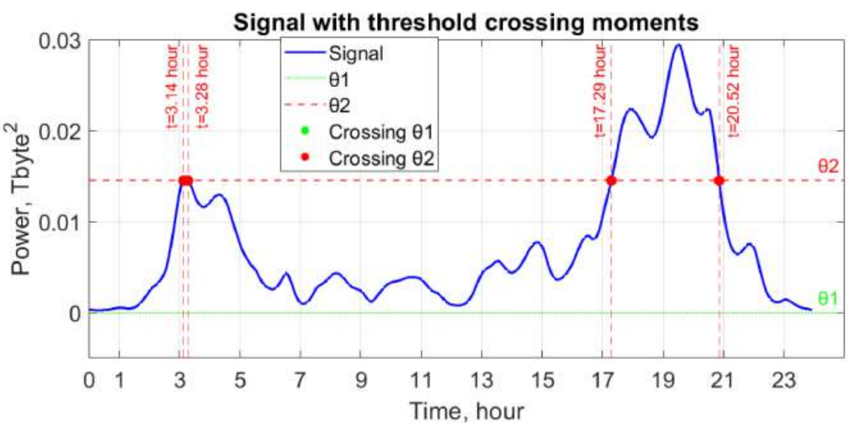

Fig. 3. The result of the automatic peak interval detection module

Between levels θ1 and θ2, the signal is in "medium load", which is the normal network operation mode. During hours when the amplitude drops below θ1 (for example, around 0-2 a.m. and after 10 p.m.), traffic is classified as "minimum load", which is optimal for preventive work.

Thus, the intelligent system receives not only a quantitative prediction of future load, but also a qualitative interpretation in the form of administrator-friendly recommendations. This allows providers to identify critical, average and minimum load time periods in advance, plan resource allocation and optimize the operation of the network infrastructure.

Conclusions

The article proposes an intelligent system for predicting computer network traffic, based on a combination of a stochastic model of periodically correlated random processes and synphase data processing algorithms. It is shown that this approach allows us to adequately take into account the stochastic nature of traffic and its daily cyclicity, which significantly increases the accuracy of forecasting.

The developed methods provide the ability to detect peak and minimum load intervals, automatically classify traffic levels, and generate operator-friendly recommendations for network resource management. Experimental studies have confirmed the system's ability to timely identify critical conditions and create a basis for proactive infrastructure management.

The practical significance of the work lies in creating a decision support tool for providers and network administrators, which allows reducing the risks of overloads, optimizing resource use, and improving the quality of service provision.

Further research is aimed at integrating the system with machine learning algorithms, as well as its adaptation for next-generation multi-level networks, which will provide expanded functionality and increased efficiency in managing complex telecommunications systems.

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