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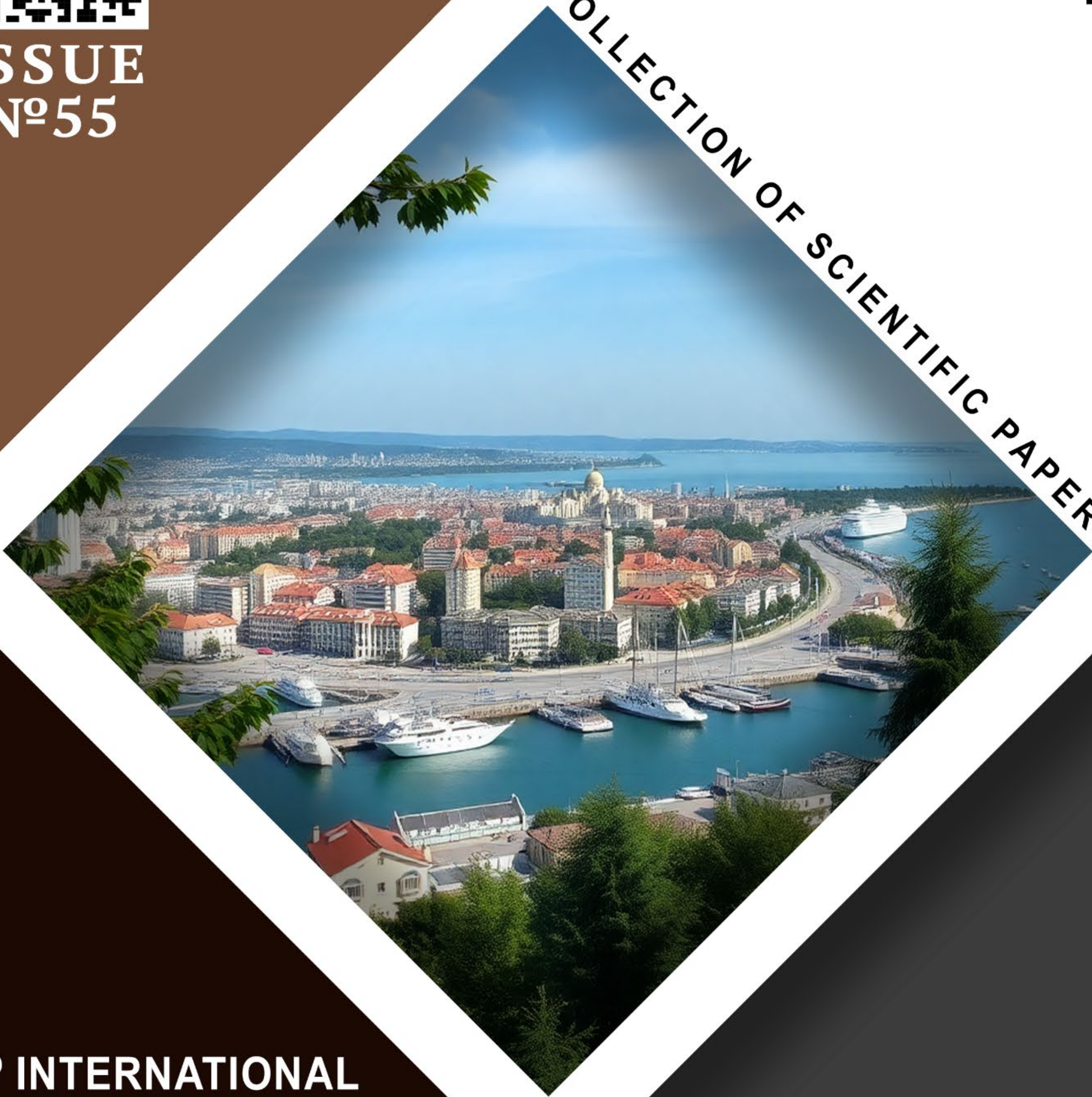

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METHOD FOR AUTOMATED DETECTION OF LOAD LEVELS IN COMPUTER NETWORKS

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The rapid development of information technologies [1] causes a significant increase in the load on computer networks. Modern telecommunication systems deal with traffic that is formed under the influence of cyclical patterns and random fluctuations. To ensure stable operation of the network, it is necessary not only to predict its states, but also to automatically detect load levels, which allows for timely identification of critical modes and make proactive decisions on resource management.

Traditional methods are based [2] on threshold criteria that do not take into account the stochastic nature of traffic and do not provide control over the probability of classification errors. In this paper, an approach to automated detection of load levels is proposed, which is based on the periodically correlated stochastic process (PCSP) model, in-phase/component signal analysis, and the Neumann–Pearson criterion.

Network load classification methods can be conditionally divided into several groups:

– Stochastic models (Poisson, Markov, ARIMA) describe randomness, but do not reproduce cyclicality.

– Fractal models (fBm) take into account self-similarity, but do not take into account diurnal fluctuations [5].

– Machine learning methods [3] provide high accuracy, but require large computational resources.

– Hybrid approaches combine different models, but are difficult to implement in practice [6].

The disadvantage of most of them is the use of simple thresholding schemes, which reduces the reliability of classification. The proposed automated detection system overcomes these limitations by integrating in-phase/component analysis and the Neumann-Pearson criterion.

Traffic load is considered as a periodically correlated stochastic process:

$$\xi(t) = S(t) + X(t), \quad t \in \mathrm{R} \tag{1}$$

where $S(t)$ – a deterministic periodic component with a daily period T, reflecting a repeating cyclicity;

$X(t)$ – stochastic component.

Thus, the model combines the regular structure of traffic and its random nature.

To move from the model to the processing tools, the random component $\xi(t)$ is given in the form of a harmonic expansion:

$$\xi(t) = \sum_{k \in Z} \xi_k(t) e^{-\frac{j2\pi k}{T}}, \quad t \in \mathrm{R} \tag{2}$$

where $\xi_k(t)$ – stochastic coefficients that vary with time, and exponential multipliers describe the periodic structure of the process.

This approach allows us to represent the random part as a superposition of in-phase harmonic components.

In-phase and component methods use these harmonic components to construct correlation features.

For centered traffic signals, a spectral-correlation representation is calculated for harmonic number k:

$$\hat{B}_k(u) = \frac{1}{N} \sum_{t \in Z} \overset{0}{\xi}(t) \overset{0}{\xi}(t-u) e^{-\frac{j2\pi k}{T}}, \tag{3}$$

where $\overset{0}{\xi}(t)$ – centered traffic signal relative to the mathematical expectation, $\overset{0}{\xi}(t) = \xi(t) - E[\xi(t)]$;

N – sample length; u – time shift;

k – harmonic number (correlation component number); Z – indexing area.

The correlation components $\hat{B}_k(u)$, which are calculated for centered traffic signals, reflect the time-frequency characteristics of the network load. However, in real data there are

– noise components (random fluctuations of short duration);

– anomalous peaks (sudden jumps due to local events) [4, 7];

– limited sample size, leading to statistical instability of estimates.

If raw correlation components $\hat{B}_k(u)$ are used, the classification results may be overly sensitive to random fluctuations.

To avoid this, a procedure of averaging over components was introduced:

$$\overline{C}(u) = \frac{1}{N} \sum_{k=1}^{K} B_k(u), \tag{4}$$

where $\hat{B}_k(u)$ – estimate of the correlation component on the u-th interval;

K – number of averaging components.

That is, averaging correlation components is a kind of «filter» of statistical features: it cuts off short-term random fluctuations and leaves long-term patterns that are truly informative for further classification of load levels.

As a result, a feature vector is formed:

$$C(u) = \left(\overline{C}(u_1), \overline{C}(u_2), \ldots, \overline{C}(u_m)\right), \tag{5}$$

which preserves the temporal dynamics of the load and is the basis for classification.

Automated detection of load levels in computer networks is formulated as a statistical hypothesis testing problem. In the simplest case, binary classification is considered:

– H_0: the load is average (normal network operation mode);

– H_1: the load is abnormal (minimum or critical).

In order to decide between hypotheses, a likelihood ratio is introduced:

$$\Lambda(C(u)) = \frac{f(C(u) \mid H_1)}{f(C(u) \mid H_0)}, \tag{6}$$

where $C(u)$ – vector of averaged in-phase/component correlation features;

$f(C(u) \mid H_1)$, $f(C(u) \mid H_0)$ – probability density of the appearance of these features when the hypotheses H_0 and H_1 are true.

The decision (classification) rule has the form:

$$\Lambda(C(u)) \underset{H0}{\overset{H1}{\lessgtr}} \eta, \tag{7}$$

where η – threshold value determined from the condition of controlling the probability of incorrect decisions (determined by the Neumann-Pearson criterion) [8].

This approach allows you to minimize the probability of missing a dangerous condition while controlling the probability of false alarms.

According to the Neumann–Pearson criterion, the optimal rule is considered to be one that minimizes the probability of missing an abnormal state (type II error):

$$\beta = P(\textit{рішення}\, H0 | H1) = \int_{\Lambda(C(u))<\eta} p(x \mid H1)dx, \tag{8}$$

provided that the probability of a false alarm (type I error):

$$\alpha = P(\textit{рішення}\, H1 | H0) = \int_{\Lambda(v)>\eta} p(x \mid H0)dx, \tag{9}$$

does not exceed a pre-set level (threshold) α0:

$$\alpha \le \alpha_0, \tag{10}$$

where α_0 – false alarm threshold.

Then the detection reliability (the probability of correctly detecting an abnormal condition) is defined as:

$$p_d = 1 - \beta. \tag{11}$$

Thus, the detection method controls the risk of false alarms (α) while minimizing the probability of missing a dangerous condition (β).

Since in practical conditions it is necessary to distinguish at least three network states, the problem is generalized to the multi-class case. The following classes are distinguished:

A_1: minimum load ($C(u) < \theta 1$) – suitable for preventive work

A_2: average load ($\theta 1 \le C(u) \le \theta 2$) – normal mode

A_3: critical load ($C(u) > \theta 2$) – a condition that carries the risk of overload

Interval classification rule:

$$A_1 : C(u) < \theta 1,\ \mathrm{A}_2 : \theta 1 \le C(u) \le \theta 2,\ \mathrm{A}_3 : C(u) > \theta 2. \tag{12}$$

Maximum likelihood classification for a multidimensional feature vector $C(u)$:

$$A(C(u)) = \arg\max_i p(C(u) \mid A_i). \tag{13}$$

Threshold values are calculated at the intersection points of the densities:

$$p(C(u) \mid A_1) = p(C(u) \mid C_2) \Rightarrow \theta_1, \tag{14}$$

$$p(C(u) \mid A_2) = p(C(u) \mid C_3) \Rightarrow \theta_2, \tag{15}$$

The combination of the likelihood ratio and the Neumann-Pearson criterion allows:

– ensure statistical optimality of decision-making;

– control the probability of misclassifications;

– generate automated decisions regarding load levels with high confidence.

As a result, the method not only detects critical modes, but also does so based on a rigorous mathematical model, taking into account the balance between first and second type errors.

The proposed method for automated detection of load levels is based on the PCVP model, centered signal values, estimation of correlation components according to the formula $\hat{B}_k(u)$, averaging over harmonic components, and application of the Neumann–Pearson criterion.

The method allows controlling the probability of type I errors, minimizing the omission of dangerous states, and applying both interval and probabilistic rules of multi-class classification.

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МОДЕРНІЗАЦІЯ ТА ДОСЛІДЖЕННЯ ПОКАЗНИКІВ ЯКОСТІ ЕЛЕКТРОПРИВОДА МЕХАНІЗМУ РОТОРНОГО ВАГОНОПЕРЕКИДАЧА З ВИКОРИСТАННЯМ СУЧАСНИХ СИСТЕМ ЕЛЕКТРОПРИВОДУ

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На сучасному етапі складної економічної ситуації в металургійній промисловості української держави склалися сприятливі та необхідні обставини для модернізації діючих виробничих фондів основного технологічного обладнання металургійних підприємств. Вдосконалення напівпровідникової техніки, розвиток, теорії керування створює умови для розробки комплектних