UDC 621.391

COGNITIVE MONITORING IN AN INFORMATION AND COMMUNICATION NETWORK OPERATION SYSTEM

Nikityuk L.A.

O. S. Popov Odesa national academy of telecommunications,
1 Kuznechna St., Odessa, 65029, Ukraine
lesyanikityuk579@gmail.com

КОГНІТИВНИЙ МОНІТОРИНГ У СИСТЕМІ ЕКСПЛУАТАЦІЇ ІНФОКОМУНІКАЦІЙНОЇ МЕРЕЖІ

Нікітюк Л.А.

Одеська національна академія зв'язку ім. О.С. Попова,
65029, Україна, м. Одеса, вул. Кузнечна, 1,
lesyanikityuk579@gmail.com

КОГНИТИВНЫЙ МОНИТОРИНГ В СИСТЕМЕ ЭКСПЛУАТАЦИИ ИНФОКОММУНИКАЦИОННОЙ СЕТИ

Никитюк Л.А.

Одесская национальная академия связи им. А.С. Попова,
65029, Украина, г. Одесса, ул. Кузнечная, 1,
lesyanikityuk579@gmail.com

Abstract. A method for increasing the functionality of existing types of monitoring used in modern information and communication networks based on the use of cognitive technologies is proposed. Modern cognitive technologies are allowed to combine the implementation of traditional monitoring procedures with predictive procedures and the ability to recognize the upcoming changes in the state of the object. The implementation of these procedures involves the consistent implementation of the stages of short-term, situational and long-term forecasting. This allows the identification in advance of the possibility of emergency situations on the object, directly recognize the moments of their occurrence and make timely decisions about the need to reconfigure the resources of the monitoring object, thus maintaining its state in accordance with the standards of technical operation. Long-term forecasting provides the identification of the emerging trend of changes in the dynamic characteristics of an object, which makes it possible to decide in advance about the need to reconstruct the information and communication network, when the means of reconfiguring its resources are already ineffective. The listed procedures are implemented by means of statistical analysis and generally solve the problem of creating a system of preventive technical operation. The paper proposes a cognitive monitoring system architecture that mediates the interaction of existing monitoring tools and control systems and technical operation. The implementation of cognitive monitoring procedures in the functional plane of the TMN concept is shown by adding prediction functions and recognizing emergency situations. The proposed method is also interpreted in terms of the concept of TINA, the introduction of the prognostic monitoring application into the software functional plane.

Key words: cognitive monitoring, dynamic characteristics of information and communication network, forecasting, polynomial extrapolation.

Анотація. Пропонується спосіб підвищення функціональності існуючих видів моніторингу, що застосовуються у сучасних інфокомунікаційних мережах на основі використання когнітивних технологій. Пропонований метод дозволяє поєднати виконання традиційних процедур моніторингу динамічних характеристик інфокомунікаційних мереж з прогностичними процедурами і здатністю розпізнавання майбутніх змін стану об'єкта. Таким чином, моніторинг отримує когнітивні функції. Реалізація зазначених процедур передбачає послідовне виконання етапів короткострокового, ситуаційного і довгострокового прогнозування. Це дозволяє завчасно виявляти можливості появи на об'єкті позаштатних ситуацій, безпосередньо розпізнавати моменти їх виникнення і своєчасно приймати рішення про необхідність реконфігурації ресурсів об'єктів моніторингу, підтримуючи таким чином його стан відповідним до передбачених норм технічної експлуатації. Довгострокове прогнозування забезпечує виявлення формування трендів зміни динамічних характеристик об'єкта, що дозволяє завчасно прийняти рішення про необхідність реконструкції інфокомунікаційної мережі, коли засоби реконфігурування її ресурсів вже неефективні. Перераховані процедури реалізуються засобами статистичного аналізу і в цілому розв’язують задачу створення системи превентивної технічної експлуатації. В роботі запропонована архітектура системи когнітивного моніторингу, яка опосередковує взаємодію існуючих засобів моніторингу та систем управління і технічної експлуатації. Показана реалізація процедур когнітивного моніторингу у функціональній площині концепції TMN шляхом додавання функцій прогнозування і розпізнавання позаштатних ситуацій. Запропонований метод також інтерпретований в термінах концепції TINA впровадженням програмного модуля прогностичного моніторингу у функціональну площину програмного забезпечення.

Ключові слова: когнітивний моніторинг, динамічні характеристики інфокомунікаційної мережі, прогнозування, поліноміальна екстраполяція.

Аннотация. Предлагается способ повышения функциональности существующих видов мониторинга, применяемых в современных инфокоммуникационных сетях на основе использования когнитивных технологий. Современные когнитивные технологии позволили совместить выполнение традиционных процедур мониторинга с прогностическими процедурами и способностью распознавания предстоящих изменений состояния объекта. Реализация указанных процедур предполагает последовательное выполнение этапов краткосрочного, ситуационного и долгосрочного прогнозирования. Это позволяет заблаговременно выявлять возможности появления на объекте внештатных ситуаций, непосредственно распознавать моменты их возникновения и своевременно принимать решения о необходимости реконфигурации ресурсов объектов мониторинга, поддерживая таким образом его состояния в соответствии с нормами технической эксплуатации. Долгосрочное прогнозирование обеспечивает выявление формирующегося тренда изменения динамических характеристик объекта, что позволяет заблаговременно принять решение о необходимости реконструкции инфокоммуникационной сети, когда средства реконфигурации ее ресурсов уже неэффективны. Перечисленные процедуры реализуются средствами статистического анализа и в целом решают задачу создания системы превентивной технической эксплуатации. В работе предложена архитектура системы когнитивного мониторинга, которая опосредует взаимодействие существующих средств мониторинга и систем управления и технической эксплуатации. Показана реализация процедур когнитивного мониторинга в функциональной плоскости концепции TMN путем добавления функций прогнозирования и распознавания внештатных ситуаций. Предложенный метод также интерпретирован в терминах концепции TINA внедрением программного модуля прогностического мониторинга в функциональную плоскость программного обеспечения.

Ключевые слова: когнитивный мониторинг, динамические характеристики инфокоммуникационной сети, прогнозирование, полиномиальная экстраполяция.

The current stage of the evolution of communication networks is characterized by convergent processes that occur simultaneously in networks, technologies and services. These innovations today are defined as post-NGN, which refers to the further active computerization of telecommunications. As a result, new generation communication networks acquire the features of information and communication networks, capable of providing services of unlimited spectrum and new quality. This, in turn, imposes new requirements for support systems that perform the functions of management and maintenance of the information and communication network. The telecom operator invests significant funds in these systems and for this reason all solutions aimed at enhancing their functionality are extremely relevant and in demand. This actualizes the transfer of such systems to new technological platforms. The main technological trend, in accordance with the forecast of the development of high-tech industries prepared by the International Association of Deloitte firms, is the use of cognitive and intellectual technologies. The principal difference between these two technologies lies in the fact that cognitive technologies allow modeling of the cognitive abilities of the human brain to solve specific applied problems, such as: pattern recognition (speech, signals, images, etc.); identification and identification of patterns in data arrays; decision making in a predictable environment, while intelligent technologies involve self-learning and adaptation in an unpredictable environment.

The most promising areas for the use of cognitive technologies today are considered to be: cognitive radio and wireless cognitive networks, designed to provide high quality service to mobile users and adaptive control of frequency resources; implementation of a friendly, customizable user interface.

Separately, it should be noted unconditional feasibility of the use of cognitive technologies for the improvement of the technical operation system. One of the main procedures performed during the technical operation of networks and communication systems, as is known, is the monitoring of the parameters of their dynamic characteristics. The effectiveness of network resource management in the event of emergency situations is largely determined by the functionality and quality of the monitoring procedures

It should be noted that, despite all the diversity of modern types of monitoring used in communication networks, all of them are mainly aimed at ensuring reliable reflection and statement of the current state of the object. It seems relevant to increase the functionality of existing types of monitoring of network objects by implementing such procedures as forecasting possible changes in the state of an object, forecasting the occurrence of emergency situations during the period of interest or degradation of object performance, in order to ensure the possibility of anticipating the negative consequences of their impact.

Cognitive technologies in monitoring procedures can be used not only for the timely detection of problems in the information and communication network, but also for predicting the occurrence of various emergency situations at different periods of time, informing about them in advance, and thereby ensuring the possibility of anticipation of negative consequences.

In addition, monitoring parameters can be supplemented by monitoring the state of the object. The principal difference between state monitoring and parameter monitoring is the possibility of obtaining some integral parameter - an interpreter of measured parameters in terms of state. This, in turn, will improve the efficiency of decisions made by the control system.

This paper discusses one of the possible approaches to the implementation of cognitive monitoring.

In this work, cognitive monitoring, from the point of view of functionality, is considered as predictive monitoring, the purpose of which is to continuously monitor the state of the object, conducted in order to identify trends emerging in the course of its operation, and to make forecasts for changes in its state in the future.

Some approaches to the implementation of prognostic monitoring can be observed in a number of scientific papers [1–13].

For example, in [10], it is indicated that it is expedient to implement the above requirements for the monitoring process, but there is no clear formalization of the prognostic monitoring procedures.

In [1–4, 11], the use of prognostic monitoring in sensor networks was considered, which ultimately reduced the amount of transmitted service information and reduced the power consumption of sensors. However, the range of monitoring parameters in this case is rather limited and cannot be considered informative in relation to infocommunication networks.

A number of papers [5–9, 12, 13] considered the implementation of prognostic monitoring procedures using artificial neural networks to solve a number of practical problems in various fields, such as:

– justification of the expediency of adding new channels in networks based on monitoring the throughput of connections of the TCP protocol [13];
– the prognosis of the deterioration of the health status of patients on the basis of such data as a cardiogram, pressure measurement, determination of the oxygen content in the blood, etc. [5, 6];
– prediction of failures in the delivery of goods, by analyzing and forecasting the dynamics of business processes and emergency situations on the railway [7, 8];
– monitoring the ratio of oxygen and fuel to predict harmful emissions (SO_2, NO_2, CO_2) of the incinerator [9].

However, it should be noted a number of factors that significantly limit the use of these methods for the implementation of cognitive monitoring procedures in information and communication networks, namely:

– the use of artificial neural networks involves a learning process that is too time consuming, which creates additional risks when managing large and complex objects;

– the accuracy of forecasting depends on the number of examples that were used during the training; and

– high requirements for computing capabilities in hardware implementation.

This paper aims to ensure the implementation of cognitive monitoring capabilities based on the use of mathematical methods of statistical analysis of time series and statistical forecasting, which greatly simplifies the implementation of forecasting procedures into existing types of monitoring and allows you to decide in advance on the need to reconfigure network resources or reconstruct it.

This goal is achieved by solving the following tasks:

– determination of prognostic monitoring procedures and criteria for making decisions about the need to reconfigure network resources or reconstruct the monitoring object depending on the results of forecasting the occurrence of abnormal situations;

– development of the architecture of the predictive monitoring system that performs the relevant procedures.

The state and behavior of the information and communication network as an object of maintenance and management is displayed by a set of parameters Y, power m, which describe its dynamic characteristics. In the specified set, such groups of parameters can be distinguished as: parameters of the technical condition, parameters of quality of service, and parameters of processes of accumulation and processing of information (content).

The task of cognitive monitoring is to predict the possibility of an emergency situation at the monitoring site with a specified lead period, during which actions can be taken to reduce the effects of negative factors. Thus, it can be stated that cognitive monitoring is predictive monitoring.

The proposed approach includes the sequential passage of the phases of short-term, situational and long-term forecasting [16].

Short-term forecasting is a prediction with a lead time of L_K, which corresponds to one step of measuring the parameter $y_k \in Y\left(k=\overline{1,m}\right)$ to be monitored.

Situational forecasting - forecasting with a lead time L_C , during which the change in the parameter $y_k \in Y\left(k=\overline{1,m}\right)$ reaches a certain, predetermined threshold value y_{kP}. The duration of the L_C period is determined by the time required to perform actions to reconfigure network resources.

Long-term forecasting - forecasting with the lead time L_D, which covers the life cycle of the monitoring object, after which the object must be reconstructed. The source data for long-term forecasting is a sample of the values of the frequency F of arising and predicted emergency situations during the observation period T_F.

Short-term forecasting allows determining the next value $y_k(i+1)$ of the parameter $y_k(i) \in Y\left(k=\overline{1,m}\right)$ to be monitored since the accumulation of the corresponding representative sample $n_{\min}^K$ and can be used to ensure the completeness of the situational forecasting sample $n_{\min}^C$ when the next value cannot be obtained from monitoring tools due to technical failures . Thus, the lead time for short-term forecasting is $L_K = 1$.

Situational forecasting is aimed at identifying an extraordinary situation, the prevention of which requires reconfiguration of the monitoring object, for example, due to a sharp increase in the network load. The corresponding alert is generated at the time point $t_z^{\kappa p}$ from which the L_C lead-up period begins, and indicates that the observed parameter $y_k(i) \in Y\left(k=\overline{1,m}\right)$ can reach the threshold value or go beyond its limits, that is:

$$\hat{y}_k\left(n_{\min}^C + L_C\right) \le y_{kP1} \vee \hat{y}_k\left(n_{\min}^C + L_C\right) \le y_{kP2}, \tag{1}$$

where y_{kP1} and y_{kP2} – respectively the lower and upper threshold values of the parameter; $n_{\min}^C$ – relevant representative sample.

The alert signal about the need to reconstruct the monitoring object is generated when the frequency F of occurrence of emergency situations (FOES) for the entire set Y of the object's parameters to be monitored during the observation period T_F reaches a certain threshold value $F \geq F_P$ established on the basis of expert estimates. In this case, the FOES is an interpreter of the state of the object. The lead period for L_D long-term forecasting can be defined as the time interval required for performing reconstruction tasks.

The initial data for the work of cognitive monitoring are:

– list of parameters $y_k(i) \in Y \; \left(k = \overline{1,m}\right)$ to be monitored;

– periods of anticipation of forecasts, respectively, L_K, L_C and L_D;

– threshold values $y_{kP} \in Y_P \; \forall \; y_k(i) \in Y \; \left(k = \overline{1,m}\right)$, where Y_P - a set of threshold values of the observed parameters, power m;

– F_P is the threshold value of the FOES and the corresponding observation period T_F.

Cognitive monitoring procedures are performed in an infinite loop and include the following steps (see Fig. 1, *a*).

After accumulating the necessary representative sample of values ($n^K_{\min}, n^C_{\min}, n^D_{\min}$) of the observed parameter, prediction is performed with the corresponding lead time (L_K, L_C, L_D).

So, from achievement of the moment $i = n^K_{\min}$ short-term forecasting can be carried out, that is the predicted value $\hat{y}_k(i+1)$ of the parameter $y_k(i) \in Y \; \left(k = \overline{1,m}\right)$ is determined, which is expected at the next point in time. For this, a serial sample of values $\left\{y_k(i)\right\}$, size $n^K_{\min}$, is analyzed for the presence of the stationarity property. Depending on the results of the test, a mathematical model is defined for describing the change in a given parameter. In the case of the presence of the property of stationarity $\left\{y_k(i)\right\}$ [15]:

$$\begin{aligned} y_k(i+L_K) &= a_1 y(i-1+L_K) + a_2 y(i-2+L_K) + \ldots + a_p y(i-p+L_K) + e(i) - \\ &- b_1 e(i-1+L_K) - b_2 e(i-2+L_K) - \ldots - b_q e(i-q+L_K), \end{aligned} \tag{2}$$

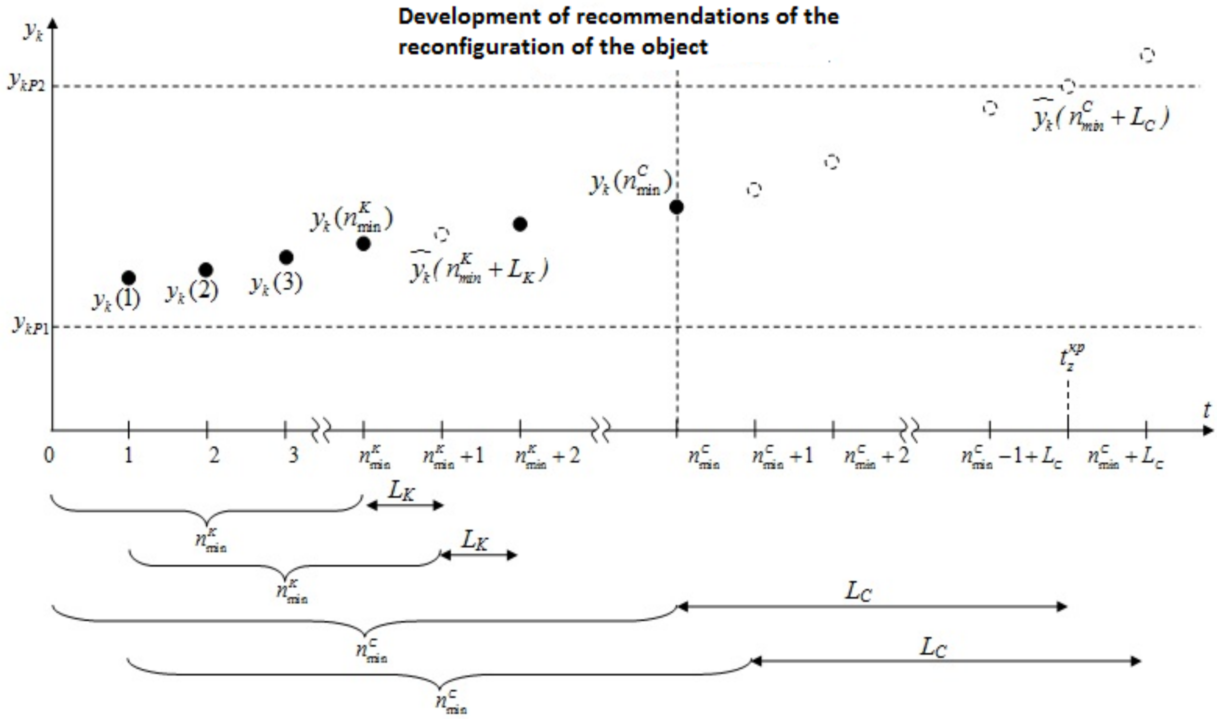
where p is the autoregression order; q is the order of the moving average a_α; $(\alpha = \overline{1,p})$ and b_β $(\beta = \overline{1,q})$ – coefficients of the ARIMA model obtained by the Box-Jenkins approach [14].

In case of non-stationarity $\left\{y_k(i)\right\}$:

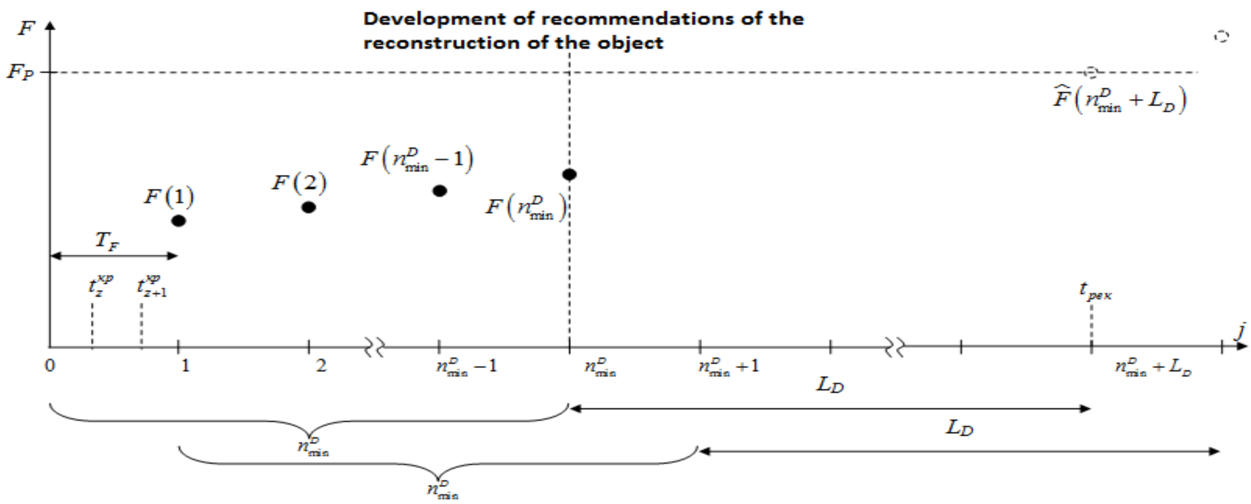
$$\hat{y}_k(i+L_K) = \widehat{Tr}(i+L_K) + e(i)\,, \tag{3}$$

where $\widehat{Tr}(i+L_K)$ is the predicted value of the trend component formalized by the polynomial model [15]; $e(i)$ - random component, with constant variance and zero expectation, the sequential values of which are independent.

Over time, the predicted value $\hat{y}_k(i+1)$ of the parameter $y_k(i) \in Y \; \left(k = \overline{1,m}\right)$ may change due to the cyclical update of values $\left\{y_k(i)\right\}$.



a)



b)

Figure 1 – Forecasting: *a)* short-term and situational; *b)* long-term

Situational forecasting can be started from the moment $i = n_{\min}^C$, i.e. accumulation of the corresponding representative sample of values of the observed parameter. Its distinctive feature is the fact that forecasting with a lead time of L_C is possible only if there is a trend component in the time series $\{y_k(i)\}$ within a representative sample $n_{\min}^C$. To track a trend, a representative sample should be updated with each subsequent monitoring step, which creates the effect of a "sliding window" in the time series of values of the observed parameter (see Fig. 1).

In the case of the detection of the trend component, in order to extrapolate the values within the lead-in period (L_K, L_C), the corresponding mathematical function is defined for describing the trend, which in general has the form:

$$Tr(i) = a_0 + a_1 \cdot i + a_2 \cdot i^2 + \cdots + a_{\lambda_\eta} \cdot i^{\lambda_\eta};$$
$$Tr(j) = a_0 + a_1 \cdot j + a_2 \cdot j^2 + \cdots + a_{\lambda_D} \cdot j^{\lambda_D} \quad . \tag{4}$$

If the condition $y_{kP1} < \hat{y}_k(i + L_C) < y_{kP2}$ is met, the normal operation of the object is ascertained.

Otherwise, an abnormal situation $(\hat{y}_k(i + L_C) \leq y_{kP1} \vee \hat{y}_k(i + L_C) \geq y_{kP2} \forall i \geq n_{\min}^C)$ is expected, about which the cognitive monitoring system at the moment $t_z^{\kappa p}$ of time gives the corresponding message.

Long-term forecasting is performed after the accumulation of the corresponding representative sample $\{F(j)\}$ of the FOES values, by dimension $n_{\min}^D$. Here, the "sliding window" effect is used in a similar way, within which the values $\{F(j)\}$ of the time series are analyzed for the presence of the trend component. When an increasing trend is detected, the condition is checked:

$$\hat{F}(j + L_D) \geq F_p,\ \hat{F}\ (j + L_D)\ \forall\ j \geq n_{\min}^D, \tag{5}$$

where F_P is the established threshold value; L_D is the lead time corresponding to long-term forecasting.

The fulfillment of condition (5) is a criterion for deciding whether to reconstruct the monitoring object and indicates that measures to reconfigure network resources do not ensure the transition of the observed object to the normal mode of operation.

Fig. 2 shows the cognitive monitoring architecture in the information and communication network operation system, reflecting the interaction of the predictive (predictive) system of monitoring with the subsystem of monitoring tools and the control system. The predictive monitoring system itself consists of two functional subsystems: the analysis subsystem and the results interpretation subsystem [16].

In the analysis subsystem, analytics of forecasts and the identification of trend states in changes in the state of the monitoring object are performed, and in the interpretation subsystem, decisions are made to develop appropriate recommendations for the management system and technical operation personnel. The control system, based on the data coming from the predictive monitoring system, characterizing the state of the object and the tendencies of its possible change, produces an appropriate control action on the object of monitoring. To improve the efficiency of this system, it is proposed to use intelligent technologies, for example, to implement the functions of decision makers (decision makers). The control system is able to change the mode of operation of the predictive monitoring system by changing the list of parameters to be monitored, lead intervals and threshold values to identify emergency situations.

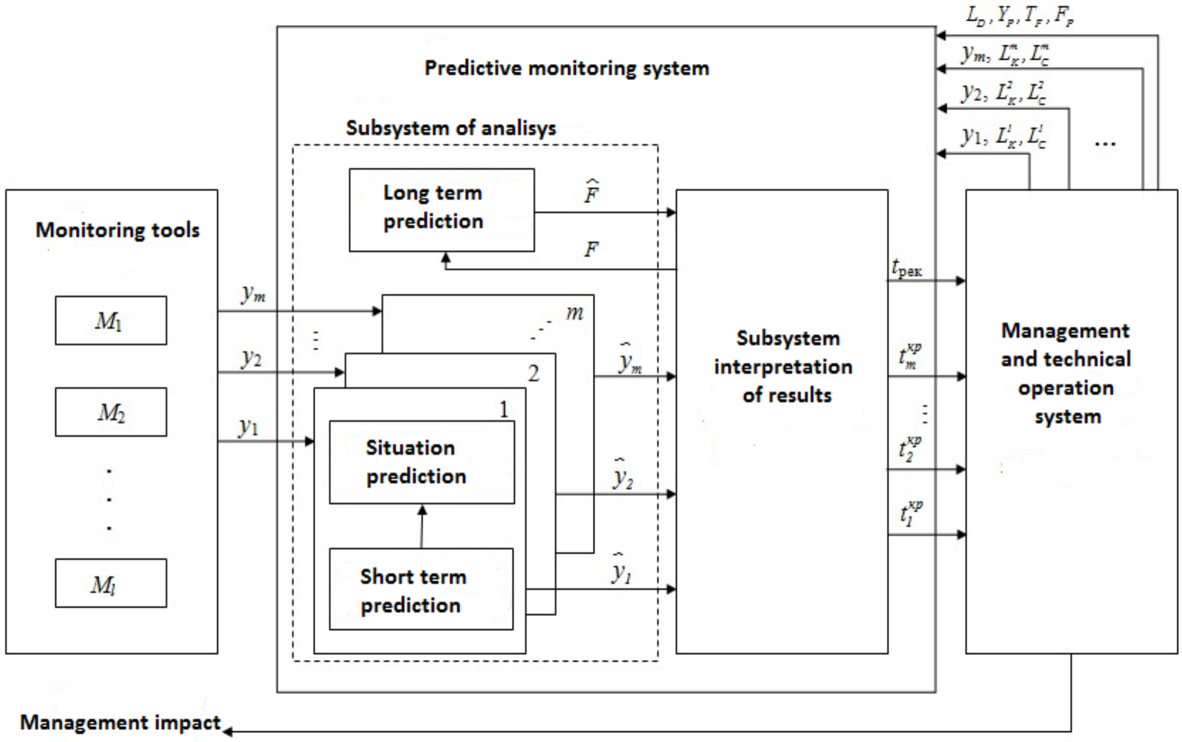


Figure 2 – Cognitive monitoring system architecture

Increasing the functionality of existing types of monitoring with predictive monitoring procedures can be illustrated in terms of the Telecommunications Management Network (TMN) concept, by implementing the additional function of the Predictive Monitoring Operations Systems Function (PM-OSF), which interacts with the existing OSF through the interface q (Fig. 3).

The Work Station Function (WSF) implements a human-machine interface for interpreting TMN information, in particular for reporting predictable emergency situations.

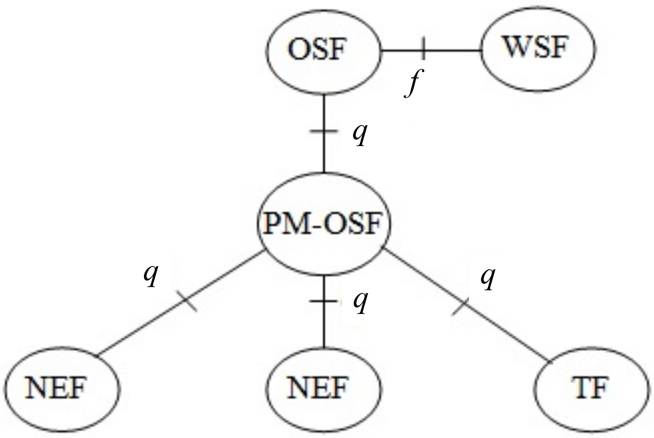


Figure 3 – Implementation of the operations systems function cognitive monitoring

The Network Element Function (NEF) function block provides a selection of the values of the parameters to be monitored and implements the functions necessary for reconfiguration. The Transformation Function (TF) function block provides equipment interaction with various communication mechanisms, for example, equipment of various technological generations.

Similarly, enhancing the functionality of existing types of monitoring with predictive monitoring procedures, in the software plane, can be illustrated in terms of the Telecommunications Information Networking (TINA) concept by adding an appropriate Predictive Monitoring Application (PMA) in the TINA application plane. This plane includes Telecommunication Service

Applications (TSA), Telecommunication Service Management Applications (TSMA) and Network and Element Management Applications (NEMA). PMA interacts with TSMA and NEMA (Fig. 4).

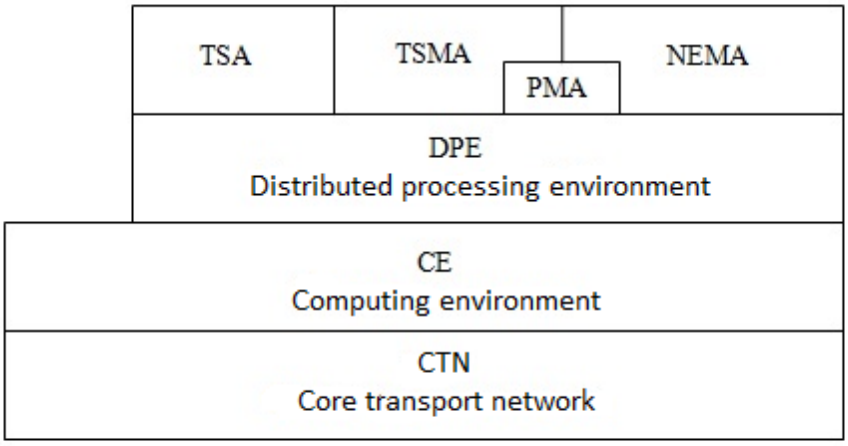


Figure 4 – Location of the cognitive monitoring application in the TINA application plane

The procedures for cognitive monitoring of the dynamic characteristics of the information and communication network, based on the methods of the theory of statistical forecasting, implement the sequential passing of the stages of short-term, situational and long-term forecasting in order to identify in advance the moments of occurrence of abnormal situations on the network. The implementation of these procedures in the monitoring process will significantly improve its functionality and provide the opportunity to provide information in advance for making decisions about the need to reconfigure network resources or reconstruct it.

The proposed architecture of the cognitive monitoring system mediates the interaction of existing monitoring tools and control systems and technical operation. The implementation of predictive monitoring procedures is shown in the functional plane of the TMN concept, by adding an additional function of the PM-OSF predictive monitoring operation system and in the software plane, in terms of the TINA concept, by implementing the PMA predictive monitoring application.

REFERENCES:

1. ITU-T Recommendation G.8001 "Terms and definitions for Ethernet frames over Transport" [Text] / Approved 2008-03-29. Geneva: ITU, 2008: 12 p.
2. Azad, A. "Map based Predictive Monitoring for Wireless Sensor Networks" [Online resource] / A. Ali, A. Khelil, K. Shaikh, N. Suri // Technische Universitat Darmstadt, http://www.gkmm.tudarmstadt.de/ publications/ files/ AKSS09.pdf.
3. Achir, M. and Ouvry, L. "Power consumption prediction in wireless sensor networks" / M. Achir, L. Ouvry // The Pennsylvania State University. Available at: http://citeseerx.ist.psu.edu/viewdoc/ download?doi=10.1.1.60.1065&rep=rep1&type=pdf.
4. Landsiedel, O. "Accurate prediction of power consumption in sensor networks" / O. Landsiedel, K. Wehrle, S. Gotz // The Pennsylvania State University. http://citeseerx.ist.psu.edu/viewdoc/ download?doi=10.1.1.112.6036&rep=rep1&type=pdf.
5. Mini, A. F. "A probabilistic approach to predict the energy consumption in wireless sensor networks". /A. F. Mini, B. Nath, A. F. Loureiro // The Pennsylvania State University. http://citeseerx.ist.psu.edu/ viewdoc/download?doi=10.1.1.11.4906&rep=rep1&type=pdf.
6. Wang, X. "Robust forecasting for energy efficiency of wireless multimedia sensor networks". [Online resource] / X. Wang, J. Ma, L. Ding, D. Bi // MDPI AG. Available at: http://www.mdpi.com/1424-8220/7/11/2779.
7. Clifton, L. (). "Predictive Monitoring of Mobile Patients by Combining Clinical Observations With Data From Wearable Sensors" / L. Clifton, D. A. Clifton, M. A. F. Pimentel, P. J. Watkinson, L. Tarassenko // IEEE Journal of Biomedical and Health Informatics. Vol.:18, Issue: 3, (2014): 722–730.
8. Moorman, J. R. "Predictive monitoring for early detection of subacute potentially catastrophic illnesses in critical care" / J. R. Moorman, C. E. Rusin, L. Hoshik, L. E. Guin, M. T. Clark, J. B.

Delos, J. Kattwinkel, D. E. Lake // Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, Boston, USA August 30 – September 3: (2011).
9. Metzger, A. "Comparing and Combining Predictive Business Process Monitoring Techniques" / A. Metzger, P. Leitner, D. Ivanovic, E. Schmieders, R. Franklin, M. Carro, S. Dustdar, K. Pohl // IEEE Transactions on Systems, Man, and Cybernetics. Vol.: PP, Issue: 99, 1. (2014): 2347265. DOI: 10.1109/TSMC.
10. Franceschinis, M. "Predictive monitoring of train wagons conditions using wireless network technologies" / M. Franceschinis, F. Mauro, C. Pastrone, M. A Spirito, M. Rossi // XXIV International Symposium on Information, Communication and Automation Technologies (ICAT). Sarajevo, Bosna i Hercegovina October 30 – November 1, 2013. DOI: 10.1109/ICAT.2013.6684032.
11. Zain, S. M. "Development of a neural network Predictive Emission Monitoring System for flue gas measurement"/ S. M Zain, Kien Kek Chua // IEEE 7th International Colloquium on Signal Processing and its Applications (CSPA). Penang, Malaysia March 4–6, 2011. DOI: 10.1109/CSPA.2011.5759894.
12. Bobalo, Iu. Ia. "Monitorynh ob'iektiv v umovakh apriornoi nevyznachenosti dzherel informatsii. Teoriia i praktyka"/ Iu. Ia. Bobalo, Iu. H. Danyk, L. O. Komarova, O. O. Luk'ianov, V. M. Maksymovych, O. O. Pysarchuk, Iu. B. Storonskyi, B. M. Strykhaliuk// Lviv: Kolo (2014): 252.
13. Yoo, W. "Network Bandwidth Utilization Forecast Model on High Bandwidth Network" / Yoo, W., Sim, A. International Conference on Computing, Networking and Communications (ICNC) Garden Grove, USA. 16-19 Feb. 2015 Page(s): 494 - 498 DOI: 10.1109/ICCNC.2015.7069393.
14. Zaman, F. "A recommender system architecture for predictive telecom network management" / Zaman, F., Hogan, G., Der Meer, S., Keeney, J., Robitzsch, S., Muntean, G.-M. Communications Magazine, IEEE (Volume:53 ,Issue: 1) Pages:, (2015): 286 – 293.
15. M. Mirza, J. Sommers, and P. Barford, "A Machine Learning Approach to TCP Throughput Prediction". IEEE/ACM Trans. Netw., vol. 18, no. 4 (2010): 1026–1039, http: //ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5378489
16. Sazhin Yu. V. "Analiz vremennih ryadov i prognozirovanie" /Yu. V. Sazhin, A. V. Katyin, Yu. V. Saraykin. Saransk: Izd-vo Mordov. Un-ta, (2013): 192.

ЛІТЕРАТУРА:

1. ITU-T Recommendation G.8001 Terms and definitions for Ethernet frames over Transport [Текст] / Approved 2008-03-29. – Geneva: ITU, 2008. – 12 p.
2. Azad A. Map based Predictive Monitoring for Wireless Sensor Networks [Электронный ресурс] / A. Ali, A. Khelil, K. Shaikh, N. Suri// Technische Universitat Darmstadt. Режим доступа: \www/ URL: http://www.gkmm.tu-darmstadt.de/publications/files/AKSS09.pdf.
3. Achir, M. and Ouvry, L. Power consumption prediction in wireless sensor networks [Электронный ресурс] /M. Achir, L. Ouvry // The Pennsylvania State University. – Режим доступа: \www/ URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.60.1065&rep=rep1&type=pdf.
4. Landsiedel, O. Accurate prediction of power consumption in sensor networks [Электронный ресурс] /O. Landsiedel, K. Wehrle, S. Gotz// The Pennsylvania State University. – Режим доступа: \www/ URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.112.6036&rep=rep1&type=pdf
5. Mini, A. F. A probabilistic approach to predict the energy consumption in wireless sensor networks. [Электронный ресурс] /A. F. Mini, B. Nath, A. F. Loureiro// The Pennsylvania State University – Режим доступа: \www/ URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.11.4906&rep=rep1&type=pdf.
6. Wang, X. Robust forecasting for energy efficiency of wireless multimedia sensor networks. [Электронный ресурс] /X. Wang, J. Ma, L. Ding, D. Bi// MDPI AG. –Режим доступа: \www/ URL: http://www.mdpi.com/1424-8220/7/11/2779.
7. Clifton, L. (2014). Predictive Monitoring of Mobile Patients by Combining Clinical Observations With Data From Wearable Sensors / L. Clifton, D. A. Clifton, M. A. F. Pimentel, P. J. Watkinson, L. Tarassenko, // IEEE Journal of Biomedical and Health Informatics. – Vol.:18, Issue: 3, 722 – 730. DOI: 10.1109/JBHI.2013.2293059.
8. Moorman, J. R. Predictive monitoring for early detection of subacute potentially catastrophic illnesses in critical care / J. R. Moorman, C. E Rusin, L. Hoshik, L. E. Guin, M. T. Clark, J. B. Delos, J. Kattwinkel, D. E. Lake // Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, 2011. – Boston, USA August 30 – September 3, 2011. DOI: 10.1109/IEMBS.2011.6091407.
9. Metzger, A. (2014) Comparing and Combining Predictive Business Process Monitoring Techniques /A. Metzger, P. Leitner, D. Ivanovic, E. Schmieders, R. Franklin, M. Carro, S. Dustdar, K. Pohl // IEEE Transactions on Systems, Man, and Cybernetics. – Vol.:PP , Issue: 99, 1. DOI: 10.1109/TSMC.2014.2347265.

10. Franceschinis, M. Predictive monitoring of train wagons conditions using wireless network technologies /M. Franceschinis, F. Mauro, C. Pastrone, M. A Spirito, M. Rossi// 2013 XXIV International Symposium on Information, Communication and Automation Technologies (ICAT). – Sarajevo, Bosna i Hercegovina October 30 – November 1, 2013. DOI: 10.1109/ICAT.2013.6684032.
11. Zain, S. M Development of a neural network Predictive Emission Monitoring System for flue gas measurement /S. M Zain, Kien Kek Chua// 2011 IEEE 7th International Colloquium on Signal Processing and its Applications (CSPA). – Penang, Malaysia March 4–6, 2011. DOI: 10.1109/CSPA.2011.5759894.
12. Бобало Ю. Я. Моніторинг об'єктів в умовах апріорної невизначеності джерел інформації. Теорія і практика // [Ю. Я. Бобало, Ю. Г. Даник, Л.О. Комарова, О.О. Лук'янов, В.М. Максимович, О.О. Писарчук, Ю. Б. Сторонський, Б. М. Стрихалюк]. – Львів: Коло, 2014. – 252 с.
13. Yoo, W. Network Bandwidth Utilization Forecast Model on High Bandwidth Network /Yoo, W., Sim, A. 2015 International Conference on Computing, Networking and Communications (ICNC) Garden Grove, USA. 16-19 Feb. 2015 Page(s): 494 - 498 DOI: 10.1109/ICCNC.2015.7069393.
14. Zaman, F. A recommender system architecture for predictive telecom network management / [Zaman, F., Hogan, G., Der Meer, S., Keeney, J., Robitzsch, S., Muntean, G.-M.]. Communications Magazine, IEEE (Volume:53, Issue: 1) Pages: 286 – 293, 2015 DOI: 10.1109/MCOM.2015.7010547.
15. M. Mirza, J. Sommers, and P. Barford. A Machine Learning Approach to TCP Throughput Prediction, IEEE/ACM Trans. Netw., vol. 18, no. 4, pp. 1026–1039, Aug. 2010. [Online]. Available at: http: //ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5378489.
16. Сажин Ю. В. Анализ временних рядов и прогнозирование /Сажин, Ю.В., Катынь, А.В., Сарайкин, Ю.В. – Саранск: Изд-во Мордов. Ун-та, 2013. – 192 с.

DOI 10.33243/2518-7139-2018-1-2-48-58