USE OF AN ALGORITHM OF CUMULATIVE SUMS TO THE DETECTION OF STEAM-GENERATOR LEAKS

I. E. Lazarevskaya and S. A. Morozov

Rapid detection of leaks in sodium-water steam generators is still important today. Modern computers with well developed capabilities for prompt processing of experimental data can be used to run complex but effective algorithms for sequential detection of changes in the properties of signals from primary transducers. Our aim here is to demonstrate that a computer using a modified algorithm of cumulative sums can indicate small leaks in sodium-water steam generators on the basis of signals from regular magnetic flowmeters.

When the tubes of a steam generator perforate suddenly the modulation of the loop cross section at the site of the leakage of the water-sodium reaction products causes an abrupt change in the sodium flow (piston effect), whereupon hydrogen bubbles appear in the loop. Magnetic flowmeter methods usually take account of piston effect that arise at high water flow rates (tens of grams per second). It was assumed that in the case of comparatively small leaks analysis of the magnetic flowmeter signals at the fluctuation level makes it possible, until a "nucleation signal" appears, to affect the changes-precursors caused by the piston effect. The detection of small leaks, therefore, was considered as a problem of sequential detection of changes in the properties of the fluctuation signal of the magnetic flowmeter. The following approach was taken to solve this problem: the stationary part of the signal was represented by a parametric model and significant changes in the parameters of the model were revealed by means of a statistical test.

The parametric description of the signals was constructed on the basis of the autoregression models $y_t = \sum_{i=1}^{P} a_i y_{t-i} + (1 - \sum_{i=1}^{P} a_i) m + e_t$, where $\{y_t, t = 1, ..., N\}$ is the observed time series with mean value $m$, $A = \{a_i, i = 1, ..., P\}$ are the coefficients of the autoregression model ($P$ is the order of the model), and $e_t$ is the white noise with zero mean and variance $\sigma^2$.

To find the changes in the parameters of the model we checked two alternative hypotheses:

$H_0$: the time series $(y_1 - m), ..., (y_N - m)$ is described by the model $M_0$ with $\theta_0 = \{A_0, m_0, \sigma_0\}$, where $m_0, \sigma_0$ are the parameters of the distribution of the residual sequence $e_t$;

$H_1$: at the time $T$ (onset of leak) there is an abrupt change of model so that the sample $(y_1 - m), ..., (y_T - m)$ is described by the model $M_0$ with $\theta_0 = \{A_0, m_0, \sigma_0\}$, and the sample $(y_{T+1} - m), ..., (y_N - m)$ is described by the model $M_1$ with $\theta_1 = \{A_1, m_1, \sigma_1\}$.

As test statistics we considered the statistics obtained from the asymptotic expansion of the logarithm of the likelihood ratio of those hypotheses [1]. The statistics involve a reasonable computing time and are very suitable for detecting small changes in the parameters of the models. Version III of the algorithm of cumulative sums was chosen because of the lack of information about the parameters of the model after the change and the segment of the signal until it disintegrates is long enough for $\theta_0$ to be determined. It is assumed for this version that after the signal decays the vector $\theta$ goes beyond the limits of the ellipsoid determined by the Fisher information matrix in parametric space, i.e., $H_0$: $\theta = \theta_0$; $H_1$: $(\theta - \theta_0) F(\theta - \theta_0) \geq \lambda^2$, where $\lambda^2$ is the limiting value of the noncentrality parameter. The initial problem of detection of a change in the properties of a sequence $(y_t - m)$ is replaced by the problem of detection of the time when the noncentrality parameter of the $\chi^2$ distribution changes from 0 to $\lambda^2$ [2]. The corresponding decision function $g_t$ is close to zero until the signal disintegrates near zero and then begins to increase and reach the threshold $h$ once the signal has passed [1]. If $g_t \geq h$, a decision is made about
the passage of the parameter vector \( \theta \) in the region of the disintegrated state. The adjustment of version III of the algorithm of cumulative sums is determined by the assignment of the autoregression model parameters and the choice of vector \( \theta \) of the monitored parameters, the noncentrality parameter \( \chi^2 \), and the threshold \( h \).

The chosen detection algorithm, giving approximations of the times of signal decay, was adjusted and checked with experimental data obtained on the MT stand at the Moscow Power Engineering Institute and section 6A1 of the N-200M steam generator of the BN-600 fast reactor facility. Small leaks (0.01 to 2 g/sec in terms of water) were simulated by injections of steam and gas on the MT stand and argon and hydrogen in the BN-600.

The signals from magnetic flowmeters installed on the exit pipes (Du 70 on the MT stand and Du 300 on the N-200M) and on the release lines (Du 40) were recorded on a magnetograph and then processed on an IBM PC/AT. Each recording of an injection was preceded by a background signal segment 120-160 sec long with a discretization interval of 0.04 sec.

The parameters of autoregression models were determined with the aid of the Levinson–Durbin algorithm. The algorithm makes a recurrent estimation of the models for an increasing order, which is adjusted to the value of the given time series. The orders of the models were chosen by the Akaike test [3].

It was found that fragments of the background fluctuations of the magnetic flowmeter signals are approximated well by pure autoregression models if the signals analyzed were not previously "distorted" instrumental filtering. Since the information given by autoregression coefficients includes information about the characteristics of the filters through which the signal passed, "spoiled" signals fit more complex higher-order or "cascade" models with

\[
y_i^{(k-1)} = \sum_{i=1}^{p_k} a_{ik} y_{i-1}^{(k-1)} + y_i^{(k)}
\]

for \( k = 1 \ldots K, K \leq 3 \), where \( y_i^{(0)} = (y_i - m) \) is the observed centered time series and \( y_i^{(K)} = e_i \) is the white noise. The ability of the model as a linear filter to stably "bleach" the initial background signal, and not the optimal structure, is important for the given application. It has been ascertained that the orders of the approximating models does not change on segments where an injection is recorded, in contrast to the nucleation effect segments.