NUCET NUCLEAR ENERGY AND TECHNOLOGY

Nuclear Energy and Technology 7(1): 67–72
DOI 10.3897/nucet.7.65446

Research Article

Efficient method for the global noise filtering in measuring channels of the VVER NPP leak monitoring systems*

Yevgeniy L. Trykov[1], Andrey A. Kudryaev[1], Konstantin I. Kotsoyev[2,3], Aleksey A. Ananyev[1]

1 *JSC STC Diaprom, 6 Koroleva St., rooms 22-23, 249031 Obninsk, Kaluga Reg. Russia*
2 *KVANT PROGRAMM Ltd, 5/12 Zeleny Av., bldg. 3, room B1, 111558 Moscow, Russia*
3 *N.E. Bauman Moscow State Technical University, 5/1 2-ya Baumanskaya St., 105005 Moscow, Russia*

Corresponding author: Yevgeniy L. Trykov (trykov@diaprom.ru)

Academic editor: Yury Korovin ♦ **Received** 12 May 2020 ♦ **Accepted** 20 December 2020 ♦ **Published** @ ##### 2021

Citation: Trykov YL, Kudryaev AA, Kotsoyev KI, Ananyev AA (2021) Efficient method for the global noise filtering in measuring channels of the VVER NPP leak monitoring systems. Nuclear Energy and Technology 7(1): 67–72. https://doi.org/10.3897/nucet.7.65446

Abstract

In accordance with Ref. (GOST R 58328-2018 "Pipelines of Nuclear Power Plants. Leak Before Break Concept"), NPPs with VVER-1200 reactors operate an acoustic leak monitoring system (ALMS) and a humidity leak monitoring system (HLMS), each performing the leak monitoring functions locally, independently of the other. The diagnostics results are conveyed to the upper level control system (LCS) to be further displayed for the main control room (MCR) operating personnel. There is also an integrated diagnostics system (IDS) intended to confirm the diagnosis and to update the leak rate values and coordinates based on analyzing the leak monitoring system readings and I&C signals. The system measuring channel readings are composed of background noise, the source for which are processes on the part of the reactor facility's key components and auxiliary systems, and the leak signal in response to the leak occurrence. A major factor that affects the capability of leak monitoring systems to detect the leak is the quality of the background noise filtering. A new efficient global noise filtering method is proposed for being used as part of the integrated diagnostics system (IDS).

Keywords

Filtering, acoustic sensors, humidity sensors, leak analysis, background noise, algorithm, safety

Introduction

The primary and secondary circuit acoustic leak monitoring systems (ALMS and ALMS-C2) are most sensitive to all of the events which occur in the reactor facility. In fact, a distinctive feature of a reactor facility as a source of acoustic noise is the complexity of the processes taking place in it, involving a great deal of constrains hard to take into account. These are physically different processes (mechanical, hydrodynamic, vibrational, impact, induced by vapor generation and bubbling, etc.). All this gives birth to a great variety of acoustic sources effective

* Russian text published: Izvestiya vuzov. Yadernaya Energetika (ISSN 0204-3327), 2020, n. 4, pp. 86–95.

in various frequency bands depending on the facility operating mode, the composition of the equipment in operation, and many other factors. By amplitude, ambient noise is comparable with the useful leak signal which may lead to malfunctions of the diagnostic system.

An algorithm has therefore been developed in this study which makes it possible to filter acoustic noise in the measuring channel readings and receive only useful leak signals in the course of acoustic measurements.

Process noise propagates over the metal surface and manifests itself in readings of most measuring channels depending, to a smaller or greater extent, on the sensor installation point. This allowed proposing a background noise filtering algorithm which is based on predicting the signal from the given measuring channel using a regression model built on the basis of the information redundancy principle.

The stability of the proposed algorithm to different background acoustic bursts has been investigated.

The developed algorithm was demonstrated based on the ALMS acoustic signals while being also fully applicable both to the HLMS system and similar secondary circuit systems.

Input

Recording of current information

The input for the integrated assessment of the reactor equipment integrity is information received from

- the ALMS and the HLMS (leak and probable leak detectors, leak rate values and coordinates, as well as values of the acoustic and humidity measuring channel (MC) signals for all piping segments monitored by the system);
- I&C process and radiation monitoring systems (inert gas reactivity sensor signals).

Data validity

Data validity monitoring is used to ensure that no invalid data is used for the calculation, and involves validity testing of the signal received.

Data validity is monitored by the connection status using the conventions adopted in the IDS architecture. Where the communication is lost for all channels, the IDS server sends out the last obtained value with the validity attribute “transmission channel failure”.

Validity monitoring based on the validity attributes of the received signal: the transmitted values of validity attributes from leak monitoring and I&C systems, in the event of being invalid, are not equal to 0x00 in the hexadecimal notation. More detailed information on the validity attributes is contained in the integrator documents and may vary among designs.

Data analysis and diagnosis formation

Computational and experimental justification of the algorithm for the ALMS

It is expected in the development of the algorithm under consideration that the reactor facility global noise is recorded identically by all of the acoustic system’s MCs. Since the cause for this noise is common for the MCs in each loop (which is confirmed by the signal cross correlation coefficients the average value of which amounts to 0.65), the signals in the presence of noise can be presented in a vector form:

$$\boldsymbol{s}(t) = \boldsymbol{q}(t) + \mathbf{d}(t), \tag{1}$$

where $\boldsymbol{s}(t)$ is the system MC readings; $\boldsymbol{q}(t)$ is the global noise; and $\mathbf{d}(t)$ is the local signal.

Therefore, the global noise filtering problem is reduced to finding the unknown function $\boldsymbol{q}(t)$ and deducing same from the known signal $\boldsymbol{s}(t)$. The values of any MC readings $\boldsymbol{s}_i(t)$ for the i-th segment can be expressed through the MC readings for the adjacent segments using a regression model. Such approach was proposed in (Skomorokhov et al. 2010) where a group data handling method (GDHM) was used as the regression model. Two types of regression models were explored in the algorithm proposed below: a two-layer neural network based on which the nonlinear regression was built, and a linear Bayesian robust regression model (both are described hereinafter). As compared with (Skomorokhov et al. 2010), good results have been achieved in predicting the global acoustic noise thanks to using exactly the Bayesian robust regression model and Kalman residual signal filtering.

Further, we shall consider the principles of building regression models separately for the primary circuit and the secondary circuit.

A very high correlation is observed in both circuits for nearly all MC signals, and the correlation coefficient represents a significant value. A regression was so built in the study for each MC signal in the particular reactor facility portion depending on the signals from all MCs in other loops (three loops), as well as on the signals from MCs in other segments in the same loop. As a result, there were four regressions obtained for each MC. This is quite enough to ensure the stability of the algorithm to a change in the state or to the failure of other MCs (predictors) since too many MCs may not fail during one life cycle.

Using the proposed grouping, one can describe the common part of the signal from each MC, $\boldsymbol{q}(t)$, as a function of the signals from other MCs in four different ways. Therefore, it is possible to predict the signal from any MC based on signals from the MCs in other loops (belonging to one pipeline type), as well as based on signals from the MCs in the same loop but in the segment in another room.

Therefore, there were four dependences obtained for each signal. A neural network (Goodfellow et al. 2016; Nikolayenko et al. 2018; Chollet 2017) with one inlet layer, one hidden layer with a dimension of 30, and one outlet layer was used initially to determine these dependences. Here

$$\boldsymbol{q}_i(t) = net\ (\ (\boldsymbol{s}_i\ (t), \sum_j \boldsymbol{s}_j\ (t)\ ), \tag{2}$$

where $\boldsymbol{s}_i\ (t)$ is the signal in the i-th MC for which the regressions were built; $\boldsymbol{s}_j\ (t)$ is the signals from MCs in another loop or another sections based on which the regression was counted; $\boldsymbol{q}_i(t)$ is the global noise vector for the i-th MC calculated using different regressions; and *net* is the trained neural network consisting of two fully connected layers with 30 neurons each, into which the values of the MC signals $\boldsymbol{s}_j\ (t)$ are plugged.

This regression model is nonlinear and, therefore, even minor changes in the operation of the measuring channels may lead to major deviations in its application results. Fig. 1 presents the results of applying two different regression models to the signal from the first acoustic MC for the life cycle that started after the preventive maintenance as from 20.04.2018.

Shown in dark-grey is the regression obtained using formula (2) based on data for the period of 20 May through 20 June 2018 and propagated to all of the currently available data. It can be seen that it describes the original signal not in the best way possible. At the same time, the light-grey curve obtained for the period of 3 May through 3 June 2018 describes pretty well the entire set of data. This curve was obtained as the result of using the linear robust Bayesian regression model (Kruschke 2013; Cameron 2016; Barber 2017)

$$\boldsymbol{q}_i(t) = \sum_j \beta_j \boldsymbol{s}_j\ (t) + \xi(t), \tag{3}$$

where $\xi(t)$ is the regression error having a Student distribution.

Student distribution has thicker "tail areas" than normal distribution and it is therefore more stable to different bursts in data (Kruschke 2013). Unlike Gaussian distribution when the problem solution is reduced to finding the pseudoinverse matrix in the least square method, the problem of minimizing the negative log-likelihood from the Student distribution needs to be addressed directly here. The result however justifies such computational efforts.

All of the further analysis was based on regression model (3). Calculations have shown that it is enough to build the regression using model (3) for one day to reproduce in an acceptable manner the lifetime data.

Sharp peaks occur in acoustic MC signals during the reactor warm-up and cooldown, this being immediately connected with the RCP operation in the reactor primary circuit. These acoustic bursts caused by the RCP startup at a low pressure in the circuit are highly significant (they have a value of about 5000 μV). With such signals, the acoustic sensor response turns heavily nonlinear, and it becomes impossible to find out if there is a leak. The thing is that the integral signal that comes from acoustic MCs is, in fact, a dispersion of the actual signal and, therefore, the signal from the leak is quadratically added to the background signal, that is

$$U_{\text{tot}}^{\ 2} = U_{\text{back}}^{\ 2} + U_{\text{leak}}^{\ 2}, \tag{4}$$

where U_{back} is the background signal; U_{leak} is the leak signal; and U_{tot} is the total signal.

The obtained regression dependences for each MC were used to calculate the values of acoustic signals with the filtered global noise $\mathbf{d}_i^j(t) = \boldsymbol{s}_i\ (t) - \boldsymbol{q}_i^j(t)$, where i is the MC number; and j is the regression dependence number. Therefore, if there is a leak in any piping segment, two different situations are possible.

- The leak occurred in the segment with the MC under consideration. Then all values $\mathbf{d}_i^j\ (t)$ will vary according to the noise caused by the leakage, and

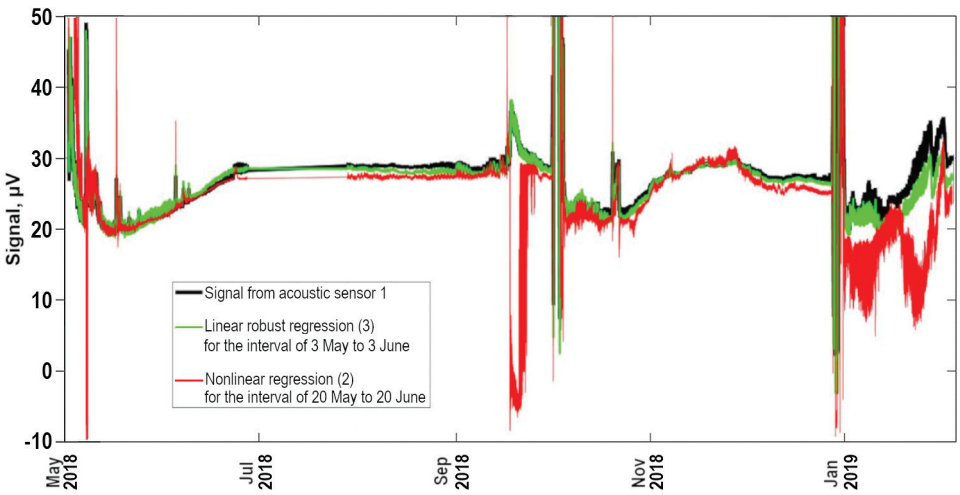

Figure 1. Application of regression models to the description of the signal from acoustic MC 1 for the 2018–2019 life cycle.

$\mathbf{d}_i(t) = |\min_{(i)} \mathbf{d}_i^j(t)|$ is the sought-after leak signal with the filtered global noise which is compared with the given setpoints.

- The leak occurred in another segment, j. Then the regression dependence $\boldsymbol{q}_i^j(t)$ for given MC i will be wrong, but the others, $\boldsymbol{q}_i^k(t)$, where $k \neq j$, will give correct values, and the expression $\mathbf{d}_i(t) = |\min_{(k)} \mathbf{d}_i^k(t)|$ will remain valid, and the value $\mathbf{d}_i(t)$ for the i-th MC will not contain the leak signal. It should be noted here that the more regressions are considered, the more reliable will be the result. Therefore, if regressions are considered not cumulatively from all MCs in the adjoining loops but from all MCs in each segment in all loops, we shall then have 11 regressions for each MC in the loop.

The resultant quantity $\mathbf{d}_i(t)$ is an observed random signal which contains a measurement error, as well as a global noise filtering (regression dependence) error. In order to obtain the optimum signal from this, we shall consider the problem at hand in a state space model where the optimum solution is achieved thanks to the use of a Kalman filter (Najim 2008; Durbin and Koopman 2012; Haykin 2014; Grewal and Andrews 2015).

It is assumed in the system model that the actual hidden state at the time t+1 results from the state at the time t according to the state equation

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\cdot\boldsymbol{x}(t) + \boldsymbol{\varepsilon}(t), \tag{5}$$

where $\boldsymbol{A}$ is the state space matrix; and $\boldsymbol{\varepsilon}$ is the state space error vector, and the measurement vector $\mathbf{d}_i$ is connected with the state vector of the equation system

$$\mathbf{d}_i(t) = \boldsymbol{C}\cdot\boldsymbol{x}(t) + \boldsymbol{\omega}(t), \tag{6}$$

where $\boldsymbol{C}$ is the measurement matrix; and $\boldsymbol{\omega}$ is the measurement error vector.

The Kalman filter iteration is divided into two phases: prediction and registration of observations. The prediction phase uses the state calculated at the previous step for obtaining the evaluated state at the current step through the system model. At the observation registration phase, information on the measurements performed at the current step is used to update information on the system state, which, as a result, makes this information more accurate. Kalman filter is the best way to make the signal obtained by measurements in a linear system with Gaussian noise as close to the actual value as possible.

Fig. 2 presents diagrams of the initial signals $\boldsymbol{s}_i(t)$ and the signals $\mathbf{d}_i(t)$ filtered of global noise using regressions and optimized by the Kalman filter. Evidently, the frequency of false responses with signals cleared of global noise decreases considerably both for the acoustic system and the humidity system.

Let us consider how the quantity $\mathbf{d}_i(t)$ will change in the j-th piping segment if the acoustic MC fails elsewhere in another segment. In this case, the regression dependence of global noise for acoustic MCs in the segment j on the segment with the failed MCs will be wrong. However, as a result of the operation of the algorithm proposed above, the resultant quantity $\mathbf{d}_i(t)$ will not differ greatly from the case when all acoustic MCs in all segments operated normally. The result of the considered situation is presented in Fig. 3.

Fig. 3a shows a standard situation, and the readings in Fig. 3b for acoustic MC 32 in the U-shaped bend in loop 4 have been artificially changed by 500 μV. It can be seen that the quantities $\mathbf{d}_i(t)$ obtained for this MC based on four and three regressions do not practically differ. Further, it is planned to consider the dependence of the signal from each MC not simply on the signals from MCs in other loops but from MCs in other segments. We shall have then 11 regressions instead of four (since there are three segments in each loop) which will make it possible for the algorithm to achieve a much greater reliability and stability of results in the event of the MC failure in other segments.

We shall note that it is possible to filter global noise exactly in the same way for the HLMS as well. Absolute

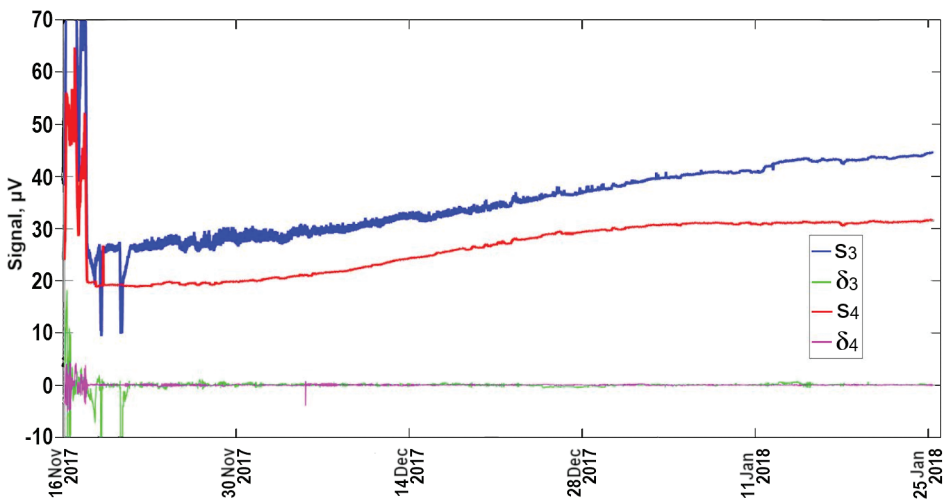

Figure 2. Signal quantities $\boldsymbol{s}_i(t)$ and $\mathbf{d}_i(t)$ for some of the acoustic MCs.

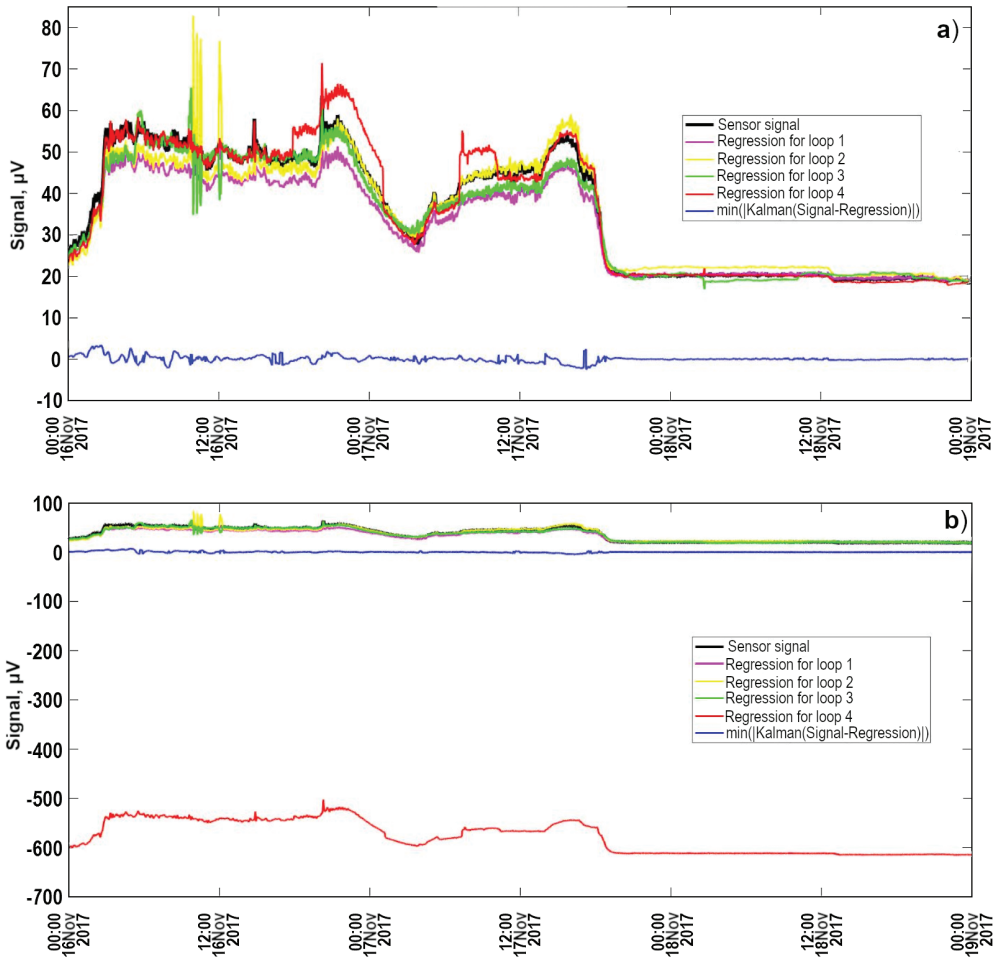

Figure 3. Signals, regressions and $\mathbf{d}_i(t)$: a) for the first acoustic MC in a standard situation; b) in the event of failed MC 32 (loop 4).

humidity is compared here with the threshold value (the threshold value is 0.375 kg/m^3). It is even easier to filter global noise in the event of a humidity system than for an acoustic system since the values of the signals from the HLMS MCs are rather smooth and do not have bursts throughout the life cycle.

Leak simulation

Let us show how the enhancement of signals from acoustic and humidity MCs is interpreted by the integrated diagnostics system (IDS). To this end, signals, which change smoothly from 0 to 300 μV and simulate the leak in this pipeline segment, were added to the current readings of the acoustic MCs in the cold leg of loop 1 (the MC numbers are 1, 2, and 3).

Since there had not been leaks from the circuit components at unit 6 with the VVER-1200 reactor at the Novovoronezh NPP the experimental data from which was used in this study, model data was used obtained based on the ALMS experimental justification at a dedicated test bench, as well as based on the available data on leaks with rated parameters of the operating reactor facilities.

The initial ALMS specifications require that a leak of 3.9 l per min and more should be detected. Therefore, based on the ALMS experimental justification results, the value of the acoustic signal sensitivity to leakage was determined as being equal to 55 μV per liter per minute. Proceeding from this, the threshold leak acoustic signal has been shown to have a value of 200 μV.

As an example, Fig. 4a shows how the quantity $\mathbf{d}_1(t)$ behaves for the given pipeline segment, and Fig. 4b shows the behavior of the signal from MC 14 and of the quantity $\mathbf{d}_{14}(t)$ in the segment, for which no leak is simulated, but the segment with a leak takes part in the regression analysis of the MC signal values.

We can see that there is a leak only in the segment, for which it is simulated, though the regression for the leaking segment (for loop 1 in Fig. 4b) is wrong. Therefore, as a result of the algorithm operation, a leak is observed only in the segment in which it is simulated.

Conclusions

A reliable and stable algorithm has been developed for the integrated analysis of the VVER reactor pipeline leakage. It is based on filtering global noises in the MC signals and

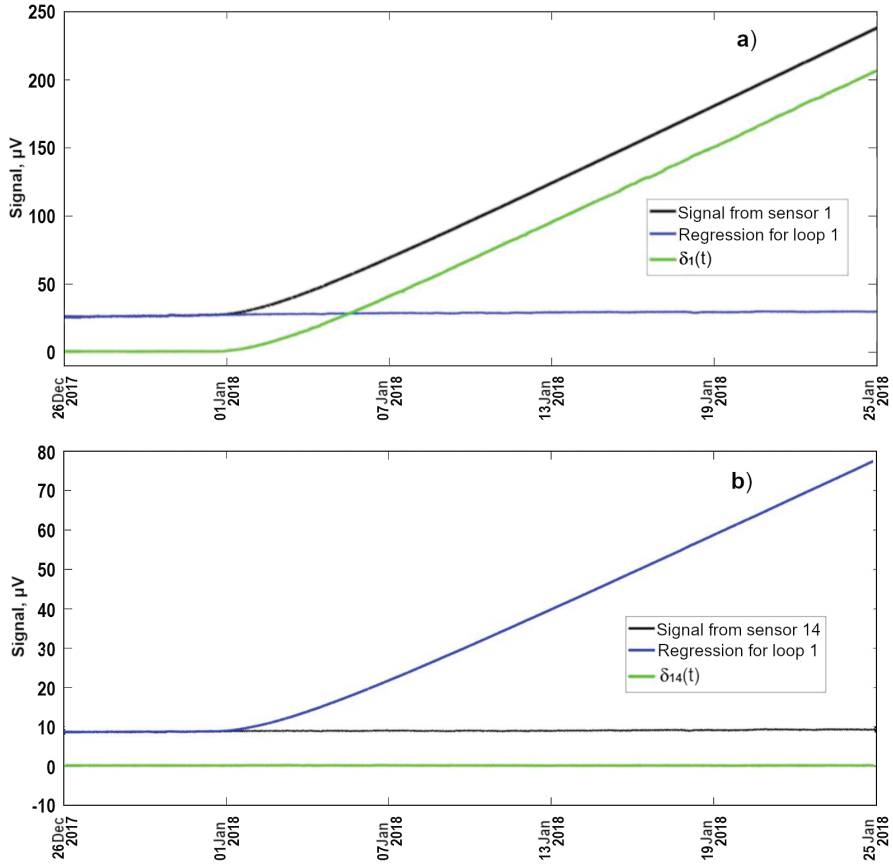

Figure 4. Quantities $\boldsymbol{\delta}_i(t)$: a) for the pipeline segment with leakage; b) for the pipeline segment without leakage.

on flattening the results obtained in a state space model using Kalman filtering.

To this end, a robust Bayesian model of linear regression was implemented which makes it possible to predict global noise for the entire life cycle with respect to a comparatively short interval of data at the cycle beginning. We shall note that the nonlinear regression model has turned out to be unstable to local background bursts.

A sequential Kalman filter, which is the best way to evaluate the actual signal in a system with additive Gaussian noise, was applied further to the obtained result.

The algorithm obtained makes it possible to improve considerably the reliability of the reactor pipeline leak detection, to improve the leak sensitivity, and to reduce the number of false alarms in the operation of the integrated leak analysis module in the IDS.

References

- Barber D (2017) Bayesian Reasoning and Machine Learning. Cambridge University Press, 666 pp.
- Cameron D-P (2016) Bayesian Methods for Hackers: Probabilistic Programming and Bayesian Inference. Addison-Wesley Data and Analytics Series, 226 pp.
- Chollet F (2017) Deep Learning with Python: Second Edition. Manning Publications, 384 pp.
- Durbin J, Koopman SJ (2012) Time Series Analysis by State Space Methods: Second Edition. Oxford Statistical Science Series. OUP Oxford, 253 pp. https://doi.org/10.1093/acprof:oso/9780199641178.001.0001
- Goodfellow I, Bengio Y, Courville A (2016) Deep Learning. MIT Press, 787 pp.
- GOST R 58328-2018. Pipelines of Nuclear Power Plants. Leak Before Break Concept. https://files.stroyinf.ru/Data/705/70505.pdf [Accessed on 05.05.2020] [in Russian]
- Grewal MS and Andrews AP (2015) Kalman Filtering: Fourth edition. Wiley, 617 pp.
- Haykin S (2014) Adaptive Filter Theory: Fifth edition. Pearson, 907 pp.
- Kruschke JK (2013) Bayesian estimation supersedes the T test. Journal of Experimental Psychology: General, 142(2): 573–603. https://doi.org/10.1037/a0029146
- Najim M (2008) Modeling Estimation and Optimal Filtering in Signal Processing. Wiley, 408 pp. https://doi.org/10.1002/9780470611104
- Nikolayenko S, Kadurin A, Arkhangelskaya Ye (2018) Deep Learning. St. Petersburg, Piter Publ., 480 pp. [in Russian]
- Skomorokhov AO, Kudryaev AA, Morozov SA (2010) Neural network models of the VVER piping leak signal filtering and diagnostics. Izvestiya vuzov. Yadernaya energetika 4: 72–80. [in Russian]