РАДІОЕЛЕКТРОНІКА ТА ТЕЛЕКОМУНІКАЦІЇ

RADIO ELECTRONICS AND TELECOMMUNICATIONS

UDC 621.391

TELETRAFFIC FORECASTING IN MEDIA SERVICE SYSTEMS

Gusiev O. Yu. – PhD, Associate Professor, Professor of the Department of Information Security and Telecommunications, Dnipro University of Technology, Dnipro, Ukraine.

Magro V. I. – PhD, Associate Professor, Professor of the Department of Information Security and Telecommunications, Dnipro University of Technology, Dnipro, Ukraine.

Nikolska O. I. – Senior Lecturer of the Department of Information Security and Telecommunications, Dnipro University of Technology, Dnipro, Ukraine.

ABSTRACT

Context. The development of information and communication technologies has led to an increase in the volume of information sent over the network. Media service platforms play an important role in the creation and processing of bitrate in the information network. Therefore, there is a need to develop a methodology for predicting bitrate in various media service platforms by creating an effective algorithm that minimizes the forecast error.

Objective. The aim of the work is to synthesize in analytical form the state transition matrix of the Kalman filter for non-stationary self-similar processes when predicting the bitrate in telecommunication networks.

Method. A methodology has been developed for predicting teletraffic in media service platforms, based on a modification of the Kalman filter for non-Gaussian processes. This methodology uses an original procedure for calculating statistics, which makes it possible to reduce the filtering and forecast error that arises due to the uncertainty of the analytical model of the process under study. The methodology does not require knowledge of the analytical model of the process, as well as strict restrictions on its stochastic characteristics.

Results. A methodology for estimating and forecasting bitrate in telecommunication systems is proposed. This methodology was used to study teletraffic processes in the media service platforms Google Meet, Zoom, Microsoft Teams. The passage of real bitrate through the specified media service platforms was studied. A comparison of real teletraffic with predicted teletraffic was carried out. The influence of the order of the state transition matrix of the Kalman filter on the error of estimation and prediction has been studied. It has been established that even a low (second) order of the state transition matrix allows one to obtain satisfactory forecast results. It is shown that the use of the proposed methodology makes it possible to predict traffic with a relative error of the order of 3–4%.

Conclusions. An original algorithm for assessing and forecasting the characteristics of media traffic has been developed. Recommendations for improving the technology for building media service platforms are formulated. It is shown that the bitrates generated by various media service platforms, in the case of applying the proposed estimation and forecasting methodology, are invariant with respect to the type of stochastic processes being processed.

KEYWORDS: Kalman filter, teletraffic, media platform, stochastic process, self-similar process.

ABBREVIATIONS

QoS – Quality of service;
LSTM – Long short-term memory;
ARIMA – Autoregressive integrated moving average;
ML – Machine learning;
CNN – Convolutional Neural Network.

NOMENCLATURE

F_n is a state transition matrix;
H_n are observation conditions matrix;
h is a disorder threshold value;
P_n is an error matrix;
S_n is a measured signal;
X_n is a useful signal;
Q_n is an additive noise;
R is a noise dispersion;
B_M is a discord statistics;
MO is an expectation operator.

INTRODUCTION

The beginning of the fourth industrial revolution (Industrie 4.0) has created new preconditions for the development of digital and intelligent production and devices that interact with each other and provide personalized product output. One of the most important components of Industrie 4.0 is not the product, but the data. Digitaliza-

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

tion of production is associated with large amounts of data (big data), which need to be read, analyzed, systematized, stored, transmitted, presented in the required form, etc. This requires appropriate infocommunication systems, software, wireless data transmission tools, cloud services exchange and storage of data. These circumstances increase the importance of network traffic forecasting as a function of data network management and operation, since traffic forecasting plays a crucial role in improving the quality of services (QoS) [1–4]. Thus, an important component of the process of studying network traffic in order to improve methods for predicting its characteristics is the development of new, more advanced methods that provide QoS.

One of the means of wireless data transmission within the framework of Industrie 4.0 is the new generation 5G, which provides very fast data transmission and which must be characterized by its QoS. This circumstance necessitates the study of various media traffic forecasting models [5–8]. In addition, predicting changes in the base station load can reduce energy consumption [7], and increasing the efficiency of big data processing by predicting traffic improves network performance [8].

Reliable and accurate prediction of QoS characteristics is essential for making effective web service recommendations to improve user experience and service management [9–12]. Network state forecasting is the process of in-depth study of network traffic in order to obtain the most complete information about the processes occurring in networks. In turn, the accuracy of analysis and estimation of network traffic characteristics is of great importance to achieve guaranteed QoS.

Computer network traffic control has been a topic of much research as it is addressed in various applications such as anomaly detection, congestion control, and bandwidth control [13–15]. On the other hand, network traffic forecasting aims to predict subsequent network traffic using previous network traffic data. This approach is used in network control and solving planning problems [16–27]. Network traffic forecasting is a critical tool for monitoring and estimation network security [19]. By predicting network traffic, you can effectively identify network failures, optimize performance, and ensure network security. Predicting telecommunications network data traffic with high accuracy is a challenging task for the network control function. It improves dynamic resource allocation and power control [22].

In this paper, the authors propose an original technique for predicting teletraffic in various media service platforms, which is based on approximating the state transition matrix of the Kalman filtering process in the case where the analytical description of the process under study is unknown.

The object of study is the process of forecasting teletraffic, created by various media service platforms in telecommunication networks.

The subject of the study is a methodology for synthesizing the Kalman filter state transition matrix for non-stationary stochastic processes in the absence of their analytical description.

The purpose of the work is to synthesize in analytical form the state transition matrix of the Kalman filter for non-stationary self-similar processes when predicting the bitrate in telecommunication networks.

1 PROBLEM STATEMENT

We consider a self-similar process that describes the behavior of traffic in media service platforms of telecommunication networks. This process is fractal in nature and, therefore, cannot be processed by classical methods, inherent in Gaussian processes.

To solve the problem, it is proposed to use a modification of the Kalman filtering method, which does not require knowledge of the process under study in analytical form. This approach is invariant to the type of stochastic process and removes the restrictions imposed on its characteristics.

The solution to the problem is sought by approximating the state transition matrix of the Kalman filter by an n-th order Taylor series at each reference point.

2 REVIEW OF THE LITERATURE

In recent years, well-known media platforms such as Microsoft Teams, Zoom, Google Meet, etc. have been widely used. When many users work simultaneously in some segments of the information and telecommunications network, overload or a significant delay may occur when processing information in the media service platform [28].

In this regard, there is a need to develop methods for optimal network traffic control in order to eliminate these negative phenomena, an integral attribute of which is the process of forecasting traffic flows.

Neural networks are currently most often used to predict network traffic, and the forecast is based on the long short-term memory (LSTM) of the neural network [1–10, 12–14, 16–23, 25–27]. In some cases, such a model is used independently [9,10, 14, 18, 21, 23, 25]. However, its composition with other models is more common: with the autoregressive integrated moving averages (ARIMA) model [4, 11, 13], with recurrent neural networks (RNN) [3, 6, 13, 16, 17, 19, 20, 22]. Less commonly used are approaches such as machine learning (ML) [5, 24], clustering model [12], and deep learning method of convolutional neural network (CNN) [27].

Forecasting methods using neural networks have a significantly complicated computational procedure; in addition, the choice of input layers and input values is, as a rule, subjective.

The use of the classical Kalman filtering method [29] also has its disadvantages, associated primarily with the requirement of the Gaussian nature of the process under study and knowledge of the analytical expression of the state transition matrix.

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

3 MATERIALS AND METHODS

The classical Kalman filtering method assumes knowledge of the initial values of the process under study and its description in analytical form, which allows one to determine the state transition matrix. In practice, as a rule, we are not able to obtain an analytical expression of the process being processed, since this process has not yet been studied.

The structure of the telecommunications system model includes traffic sources (voice traffic and video traffic) and the Internet network, which connects traffic receivers and transmitters with media service platforms. Using specialized programs, you can obtain data about teletraffic on the network. Estimation and forecast of teletraffic characteristics can be obtained using the Kalman filtering procedure. In this case, the obtained data can be used as input measurements for the Kalman filter. Kalman filters use system state information as well as measurements to estimate the current state of the system. It calculates a real-time forecast of the state of the system, taking into account new data and measurements. The resulting forecast allows the system to adapt to changes in traffic and promptly identify anomalies or problems in the telecommunications network.

In this paper, we propose a modification of the Kalman filter, which consists in approximating the state transition matrix at each reference point by a Taylor series. This approach has one significant drawback due to the divergence of the filtering procedure (due to the finite order of the polynomial) when processing non-stationary processes. It would seem that this drawback can be eliminated by increasing the order of the approximating polynomial. However, it has been established (easy to verify in practice) that as the order of the polynomial increases, the filter becomes more prone to self-excitation, since this increases the depth of feedback and, consequently, a large number of poles and zeros appears, leading to an increase in the probability of self-excitation. Therefore, a low order of the polynomial should be chosen, and to eliminate the divergence of the filter, an original procedure for detecting a disorder in the filtering process is proposed.

The procedure is as follows. Along the time series, a time window is allocated, with a dimension of, for example, ten samples. A certain threshold is assigned, with a dimension, for example, seven. In this case, each new sample is accompanied by a shift of the window one sample forward. Within the window between two adjacent samples, the difference between the true (measured) signal and its filtered (predicted) value is determined and the sign of this difference is determined. Next, statistics are calculated, which is the algebraic sum of positive and negative signs. The calculated statistics are compared with the threshold and, if its value is equal to or exceeds the threshold value, a decision is made to disturb the filter. In this case, the transition to the beginning of the time window occurs, the initial filter parameters are set, and filtering is repeated within the window boundaries, and the previously obtained values are replaced with the current ones. In this case, a slight increase in the variance of the estimation noise is possible; however, studies have shown that this increase is small and can be neglected. Next, filtering occurs as usual until a new disorder occurs. Thus, the considered procedure allows us to avoid the divergence of the filtering process, that is, the bias of the estimate, and to study non-stationary processes with a significant degree of correctness.

In analytical form, the modified Kalman filter can be represented as follows. For the case of discrete measurements of the signal S_n, which is an additive mixture,

$$S_n = X_n + Q_n,$$

where X_n is the useful signal, Q_n is additive noise with mathematical expectation MO[Q_n] = 0 and variance R, the Kalman filtering procedure can be represented in the following form

$$\overline{X}_n = F_n \overline{X}_{n-1} + P_n H_n^{'} R^{-1}(S_n - H_n F_n \overline{X}_{n-1});$$
$$P_n = (A_n^{-1} + H_n^{'} R^{-1} H_n)^{-1};$$
$$A_n = F_n P_{n-1} F_n^{'},$$

where index “′” means the transposition of the matrix.

The procedure for detecting a filter discord comes down to calculating statistics of the form

$$B_M = \sum_{l=1}^{M} b_l, \quad B_0 = 0, \quad l = 1,2,...M \;;$$
$$b_l = \mathrm{sgn}(S_l - \overline{X}) = +l, \quad S_l - \overline{X} \geq 0\;;$$
$$b_l = \mathrm{sgn}(S_l - \overline{X}) = -l, \quad S_l - \overline{X} < 0$$

on the interval $[n - M, n]$. Values determined on this interval ($B_m - \min B_m$) and ($\max B_m - B_m$) are compared with the threshold h. When the value h exceeds one of the quantities, a decision is made on discord, the filter parameters are assigned initial values, and filtering continues from moment $n - M$.

The above algorithm was once used by the authors to study processes in blast furnace production, but it has never been used to study temporary self-similar traffic.

4 EXPERIMENTS

During the experiment, teletraffic analysis was carried out in the following media service platforms: Microsoft Teams, Google Meet, Zoom. For this purpose, the cross-platform client-server program iperf3 was used, which allows testing network throughput. With its help, the maximum network bandwidth was measured and load testing of the communication channel was carried out. Statistical information about the state of the communication channel was collected using the Wireshark traffic analyzer program, which allows us to view all traffic passing through the network in real time. Various types of traffic were considered: audio traffic; audio traffic plus video traffic with minimal change over time; audio traffic

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

plus video traffic with a maximum change in video image in video time [30].

This information served as the basis for forecasting the bitrate in the media service platform under study. Based on the same information, the relative forecast error was calculated.

5 RESULTS

A study was conducted of the dynamic changes in voice and video traffic over time (Fig. 1–6). Here the real traffic statistics are shown in red; traffic estimate is shown in blue; the predicted bitrate is shown in green.

The dependence of traffic intensity (bit/s) on time at the input of the Google Meet media service platform was obtained for real statistics, estimation and forecast.

The studies were carried out for the case of voice traffic (Fig. 1).

The dependence of traffic intensity on time at the output of the Google Meet media service platform was studied for real statistics, eыштated and forecast. The studies were carried out for the case of voice traffic (Fig. 2).

The dependence of traffic intensity on time at the input of the Zoom media service platform was obtained for real statistics, estimated and forecast. The studies were carried out for the case of voice traffic with minimal changes in the video image over time (Fig. 3).

The dependence of traffic intensity on time at the output of the Zoom media service platform was studied for real statistics, estimated and forecast. The studies were carried out for the case of voice traffic with minimal changes in the video image over time (Fig. 4).

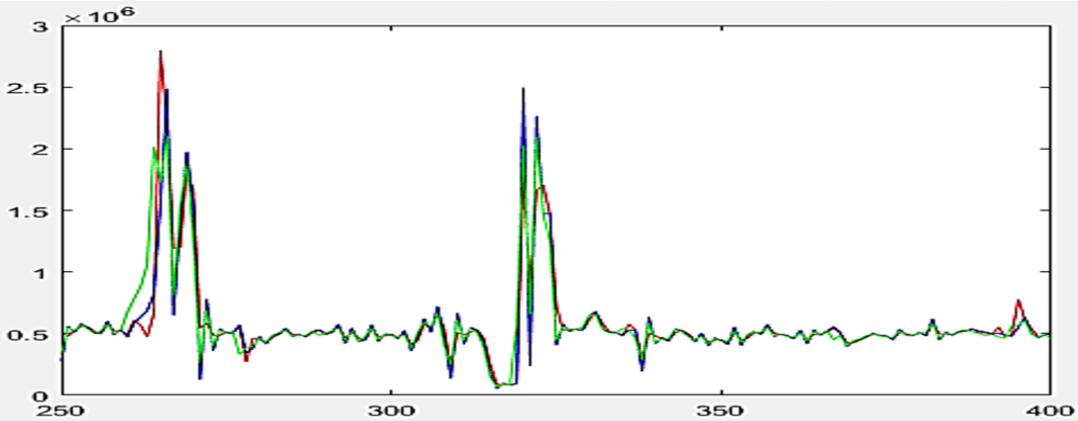

Figure 1 – Dependence of traffic intensity on time at the input of the Google Meet media service platform

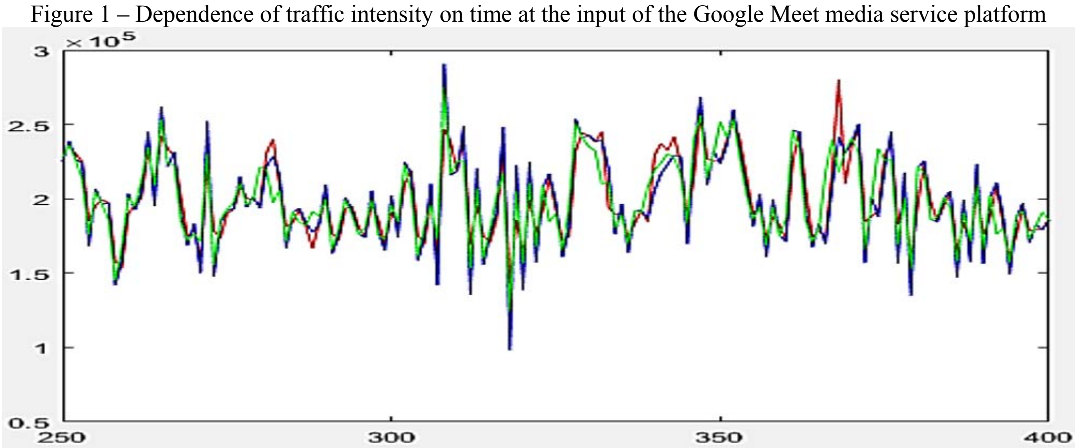

Figure 2 – Dependence of traffic intensity on time at the output of the Google Meet media service platform

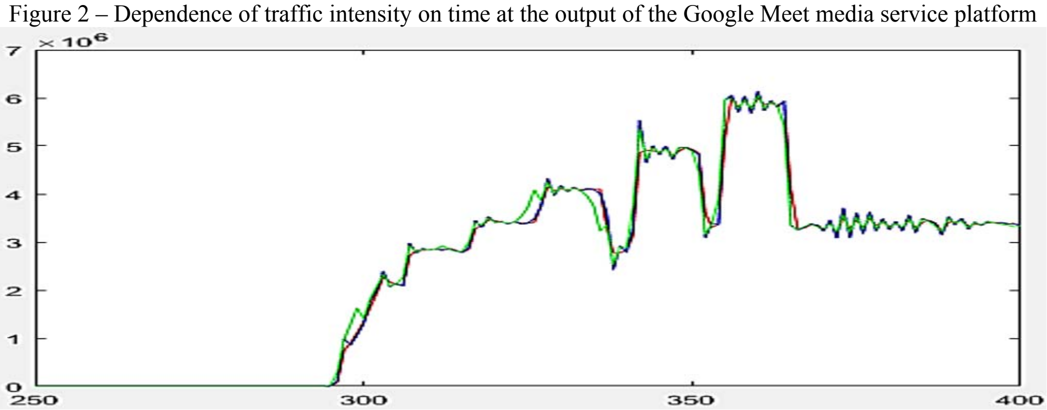

Figure 3 – Dependence of traffic intensity on time at the input of the Zoom media service platform

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

OPEN ACCESS

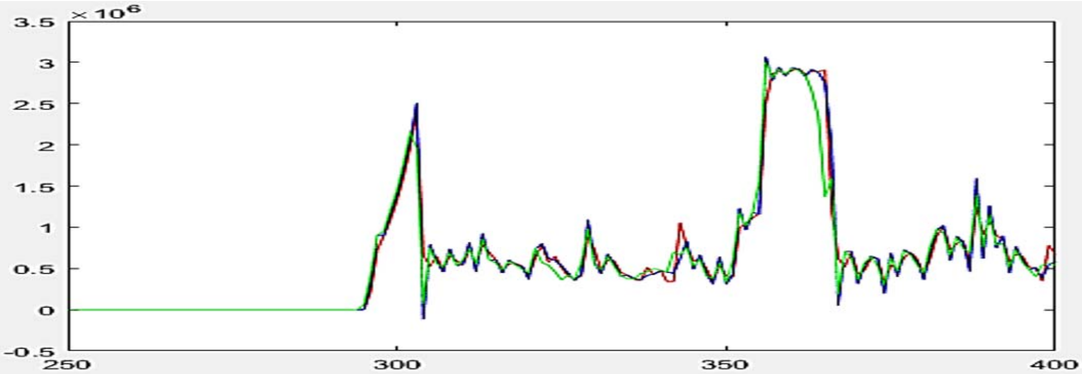

Figure 4 – Dependence of traffic intensity on time at the output of the media service Zoom platforms

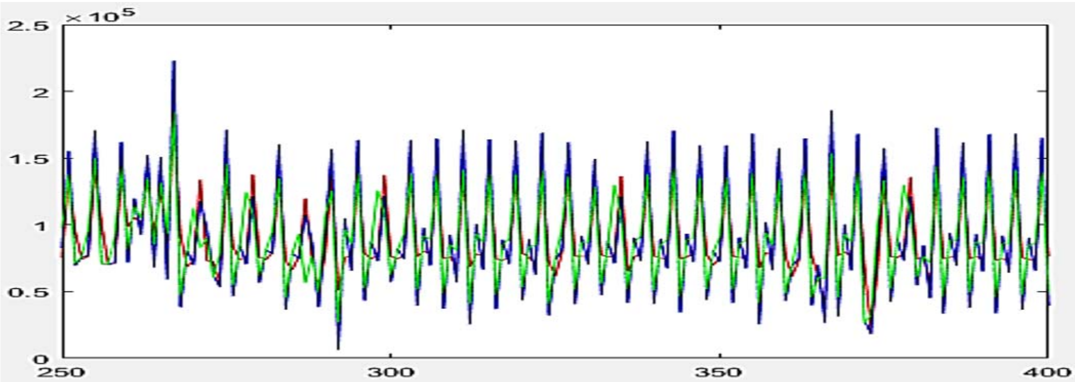

Figure 5 – Dependence of traffic intensity on time at the input of the Microsoft Teams media service platform for the case of voice traffic only

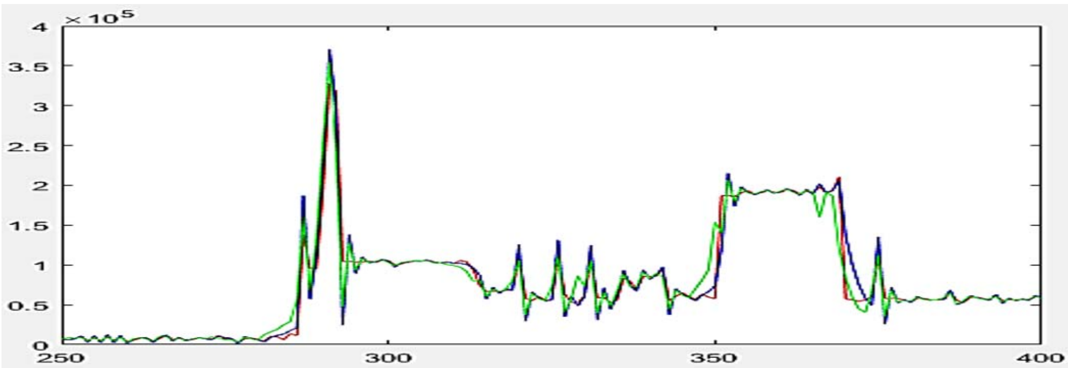

Figure 6 – Dependence of traffic intensity on time at the input of the Microsoft Teams media service platform for the case of video traffic with a maximum change in the video image over time

The dependence of traffic intensity on time at the input of the Microsoft Teams media service platform was obtained for real statistics, estimated and forecast. The studies were carried out for the case of voice traffic only (Fig. 5).

The dependence of traffic intensity on time at the input of the Microsoft Teams media service platform was studied for real statistics and forecast. The studies were carried out for the case of video traffic with a maximum change in the video image over time (Fig. 6).

6 DISCUSSION

In this work, we implemented a method for estimating and forecasting non-stationary time series based on a polynomial representation of the state transition matrix of the Kalman filtering procedure. The problem of filter discord due to the finite order of the approximating polynomial was solved by means of an original algorithm for detecting discord in tempo with the process. The algorithm is quite simple and does not require large time and software resources. It should also be noted that the proposed modification removes the requirements for stationarity and normality of the processed processes, as well as for knowledge of the initial conditions.

The analysis of the dependence of traffic intensity on time showed that the assessment of incoming traffic and traffic forecast in media service platforms (Fig. 1, Fig. 3) have relative errors of 4.44% and 0.64%, respectively.

At the same time, traffic leaving the media service platform has a significantly lower level of relative errors,

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

0.028% and 0.037%, respectively. This indicates fairly accurate forecasting.

The analysis of experimental data showed that the method can be effectively (with a small error) used to predict teletraffic in media service systems.

In addition, since the stochastic characteristics of the processes under study differ from classical Gaussian ones, it can be argued that the proposed estimation and forecast procedure is invariant to the stochastic properties of the processes and does not require strict restrictions.

CONCLUSIONS

The explosive and self-similar type of traffic in modern information and communication networks requires the development of forecasting methodology to prevent network "overload". The analysis of teletraffic in media service platforms requires special attention. The development of a universal methodology for analyzing traffic behavior in media service platforms will make it possible to "include" various methodology in order to prevent "overload" of the network.

Traffic forecasting allows network operators to monitor the health of the network and respond to the occurrence of anomalies or problems, including reporting a cyber-attack on the network. Traffic forecasting methodology allow you to plan customer service, including setting limits on the volume of traffic during peak load.

The scientific novelty of the results obtained lies in the fact that for the first time an original methodology for predicting bitrate in various media service platforms was proposed, and proposals were also developed for choosing the optimal characteristics of the signal model to achieve a minimum prediction error.

The practical significance of the results obtained is that an original algorithm for estimation and predicting the characteristics of media traffic has been developed. Recommendations for improving the technology for building media service platforms are formulated. It is shown that the bitrates generated by various media service platforms, in the case of applying the proposed estimation and forecast methodology, are invariant with respect to the type of stochastic processes undergoing assessment and forecast. The results obtained can be applied to the study of fractal random processes.

Prospects for further research is research in the direction of comparative analysis of forecasting results for various types of approximating polynomials.

ACKNOWLEDGEMENTS

The work was carried out with the assistance of the Department of Information Security and Telecommunications of the Dnipro University of Technology.

REFERENCES

1. Abdellah A. R., Mahmood O. A. K., Paramonov A., Koucheryavy A. IoT traffic prediction using multi-step ahead prediction with neural network, *IEEE 11th International congress on ultra modern telecommunications and control systems and workshops (ICUMT)*, 2019, IEEE, 2019, pp. 1–4. https://doi.org/ 10.1109/ICUMT48472.2019.8970675
2. Pan C., Wang Y., Shi H., Shi J., Cai R. Network traffic prediction incorporating prior knowledge for an intelligent network, *Sensors,* 2022, Vol. 22, No. 7, 2674. https://doi.org/ 10.3390/s22072674
3. Kumar B. P., Hariharan K. Multivariate time series traffic forecast with long short term memory based deep learning model, *IEEE International conference on power, instrumentation, control and computing (PICC),* 2020, IEEE, 2020. pp. 1–5. https://doi.org/ 10.1109/PICC51425.2020.9362455
4. Liu B., Tang X., Cheng J., Shi P. Traffic flow combination forecasting method based on improved LSTM and ARIMA, *International Journal of Embedded Systems,* 2020, Vol. 12, No. 1, pp. 22–30. https://doi.org/ 10.1504/IJES.2020.10026902
5. Refaee A., Volkov A., Muthanna A., Gallyamov D., Koucheryavy A. Deep Learning for IoT traffic prediction based on edge computing, *Distributed computer and communication networks: control, computation, communications,* 2021, pp. 18–29. https://doi.org/ 10.1007/978-3-030-66242-4_2
6. Jaffry S., Hasan S. F. Cellular traffic prediction using recurrent neural networks, *IEEE 5th International Symposium on Telecommunication Technologies (ISTT),* 2020, IEEE, 2020, pp. 94–98. https://doi.org/ 10.1109/ISTT50966.2020.9279373
7. Xu X., Gao S., Jiang Z. LSTCN: An attention-based deep neural network model combining LSTM and TCN for cellular network traffic prediction, *IEEE 5th International conference on communication and information systems (ICCIS),* 2021, IEEE, 2021, pp. 34–38. https://doi.org/ 10.1109/ICCIS53528.2021.9645961
8. De Klerk M. L., Saha A. K. A review of the methods used to model traffic flow in a substation communication network, *IEEE Access,* 2020, Vol. 8, pp. 204545–204562. https://doi.org/ 10.1109/ACCESS.2020.3037143
9. Jirsik T., Trčka Š., Celeda P. Quality of service forecasting with LSTM neural network, *IFIP/IEEE Symposium on integrated network and service management (IM),* 2019, IEEE, 2019, pp. 251–260
10. Zhang L., Zhang H., Tang Q., Dong P., Zhao Z., Wei Y., Mei J., Xue K. LNTP: An End-to-End Online Prediction Model for Network Traffic, *IEEE Network,* 2021, Vol. 35, pp. 226–233. https://doi.org/ 10.1109/MNET.011.1900647
11. Fanjiang Y.-Yi., Huang Y. S. W.-L. Time series QoS forecasting for Web services using multi-predictor-based genetic programming, *IEEE Transactions on Services Computing,* 2022, Vol. 15, pp. 1423–1435. https://doi.org/ 10.1109/TSC.2020.2994136
12. Aldhyani T. H. H., Alrasheedi M., Alqarni A. A., Alzahrani M.Y., M.Y. Bamhdi M.Y. Intelligent hybrid model to enhance time series models for predicting network traffic, *IEEE Access,* 2020, Vol. 8, pp. 130431–130451. https://doi.org/ 10.1109/ACCESS.2020.3009169
13. Madan R., Mangipudi P. S. Predicting computer network traffic: A time series forecasting approach using DWT, ARIMA and RNN, *IEEE Eleventh International conference on contemporary computing (IC3),* 2018, IEEE, 2018, pp. 1–5. https://doi.org/ 10.1109/IC3.2018.8530608
14. Nihale S., Sharma S., Parashar L., Singh U. Network traffic prediction using long short-term memory, *IEEE International conference on electronics and sustainable communication systems (ICESC),* 2020, IEEE, 2020, pp. 338–343. https://doi.org/ 10.1109/ICESC48915.2020.9156045

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

15. Drieieva H., Smirnov O., Drieiev O., Polishchuk Y., Brzhanov R., Aleksander M. Method of fractal traffic generation by a model of menerator on the graph, *2nd International Workshop on Control, Optimisation and Analytical Processing of Social Networks (COAPSN),* 2020, pp. 366–379.
16. Alizadeh M., Beheshti M., Ramezani A., Saadatinezhad H. Network traffic forecasting based on fixed telecommunication data using deep learning, *IEEE 6th Iranian conference on signal processing and intelligent systems (ICSPIS),* 2020, IEEE, 2020, pp. 1–7. https://doi.org/ 10.1109/ICSPIS51611.2020.9349573
17. Vinayakumar R., Soman K. P., Poornachandran P. Applying deep learning approaches for network traffic prediction, *IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI),* 2017, IEEE, 2017, pp. 2353–2358. https://doi.org/ 10.1109/ICACCI.2017.8126198
18. Aloraifan D., Ahmad I., Alrashed E. Deep learning based network traffic matrix prediction, *International Journal of Intelligent Networks,* 2021, Vol. 2, pp. 46–56. https://doi.org/10.1016/j.ijin.2021.06.002
19. 19. Fan J., Mu D., Liu Y. Research on network traffic prediction model based on neural network, *IEEE 2nd International conference on information systems and computer aided education (ICISCAE),* 2019, IEEE, 2019, pp. 554–557. https://doi.org/ 10.1109/ICISCAE48440.2019.221694
20. Hua Y., Zhao Z., Liu Z., Chen X., Li R., Zhang H. Traffic prediction based on random connectivity in deep learning with long short-term memory, *IEEE 88th Vehicular technology conference (VTC-Fall),* 2018, IEEE, 2018, pp. 1–6. https://doi.org/ 10.1109/VTCFall.2018.8690851
21. Lu H., Yang F. Research on network traffic prediction based on long short-term memory neural network, *IEEE 4th International conference on computer and communications (ICCC),* 2018, IEEE, 2018, pp. 1109–1113. https://doi.org/ 10.1109/CompComm.2018.8781071
22. Do Q. H., Doan T. T. H., Nguyen T. V. A., Linh V. V. Prediction of data traffic in telecom networks based on deep neural networks, *Journal of computer science,* 2020, Vol. 16, No. 9, pp. 1268–1277. https://doi.org/ 10.3844/jcssp.2020.1268.1277
23. Guo D., Xia X., Zhu L., Zhang Y. Dynamic modification neural network model for short-term traffic prediction, *Procedia Computer Science,* 2021, Vol. 187, pp. 134–139. https://doi.org/10.1016/j.procs.2021.04.043
24. Jain G., Prasad R. R. Machine learning, prophet and XGBoost algorithm: analysis of traffic forecasting in telecom networks with time series data, *IEEE 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO),* 2020, IEEE, 2020, pp. 893–897. https://doi.org/ 10.1109/ICRITO48877.2020.9197864
25. Shihao W., Qinzheng Z., Han Y., Qianmu L., Yong Q. A network traffic prediction method based on LSTM, *ZTE Communications,* 2019, Vol. 17, No. 2. pp. 19–25. https://doi.org/ 10.12142/ZTECOM.201902004
26. Bi J., Zhang X., Yuan H., Zhang J., Zhou M.C. A hybrid method for realistic network traffic with temporal convolutional network and LSTM, *IEEE Transactions on Automation Science and Engineering,* 2022, Vol. 19, No. 3, pp. 1869–1879. https://doi.org/ 10.1109/TASE.2021.3077537
27. Ko T., Raza S. M., Binh D. T., Kim M., Choo H. Network prediction with traffic gradient classification using convolutional neural networks, *IEEE 14th International conference on ubiquitous information management and communication (IMCOM),* 2020, IEEE, 2020, pp. 1–4. https://doi.org/ 10.1109/IMCOM48794.2020.9001712
28. Magro V., Svyatoshenko V., Tymofieiev D. Method for evaluating the delay time in a stream broadcast process, *Information Processing Systems,* 2019, Vol. 159, No. 4, pp. 28–35. https://doi.org/10.30748/soi.2019.159.03
29. Sage A.P., Melsa J.L. Estimation theory with applications to communications and control, New York, McGraw-Hill, 1971, 529 pp.
30. Magro V. I., Plaksin S. V., Syatoshenko V. O. Investigation of information network loading in the condition of remote education and remote monitoring, *Applied questions of mathematical modeling,* 2021, Vol. 4, No. 2.1, pp. 142–149. https://doi.org/10.32782/KNTU2618-0340/2021.4.2.1.15

Received 05.10.2023.
Accepted 28.11.2023.

УДК 621.391

ПРОГНОЗУВАННЯ ТЕЛЕТРАФІКА В МЕДІАСЕРВІСНИХ СИСТЕМАХ

Гусєв О. Ю. – канд. фіз.-мат. наук, доцент, професор кафедри безпеки інформації та телекомунікацій Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

Магро В. И. – канд. фіз.-мат. наук, доцент, професор кафедри безпеки інформації та телекомунікацій Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

Нікольська О. І. – старший викладач кафедри безпеки інформації та телекомунікацій Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

АНОТАЦІЯ

Актуальність. Розвиток інформаційно-комунікаційних технологій призвело до зростання обсягу інформації, що пересилається через мережу. Медіасервісні платформи відіграють важливу роль у створенні та обробці бітрейту в інформаційній мережі. Тому існує необхідність у розробці методики прогнозування бітрейту в різних медіасервісних платформах шляхом створення ефективного алгоритму, що мінімізує помилку прогнозу.

Мета. Метою роботи є синтез в аналітичній формі матриці переходу фільтра Калмана для нестаціонарних самоподібних процесів при прогнозуванні бітрейту в телекомунікаційних мережах.

Метод. Розроблено методику прогнозування телетрафіку в медіасервісних платформах, засновану на модифікації фільтра Калмана для негаусівських процесів. Ця методика використовує оригінальну процедуру підрахунку статистики, яка дозволяє знижувати помилку фільтрації та прогнозу, що виникає внаслідок невизначеності аналітичної моделі досліджуваного

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

процесу. Методика не вимагає знання аналітичної моделі процесу, а також жорстких обмежень на його стохастичні характеристики.

Результати. Запропоновано методику оцінки та прогнозу бітрейту в телекомунікаційних системах. Дана методика застосована для дослідження процесів телетрафіку в медсервісних платформах Google Meet, Zoom, Microsoft Teams. Досліджено проходження реального бітрейту через зазначені медіасервісні платформи. Проведено порівняння реального телетрафіку з прогнозованим телетрафіком. Досліджено вплив порядку матриці переходу фільтра Калмана на похибку оцінки та прогнозу. Встановлено, що навіть невисокий (другий) порядок матриці переходу дозволяє отримати задовільні результати прогнозу. Показано, що застосування запропонованої методики дозволяє прогнозувати трафік з відносною помилкою близько 3–4%.

Висновки. Розроблено оригінальний алгоритм оцінки та прогнозу характеристик медіатрафіку. Сформульовано рекомендації щодо удосконалення технології побудови медіасервісних платформ. Показано, що бітрейти, що породжуються різними медіасервісними платформами, у разі застосування запропонованої методики оцінки та прогнозу інваріантні щодо типу оброблюваних стохастичних процесів.

КЛЮЧОВІ СЛОВА: фільтр Калмана, телетрафік, медіасевісна платформа, стохастичний процес, самоподібний процес.

ЛІТЕРАТУРА

1. IoT traffic prediction using multi-step ahead prediction with neural network / [A. R. Abdellah, O. A. K. Mahmood, A. Paramonov, A. Koucheryavy] // Proceeding of the IEEE 11th International congress on ultra modern telecommunications and control systems and workshops (ICUMT). – 2019. – P. 1–4. https://doi.org/ 10.1109/ICUMT48472.2019.8970675
2. Network traffic prediction incorporating prior knowledge for an intelligent network / [C. Pan, Y. Wang, H. Shi et al.] // Sensors. – 2022. – Vol. 22, No. 7. – 2674. https://doi.org/ 10.3390/s22072674
3. Kumar B. P. Multivariate time series traffic forecast with long short term memory based deep learning model / B. P. Kumar, K. Hariharan // Proceeding of the IEEE International conference on power, instrumentation, control and computing (PICC). – 2020. – P. 1–5. https://doi.org/ 10.1109/PICC51425.2020.9362455
4. Traffic flow combination forecasting method based on improved LSTM and ARIMA / [B. Liu, X. Tang, J. Cheng, P. Shi] // International Journal of Embedded Systems. – 2020. – Vol. 12, No. 1. – P. 22–30. https://doi.org/ 10.1504/IJES.2020.10026902
5. Deep Learning for IoT traffic prediction based on edge computing / [A. Refaee, A. Volkov, A. Muthanna et al.] // Distributed computer and communication networks: control, computation, communications. – 2021. – P. 18–29. https://doi.org/ 10.1007/978-3-030-66242-4_2
6. Jaffry S. Cellular traffic prediction using recurrent neural networks / S. Jaffry, S. F. Hasan // Proceeding of the IEEE 5th International Symposium on Telecommunication Technologies (ISTT). – 2020. – P. 94–98. https://doi.org/ 10.1109/ISTT50966.2020.9279373
7. Xu X. LSTCN: An attention-based deep neural network model combining LSTM and TCN for cellular network traffic prediction / X. Xu, S. Gao, Z. Jiang // Proceeding of the IEEE 5th International conference on communication and information systems (ICCIS). – 2021. – P. 34–38. https://doi.org/ 10.1109/ICCIS53528.2021.9645961
8. De Klerk M. L. A review of the methods used to model traffic flow in a substation communication network / M. L. De Klerk, A. K. Saha // IEEE Access. – 2020. – Vol. 8. – P. 204545–204562. https://doi.org/ 10.1109/ACCESS.2020.3037143
9. Jirsik T. Quality of service forecasting with LSTM neural network / T. Jirsik, Š. Trčka, P. Celeda // Proceeding of the IFIP/IEEE Symposium on integrated network and service management (IM). – 2019. – P. 251–260.
10. LNTP: An End-to-End Online Prediction Model for Network Traffic / [L. Zhang, H. Zhang, Q. Tang et al.] // IEEE Network. – 2021. – Vol. 35. – P. 226–233. https://doi.org/ 10.1109/MNET.011.1900647
11. Fanjiang Y.-Yi. Time series QoS forecasting for Web services using multi-predictor-based genetic programming / Y.-Yi. Fanjiang, Y. S. W.-L. Huang // IEEE Transactions on Services Computing. – 2022. – Vol. 15. – P. 1423–1435. https://doi.org/ 10.1109/TSC.2020.2994136
12. Intelligent hybrid model to enhance time series models for predicting network traffic / [T. H. H. Aldhyani, M. Alrasheedi, A. A. Alqarni et al.] // IEEE Access. – 2020. – Vol. 8. – P. 130431–130451. https://doi.org/ 10.1109/ACCESS.2020.3009169
13. Madan R. Predicting computer network traffic: A time series forecasting approach using DWT, ARIMA and RNN / R. Madan, P. S. Mangipudi // Proceeding of the IEEE Eleventh international conference on contemporary computing (IC3). – 2018. – P. 1–5. https://doi.org/ 10.1109/IC3.2018.8530608
14. Network traffic prediction using long short-term memory / [S. Nihale, S. Sharma, L. Parashar, U. Singh] // Proceeding of the IEEE International conference on electronics and sustainable communication systems (ICESC). – 2020. – P. 338–343. https://doi.org/ 10.1109/ICESC48915.2020.9156045
15. Method of fractal traffic generation by a model of menerator on the graph / [H. Drieieva, O. Smirnov, O. Drieiev et al.] // Proceedings of the 2nd International Workshop on Control, Optimisation and Analytical Processing of Social Networks (COAPSN). – 2020. – P. 366–379.
16. Network traffic forecasting based on fixed telecommunication data using deep learning / [M. Alizadeh, M. Beheshti, A. Ramezani, H. Saadatinezhad] // Proceeding of the IEEE 6th Iranian conference on signal processing and intelligent systems (ICSPIS). – 2020. – P. 1–7. https://doi.org/ 10.1109/ICSPIS51611.2020.9349573
17. Vinayakumar R. Applying deep learning approaches for network traffic prediction / R. Vinayakumar, K. P. Soman, P. Poornachandran // Proceeding of the IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI). – 2017. – P. 2353–2358. https://doi.org/ 10.1109/ICACCI.2017.8126198
18. Aloraifan D. Deep learning based network traffic matrix prediction / D. Aloraifan, I. Ahmad, E. Alrashed // International Journal of Intelligent Networks. – 2021. – Vol. 2. – P. 46–56. https://doi.org/10.1016/j.ijin.2021.06.002
19. Fan J. Research on network traffic prediction model based on neural network / J. Fan, D. Mu, Y. Liu // Proceeding of the IEEE 2nd International conference on information systems and computer aided education (ICISCAE). – 2019. – P. 554–557. https://doi.org/ 10.1109/ICISCAE48440.2019.221694

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1

20. Traffic prediction based on random connectivity in deep learning with long short-term memory / [Y. Hua, Z. Zhao, Z. Liu et al.] // Proceeding of the IEEE 88th Vehicular technology conference (VTC-Fall). – 2018. – P. 1–6. https://doi.org/ 10.1109/VTCFall.2018.8690851
21. Lu H. Research on network traffic prediction based on long short-term memory neural network / H. Lu, F. Yang // Proceeding of the IEEE 4th International conference on computer and communications (ICCC). – 2018. – P. 1109–1113. https://doi.org/ 10.1109/CompComm.2018.8781071
22. Prediction of data traffic in telecom networks based on deep neural networks / [Q. H. Do, T. T. H. Doan, T. V. A. Nguyen, V. V. Linh] // Journal of computer science. – 2020. – Vol. 16, No. 9. – P. 1268–1277. https://doi.org/ 10.3844/jcssp.2020.1268.1277
23. Dynamic modification neural network model for short-term traffic prediction / [D. Guo, X. Xia, L. Zhu, Y. Zhang] // Procedia Computer Science. – 2021. – Vol. 187. – P. 134–139. https://doi.org/10.1016/j.procs.2021.04.043
24. Jain G. Machine learning, prophet and XGBoost algorithm: analysis of traffic forecasting in telecom networks with time series data / G. Jain, R. R. Prasad // Proceeding of the IEEE 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). – 2020. – P. 893–897. https://doi.org/ 10.1109/ICRITO48877.2020.9197864
25. A network traffic prediction method based on LSTM / [W. Shihao, Z. Qinzheng, Y. Han et al.] // ZTE Communications. – 2019. – Vol. 17, No. 2. – P. 19–25. https://doi.org/ 10.12142/ZTECOM.201902004
26. A hybrid method for realistic network traffic with temporal convolutional network and LSTM / [J. Bi, X. Zhang, H. Yuan et al.] // IEEE Transactions on Automation Science and Engineering. – 2022. – Vol. 19, No. 3. – P. 1869–1879. https://doi.org/ 10.1109/TASE.2021.3077537
27. Network prediction with traffic gradient classification using convolutional neural networks / [T. Ko, S. M. Raza, D. T. Binh et al.] // Proceeding of the IEEE 14th International conference on ubiquitous information management and communication (IMCOM). – 2020. – P. 1–4. https://doi.org/ 10.1109/IMCOM48794.2020.9001712
28. Magro V. Method for evaluating the delay time in a stream broadcast process / V. Magro, V. Svyatoshenko, D. Tymofieiev // Information Processing Systems. – 2019. – Vol. 159, No. 4. – P. 28–35. https://doi.org/10.30748/soi.2019.159.03
29. Sage A. P. Estimation theory with applications to communications and control / A. P. Sage, J. L. Melsa. – New York : McGraw-Hill, 1971. – 529 p.
30. Magro V. I. Investigation of information network loading in the condition of remote education and remote monitoring / V. I. Magro, S. V. Plaksin, V. O. Syatoshenko // Applied questions of mathematical modeling. – 2021. – Vol. 4, No. 2.1. – P. 142–149. https://doi.org/10.32782/KNTU2618-0340/2021.4.2.1.15

© Gusiev O. Yu., Magro V. I., Nikolska O. I., 2023
DOI 10.15588/1607-3274-2023-4-1