Intelligent signal detectors with random moment of appearance in rail lines monitoring systems

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Abstract. The article discusses the issues of building intelligent receivers of pulsed signals with an unknown arrival time without restrictions on the value of the signal-to-noise ratio under the influence of a complex of interfering factors. Using recurrent methods for detecting disturbances of random processes and an algorithm of cumulative sums, the problem of synthesizing algorithms for detecting Markov signals with random moments of appearance against the background of various combinations of destabilizing factors acting in control systems for the states of rail lines in normal and shunt operating modes is solved. To assess the efficiency of detecting a random signal by the method of cumulative sums, statistical modeling of the specified algorithm was carried out.

1 Introduction

When building intelligent receivers of pulse signals with an unknown arrival time without restrictions on the value of the signal-to-noise ratio under the influence of a complex of interfering factors, good results are obtained using the mathematical apparatus for detecting the disorder of random processes [1-3]. The disorder is understood as an abrupt change in the properties of a random process. This can be, for example, the scalar parameter of the probability density distribution $w(y_h)$ of observation y_h, where h is the number of the time sample of the signal. The issue of signal detection is solved based on the analysis of the realizations of the input action that are successively received at the input of the receiver. Since this increases the amount of memory required to memorize all observations h received at an arbitrary moment, the question arises of finding recurrent algorithms. Such algorithms are based on sufficient statistics that allow recalculating the previous values of observations taking into account the newly received ones [4, 5].

2 Methods

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Of the recurrent methods for detecting single disturbances, the cumulative sum algorithm (CSA) with a reflecting screen has found wide application [6]. It is a modified Wald sequential analysis [7]. Discrepancy detection is based on a comparison at the $(h+1)$ - the step of some decision statistics S_{h+1}, with fixed thresholds $U_{ПВ}$ and $U_{ПН}$:

$$S_{h+1} = \left[S_h + \Omega_{h+1} \right]_{U_{ПН}}^{+} \geq U_{ПВ} \; ,$$

where the sign "+" means the setting of zero of the cumulative sum at the moments of time $h(t); \quad t = 1, \ 2, \ ..., \ h(t)$ are successive times when $S_{h+i} = 0$;

$$\Omega_{h+1} = \ln \frac{w\left(y_{h+1} \big| \theta_2 \right)}{w\left(y_{h+1} \big| \theta_1 \right)} \tag{1}$$

The $U_{ПВ}$ threshold is set according to the required probability of a false detection F and determines the probability of skipping a breakdown. Thus, if at the h – the step $S_h > U_{PV}$, the hypothesis H_1 is accepted (there is a disorder): $\theta = \theta_2$. If $S_h < -U_{PN}$, the hypothesis H_0 is accepted (no discord): $\theta = \theta_1$. Otherwise, if $-U_{PN} < S_h < U_{PN}$, $(h+1)$ – the observation. However, since this violates the assumption that the entire sample belongs to the hypothesis H_1 or H_0, then in the case when the hypothesis H_0 is accepted at the h – the step, the cumulative sum is zeroed at the next step, etc., $S_{h+1} = 0$ [8-10].

3 Results and Discussions

Let us consider the problem of synthesizing algorithms for detecting Markov signals with random moments of appearance against the background of various combinations of destabilizing factors acting in control systems for the states of rail lines [11].

a. Case 1:

Let there be a sequence $\left\{ y_h \right\}, h = \overline{1, H}$

$$y_h = \theta_\tau s\left(\lambda_{ch}, \xi_h \right) + \eta\left(\xi_h \right) + n_h \; , \tag{2}$$

where λ_{ch}, ξ_h are the parameters of the useful signal $s(\lambda_{ch}, \xi_h)$ and interference $\eta(\xi_h)$, which are homogeneous discrete Markov chains with l – and r – states, transition $p_{\alpha\beta}$, $p_{\gamma\chi}$ and initial $p(\lambda_1)$ – and $p(\xi_1)$ – probabilities. The sequences $\{\lambda_{ch}\}$ and $\{\xi_h\}$ are assumed to be statistically independent. Impulse noise $\eta(\xi_h)$ is a random process emissions caused by instability of the train shunt resistance [12]. Fluctuation noise $\left\{ n_h \right\}$ is a correlated random process with a known conditional probability density $w_P\left(n_h \mid n_h - 1 \right)$.

Two hypotheses are considered regarding the parameter θ_τ:

$$\left. \begin{array}{l} H_0 : \theta_\tau = \theta_1 = 0; 0 \leq h \leq H; \\ H_1 : \theta_\tau = 0; 0 \leq h \leq \tau; \\ \theta_\tau = \theta_2 = 1; \tau \leq h \leq \tau + T; \\ \theta_\tau = 0; \tau + T < h \leq H \end{array} \right\}$$

where T is the signal duration.

The decision about the disorder is made at the moment of time h^* satisfying the condition [13]

$$h^* = \inf\{h \geq 1 : S_h \geq U_{PV}\}$$

If we restrict ourselves to considering the case of a high SIR and assume that the duration of the pulse signal T is such that $mh^* < \tau + T$, then the detection of a pulse of limited duration will be equivalent to recording a disorder of a random process (detection of the leading edge of the pulse) [14, 15]. As a result, the detection problem is solved by forming a cumulative sum:

$$S_{h+1} = \left\{ S_h + \ln I_{h+1} \left[y_{h+1}, w_P(n_h), w_h\left(\lambda_c^\beta, \xi^\gamma\right) \right] \right\}_{h(t)}^+$$

where

$$I_{h+1}(.) = \frac{\sum\limits_{\alpha,\beta}^{l} \sum\limits_{\gamma,\chi}^{r} w_{P1} p_{\alpha\beta} p_{\gamma\chi} w_{1h}\left(\lambda_c^\beta, \xi^\gamma\right)}{\sum\limits_{\gamma\chi}^{r} w_{P0} p_{\gamma\chi} w_{0h}\left(\xi^\gamma\right)} \tag{3}$$

$$\left. \begin{array}{c} w_{P1} = w_P\left[y_{h+1} - s\left(\lambda_{ch+1}^\alpha, \xi_{h+1}^\gamma\right) - \eta\left(\xi_{h+1}^\chi\right) \middle| y_h - s\left(\lambda_{ch}^\alpha, \xi_h^\gamma\right) - \eta\left(\xi_h^\chi\right) \right] \\ w_{P0} = w_P\left[y_{h+1} - \eta\left(\xi_{h+1}^\chi\right) \middle| y_h - \eta\left(\xi_h^\chi\right) \right] \end{array} \right\} \tag{4}$$

The posterior joint probability distribution densities (PDD) of the values of the signal and noise parameter $w_{1h}(\lambda_c^\beta, \xi^\gamma) = p(\lambda_c^\beta, \xi^\gamma \mid y^h{}_{h(t)}, \theta_2)$ and one noise $w_{0h}\left(\xi^\gamma\right) = p(\xi^\gamma \mid y_0{}^h, \theta_1)$ satisfy the following recurrent equations:

$$w_{1h+1}(\lambda_c^\alpha, \xi^\chi) = \frac{w_{P1}\sum\limits_{\beta,\gamma}^{l,r} p_{\alpha,\beta} p_{\gamma,\chi} w_{1h}\left(\lambda_c^\beta, \xi^\gamma\right)}{\sum\limits_{\alpha,\beta}^{l}\sum\limits_{\gamma,\chi}^{r} w_{P1} p_{\alpha,\beta} p_{\gamma,\chi} w_{1h}\left(\lambda_c^\beta, \xi^\gamma\right)};$$

$$w_{0h+1}\left(\xi^\chi\right) = \frac{w_{P0}\sum\limits_{\gamma=1}^{r} p_{\gamma,\chi} w_{0h}\left(\xi^\gamma\right)}{\sum\limits_{\gamma}^{l}\sum\limits_{\chi}^{r} w_{P0} p_{\gamma,\chi} w_{0h}\left(\xi^\gamma\right)}, \qquad (5)$$

$$\alpha, \beta = \overline{1, l}; \gamma, \chi = \overline{1, r}.$$

The recurrent algorithm for the formation of a posteriori PDD allows not to keep in memory all the previously received count of signals $y_1, y_2, ..., y_h$, since they are included in the PDD $w_{1h}\left(\lambda^\alpha, \xi^\gamma\right)$ already formed at the previous step. This algorithm can be divided into two procedures performed in stages. Let us analyze this by the example of the PDD $w_{0h+1}\left(\xi^\chi\right)$. At the first stage of calculating the PDD, extrapolation of the previous posteriori PDD is carried out by the step size T_0 to the moment of the next observation [16, 17]. The extrapolated estimate of the probability distribution density has the form:

$$w_{0h+1_3}\left(\xi^\chi\right) = \sum_{\gamma=1}^{r} p_{\gamma\chi} w_{0h}\left(\xi^\gamma\right)$$

At the second stage, a new posteriori PDD is formed based on the extrapolated estimate $w_{0h+1_3}\left(\xi^\chi\right)$ and the next observation y_{h+l}. As a result, we get:

$$w_{0h+1}\left(\xi^\chi\right) = \frac{w_{P0} w_{0h+1_3}\left(\xi^\chi\right)}{\sum\limits_{\gamma=1}^{r} w_{P0} w_{0h+1_3}\left(\xi^\chi\right)}$$

The last entry allows us to consider the extrapolated PDD $w_{0h+1_3}\left(\xi^\chi\right)$ as a priori with respect to the next observation.

Similar ratios can be written for posteriori PDD $w_{1h+1}(\lambda_c^\alpha, \xi^\chi)$.

At the moment of zeroing the cumulative sums h (t), each time, it is necessary to form a new initial PDD $w_{1h(t)}(\lambda^\beta_{h(t)}, \xi^\gamma_{h(t)})$.

From the above algorithm, we single out a particular case of signal detection against the background of interference with independent values [18]. For this, in the presented formulas, instead of conditional PDD and calculated based on expressions (4), it is sufficient to substitute one-dimensional PDD:

$$w_{n1} = w_n \left[y_{h+1} - s\left(\lambda^\alpha_{ch+1}, \xi^\gamma_{h+1} \right) - \eta\left(\xi^\chi_{h+1} \right) \right],$$
$$w_{n0} = w_n [y_{h+1} - \eta(\xi^\chi_{h+1})]$$

b. Case 2

Let the observation have access to the sequence

$$y_h = \theta_\tau + \xi_h + n_h \qquad (6)$$

where θ_τ is the signal amplitude varying at an unknown time moment τ; n_h is fluctuation noise with a known non-Gaussian PDD $w_n(n_h)$, the parameters of which change at the time of the breakdown; impulse noise described by a Markov chain with discrete time and a finite number of inconsistent states $\xi^{(1)}, \xi^{(2)}, \dots \xi^{(l)}$. The random variables $\{\xi h\}$ are given by the matrix of transition probabilities:

$$\left\| p\left\{ \xi_{h+1} = \xi^\alpha \middle| \xi_h = \xi^\beta \right\} \right\| = \left\| p_{\alpha\beta} \right\|, \alpha, \beta = \overline{1,l}$$

vector of initial probabilities $\| p_1, p_2, \dots, p_l \|$ and vector of initial values $\| \xi_0^{(1)}, \xi_0^{(2)}, \dots, \xi_0^{(l)}, \|$

Obviously, (6) is a special case of (2) for $s(.) = l; \eta(\xi) = \xi$. Two hypotheses are considered regarding the parameter θ_τ:

$$H_0 : \theta_\tau = \theta_1, w_P\left(n_h, \sigma_p^2 \neq 0 \right), h = \overline{1,H};$$
$$H_1 : \theta_\tau = \theta_1, w_P\left(n_h, \sigma_p^2 \neq 0 \right), h = \overline{1, \tau - 1};$$
$$\theta_\tau = \theta_2, w_P\left(n_h, \sigma_p^2 = 0 \right), h = \overline{\tau, H}$$

For the case under consideration, we write the CSA in the form [19, 20]:

$$S_{h+1} = \left\{ S_h + \ln I_{h+1} \left[y_0^{h+1}, w\left(\xi_h \middle| y_0^h \right), \theta_\tau \right] \right\}^+ \qquad (7)$$

where $y_0^{h+1} = \{ y_1, y_1, \dots, y_{h+1}, \}$ is vector of observed realization; $w(\xi_h \mid y_0^h)$ is posteriori PDD of the unobservable Markov component ξ_h. Function:

$$I_{h+1}[.] = \frac{\sum\limits_{\xi_h, \xi_{h+1}}^{l} w_{P2}\left(y_{h+1} \middle| \xi_{h+1}, \theta_\tau = \theta_2 \right) w\left(\xi_h \middle| y_0^h, \theta_\tau = \theta_2 \right) p_{\alpha\beta}}{\sum\limits_{\xi_h, \xi_{h+1}}^{l} w_{P1}\left(y_{h+1} \middle| \xi_{h+1}, \theta_\tau = \theta_1 \right) w\left(\xi_h \middle| y_0^h, \theta_\tau = \theta_1 \right) p_{\alpha\beta}} \qquad (8)$$

characterizes the change in the likelihood ratio at the $(h + 1)$ – the step, where $w_{n1}(.) = w_n(n_h, \sigma_p^2 = 0)$, $w_{n2}(.) = w_n(n_h, \sigma_p^2 \neq 0)$.

The initial posteriori PDD are calculated as follows:

$$w\left(\xi_1 \middle| y_1, \theta_i\right) = \frac{w_{P2}\left(y_1 - \xi_2 - \theta_i\right) p_\alpha}{\sum\limits_{\alpha=1}^{l} w_{P1}\left(y_1 - \xi_1 - \theta_i\right) p_\alpha}, \alpha = \overline{1,2}$$

In what follows, calculations using the CSA are performed similarly to case 1.

c. Evaluation of the efficiency of algorithms for detecting signals with an unknown appearance time by the CSA method against the background of a complex of destabilizing factors

Let us consider specific examples of the synthesis of algorithms for detecting signals by the CSA method and evaluating their work efficiency. Let it be required to detect a change in the voltage amplitude θ_τ at the receiver's input under the action of white Gaussian noise n_h, $n_h \in N\left(0, \sigma^2\right)$. Observationally available implementation:

$$y_h = \theta_\tau + n_h.$$

Two hypotheses are considered regarding the amplitude of the useful signal θ_τ:

$$H_0 : \theta_\tau = \theta_1; n_h \in N\left(0, \sigma^2\right);$$
$$H_1 : \theta_\tau = \theta_1; n_h \in N\left(0, \sigma^2\right);$$
$$\theta_\tau = \theta_2; n_h \in N\left(0, \sigma^2\right)$$

Using the cumulative sum algorithm [2], we write:

$$S_{h+1} = \left\{ S_h + \ln \frac{w_N\left(y_{h+1} \middle| \theta_2\right)}{w_{sh}\left(y_{h+1} \middle| \theta_1\right)} \right\}^+ \geq U_{PV}, S_0 = 0,$$

where w_H, $w_{ш}$ are the probability distribution densities of the signal y_h in normal and shunt modes:

$$w_{sh}(y_{h+1} \middle| \theta_1) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ -\frac{\left(y_{h+1} - \theta_1\right)^2}{2\sigma^2} \right\},$$
$$w_N(y_{h+1} \middle| \theta_2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ -\frac{\left(y_{h+1} - \theta_2\right)^2}{2\sigma^2} \right\}$$

To assess the efficiency of detecting a random signal by the method of cumulative sums for this observation, statistical modeling of the specified algorithm was carried out. Sampled values of the realization y_h were fed to the input of the receiving device, in which, after a certain number of reports, the amplitude of the useful signal changed. The amplitude of the useful signal θ was considered known: $\theta_1 = 4.8$ V in the shunt mode, $\theta_2 = 6.572$ V – in the normal mode and unchanged in the observation interval. Figure 1 illustrates the wave diagrams of the input process y_h and the behavior of the cumulative sum S_h; the detection of a disorder from the moment the pulse front appears and the solution of the receiver H. Parameters of white Gaussian noise, respectively $\sigma = 0.32$ V.

In total, 31500 realizations of the described random process were considered: 13500 realizations in the normal one; 18000 realizations in shunt mode. Based on the results of

statistical modeling, estimates of the probabilities of missing a useful signal P_{PR} in the normal mode and false signal detection in the shunt mode P_{LO}

$$P_{PR} = \frac{n_{PR}}{N_N},$$

$$P_{LO} = \frac{n_{LO}}{N_{Sh}}$$

where n_{PR}, n_{LO} is the number of cases of missing and false signal detection; N_N, N_{Sh} is total number of realizations in normal and shunt modes.
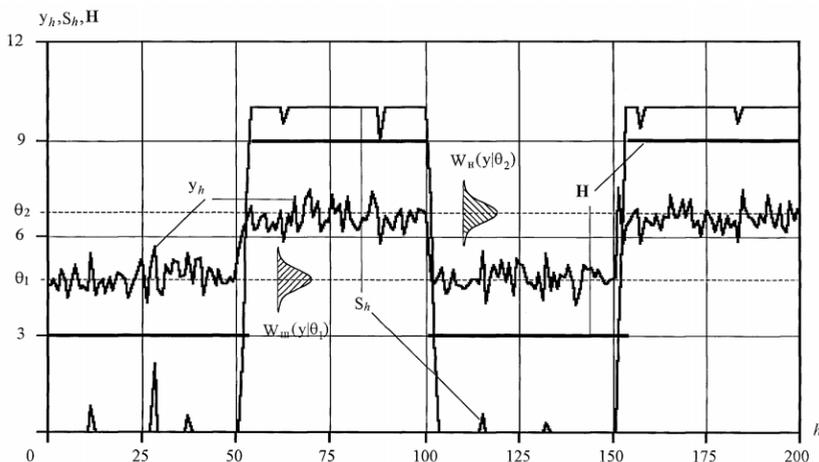

Fig.1. Wave diagrams of the observed realization y_h, the cumulative sum Sh and the solution of the receiver H

Figure 2, *a* illustrates the dependence of the probability of missing a useful signal P_{PR} on the root-mean-square deviation of the noise σ for various thresholds of disorder U_{PR}. From the analysis of the obtained dependences, it follows that with an increase in the standard deviation of the interference σ, the probability of missing the useful signal P_{PR} increases.

In figure 2, *b* shows the probabilities of false detection of R_{LO} from the standard deviation of white Gaussian noise σ for different values of the thresholds of the mismatch U_{PV}. With an increase in the value of the threshold U_{PV}, the probability of false detection R_{LO} decreases.
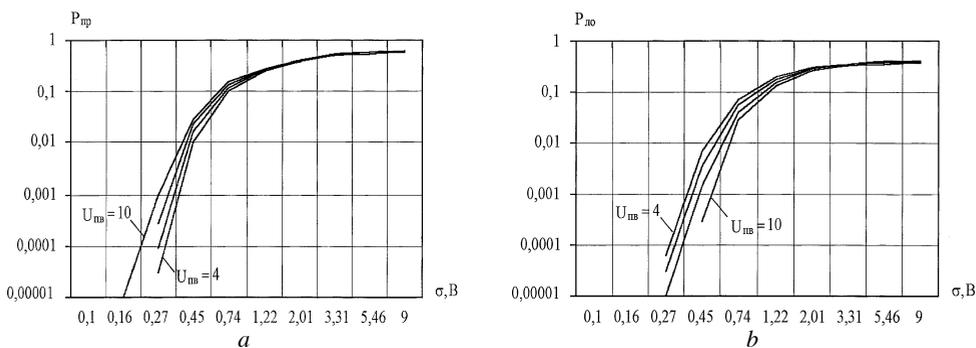
Fig.2. Dependences of the probabilities of missing P_{PR} (a) and false detection P_{LO} (b) on the values of the standard deviation of fluctuation noise σ

Let us consider the case when, in the shunt mode, both fluctuation noise n_h and impulse noise ξ_h, caused by the instability of the resistance of the train shunt. Let ξ_h be the impulse component described by a Markov chain with discrete time and a finite number of inconsistent states. The random variables $\{\xi_h\}$ are given by the matrix of transition probabilities

$$\left\|P_{\alpha\beta}\right\| = \left\|P\left\{\xi_{h+1} = \xi^\alpha \middle| \xi_h = \xi^\beta\right\}\right\|, \alpha, \beta = \overline{1,2}$$

vector of initial probabilities $\| P_1 \; P_2 \|$ and vector of initial values $\left\|\xi_0^{(1)} \xi_0^{(2)}\right\|$. The implementation at the receiver input has the form:

$$y_h = \theta_\tau + \xi_h + n_h$$

Using the cumulative sum algorithm, we write:

$$S_{h+1} = \left\{S_h + \ln I_{h+1}\left[y_0^{h+1}, w\left(\xi_h \middle| y_0^h\right), \theta_\tau\right]\right\}^+ \geq U_{PV}, S_0 = 0$$

where $\theta_1 = 4.8 \; B$, $\theta_2 = 6.572 \; B$;

$y_0^{h+1} = \{y_1, y_2, \ldots, y_{h+1}\}$ is vector of observed realization;

$w(\xi_h \mid y_0^h)$ is the posterior probability density of the unobservable component ξ_h;

$$I_{h+1}[.] = \frac{w_{sh}\left(y_{h+1} \middle| \theta_\tau = \theta_2\right)}{\sum\limits_{\xi_h, \xi_{h+1}}^{l} w_{sh}\left(y_{h+1} \middle| \xi_{h+1}, \theta_\tau = \theta_1\right) w\left(\xi_h \middle| y_0^h, \theta_\tau = \theta_1\right) P_{\alpha\beta}}$$

4 Conclusions

In the simulation, 18000 realizations were considered in shunt mode. As a result of the research, the dependence of the probabilities of false detection $P_{ЛO}$ on the variance of interference. With an increase in the value of the root-mean-square deviation of the noise σ, the probability of false detection $P_{ЛO}$ increases.
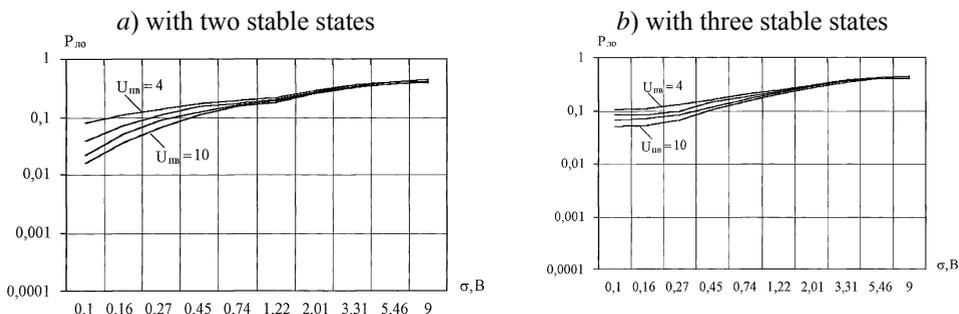
Fig.3. Dependences of the probabilities of false detection under the influence of a complex of fluctuation noise and an impulse component of interference caused by the instability of the resistance of the train shunt of a two-axle railcar
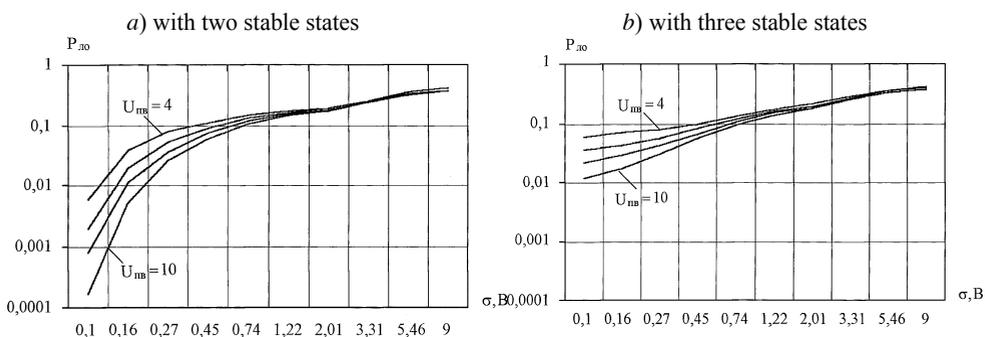

Fig. 4. Dependences of the probabilities of false detection under the influence of a complex of fluctuation noise and an impulse component of interference caused by the instability of the resistance of the train shunt of a three-axle railcar
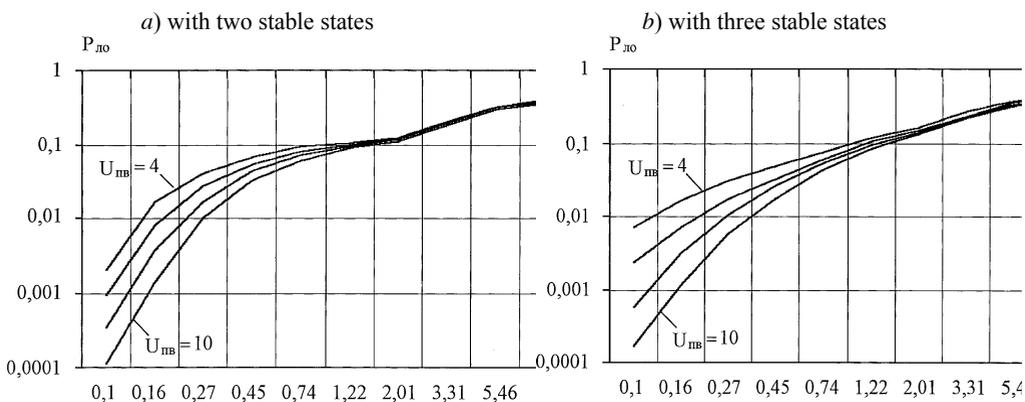

Fig. 5. Dependences of the probabilities of false detection under the influence of the complex of fluctuation noise and the impulse component of the noise caused by the instability of the resistance of the train shunt of the diesel locomotive

   d. In figure 3 shows the probabilities of false detection $P_{ЛО}$ from the standard deviation of white Gaussian noise σ when in the shunt mode, impulse noise is affected due to the instability of the resistance of the train shunt of a biaxial railcar for various states of the tread surface: a - clean and b - contaminated.

   e. Figure 4 illustrates the dependence of the probabilities of false detection $P_{ЛО}$ when in the shunt mode there is interference caused by the instability of the resistance of the train shunt of the TU-5 diesel locomotive on the section with a clean rolling surface - a and with a rust-covered layer - b.

   f. In figure 5 shows the probabilities of false detection $P_{ЛО}$ from the standard deviation of white Gaussian noise σ when in the shunt mode there is interference caused by the instability of the resistance of the train shunt of a triaxial railcar for various states of the rolling surface: a - clean and b - contaminated.

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