



ADVANCED SIGNAL PROCESSING TECHNIQUES FOR ACOUSTIC DETECTION OF SODIUM/WATER REACTION

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Abstract

In this paper results of development of a neural network technique for processing of acoustic background noise and injection noise of various media (argon, water steam, hydrogen) at test rigs and industrial steam generator are presented.

1. Introduction

In the report of the Russian participants of the Coordinated Research Program on Acoustic Signal Processing for the Detection of Boiling or Sodium / Water Reaction in LMFBR the results of development of a neural network technique for processing of acoustic background noise and injection noise of various media (argon, water steam, hydrogen) at test rigs and industrial steam generators are presented.

Being a logic continuation of the investigation on sodium boiling noise processing in reactor core, the Coordinated Research Program on Acoustic Signal Processing for the Detection of Boiling or Sodium / Water Reaction in LMFBR was initiated in December 1989, when the Russian side transferred to the participants the data on acoustic leak simulation on IPPE test rig. These data consisted of 8 records of noise of water injections with various flow rates (0.01-0.6 g / s) at sodium temperatures 300, 400 and 500 C °.

During the research program the participants used various methods of signals processing and from fragmented knowledge on leak noise peculiarities came to the development of a prototype acoustic system.

The largest contribution to recording of background noise of SGU and leak simulation noise in various conditions have been made by British experts which are the pioneers of acoustic leakage detection in LMFBR.

The knowledge about background noise would not be comprehensive without participation of French experts, possessing large experience in the area. For leak detection French participants used root-mean-square value calculated in a narrow band of frequencies, determined by empirical way.

The Japanese experts have demonstrated excellent technical opportunities, analyzing characteristic of pulses of background noise, and have proposed a method of twice squaring and integration for leak detection. The method proposed for leak location is also interesting.

Australian experts applied the newest techniques of signals processing such as Wavelet transform not leaving without attention theoretical aspects of leak noise generation.

The Holland experts have joined the other participants of the program in 1994, however they proposed an interesting method for detection of abnormal signals. The method is based on estimation of residual noise distribution.

The Indian experts performed the careful analysis of power spectral densities of the signals and detect leak by changes in determinant and trace of covariance matrix.

Results of researches on integration of an acoustic system into a distributed computer network, presented by German representative should be considered as perspective, as far as acoustic leakage detection system should be included in a system for complex diagnostics of the NPP equipment.

The IPPE experts, having tried various statistical characteristics of signals as diagnostic features, came to a conclusion that statistical features do not exclude false alarms in real conditions, since 1992 develop adaptive filtering for background noise canceling and applied neural network for recognition of acoustic noise patterns

2. A status of the acoustic Surveillance Technology Development for SGU leak monitoring

As experiments have shown, a real water leak will escalate rapidly in a time with a fast increase of flow rate from microleak up to ~ 4.5 g /s within few seconds /1/, with subsequent stabilization of the flow rate. At this time the steam jet, interacting with sodium, begins to destroy neighbour tubes, that results in a global accident. The character of leak escalation depends on sodium temperature, tube materials and on the other conditions.

To undertake proper action to prevent the accident it is necessary to detect a leak with the flow rate of 1-5 g /s within 1 sec and with false trip rate not more than 1 per 10 years /2/. Hydrogen monitoring system allows to detect a leak not faster than in 40 sec. Leak generates noise due to the steam jet and due to hydrogen bubbles oscillations and collapses.

Acoustic method of leak detection has a very fast response and provides required sensitivity. However, the problem of false trip rate minimization is the mostly challenging task for acoustic systems.

The variety of physico-chemical processes under leak conditions, generates noise in a wide range of frequencies from hundreds of Hertz up to hundreds of kilohertz. In a range of frequencies up to ~ 100 kHz a powerful masking noise take place consisting of background noise and abnormal impulsive noise which has a random nature and depends on a number of conditions. Theoretically it is promising to use high frequency band meanwhile the area of frequencies 200-800 kHz is practically not investigated. But in the area of ultra sound a masking noise can appear due to acoustic emission of constructional materials.

Thus, to avoid false trips and to achieve maximum sensitivity in acoustic system it is necessary to differentiate between leak noise, normal background noise and abnormal background noise.

3. Advanced signal processing techniques for acoustic detection of sodium-water reaction

The adaptive method of vibro-acoustical signals identification consists of adaptive filtering for extraction of weak signals from background noise, generation of compact time-frequency acoustic patterns and a neural network for their recognition.

Adaptive filtering being applied to acoustic leak detection is based on the fact that leak noise is less correlated than background noise. Being learned on background noise adaptive filter is able to filter out powerful frequency components of the background noise meanwhile preserving uncorrelated components of leak noise. If background noise and leak noise overlap in frequency range significantly it is purposewise to use nonlinear adaptive filtering. The general layout of different adaptive filters are shown in Fig.1. If background noise changes(which is true) during plant operation adaptive filter changes its amplitude - frequency characteristics, thus adapting to new conditions. The main problem in application of adaptive filtering is a

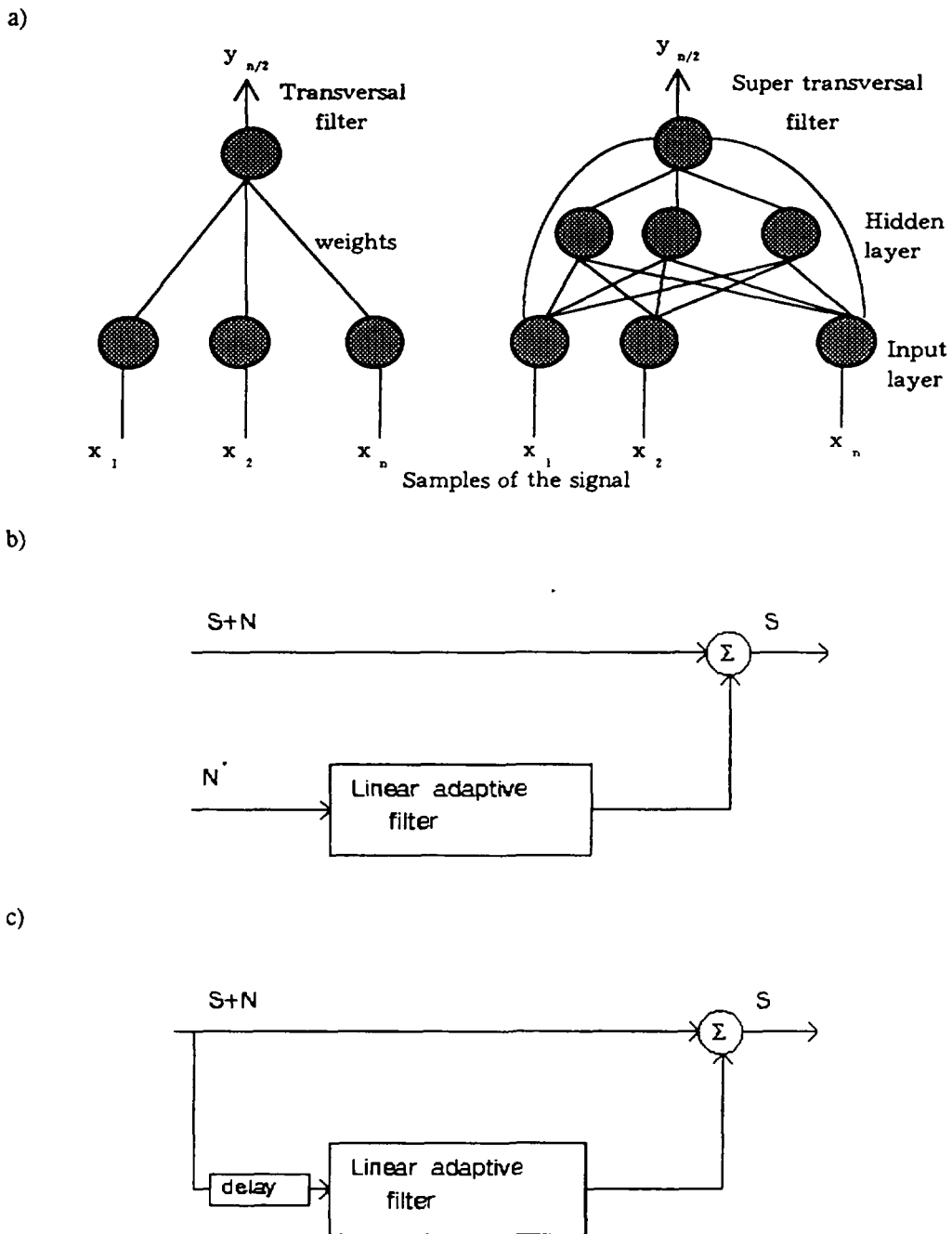


Fig.1 a) General layout of transversal and super transversal filters
 b) Principle of noise canceling
 c) Principle of noise canceling without external reference signal

proper reference signal which must be correlated with background noise and not correlated with leak noise. For acoustic leakage detection system it is proposed to get such reference signal via delay in processing signal. The digital adaptive filters, implemented in hardware, can work in a time scale, close to real. However the highest frequency of working band is limited because of the large requirements to computing resources.

The pattern generation is necessary to extract useful information from the signal and to reduce the dimensionality of patterns which should be recognized by neural network. To determine the contribution of each frequency into total power of the signal, FFT is used which can be carried out using FFT processors. To achieve necessary frequency resolution FFT is calculating over 2048 samples thus resulting in 1024 of spectral points.

The dimensionality of this array is too big to be fed into neural network and to ensure robust convergence. That is why a feature extraction is necessary. Different techniques are used to carry out this feature extraction and one of the most popular is principal component analysis. Several spectra calculated at different time provide more complex pattern and describe the frequency components behaviour in time.

The most known neural network which is used for recognition of complex patterns is multy-layer perseptron with backpropagation learning rule [3]. Each layer consists of nonlinear threshold elements neurons, thus if x - input value then the output will be as follows: $y=(1+\exp(-x+\theta))^{-1}$ where θ - some threshold value. Neurons of one layer are linked with neurons of the other layer by a principle each with each. The strength of coupling between neurons is described by weights which are modified during training. A desired vector is presented to the output layer during training phase. An input pattern is presented into input layer. The training consists in minimization of an error between desired and actual output of the network. Then derivative for each weight of output layer is calculated using error value, the derivatives propagates through layers starting from the output to input that is why the name - backpropagation. The weights are modified by gradient descent technique. For acceleration of training and avoiding local minima a variable learning step is used, which depends on the success of the previous iteration. Process of training proceeds until then while the error on output layer of the network will not become less a beforehand given value. The training will be correct, if training set really consists of two classes: background noise and leak noise. If there are abnormal noises in background noise, which also take place during leak noise then the network will permanently relearn and unconvergence can take place. Therefore before training a careful preselecting of training patterns should be made and may be new classes must be added during learning procedure. For this purpose self-organizing neural networks can be used to share the incoming signal into a preselected number of classes. Being trained the network can generalize the new information. Then the output layer provides the classification result. During the processing of benchmark data the network did not relearned but in practice it is necessary to perform this procedure to adapt the weights to slow changes of background noise. The time constrain during the recognition of complex acoustic patterns will require a hardware implementation of neural network.

All the procedures of the data processing are written in Borland Pascal with graphic display of the information and run under operating system DOS 5.0 Algorithms of main procedures can be used for development of the software for leak detection.

Process of training can take a time from several seconds up to several minutes depending on the computational power of the hardware and on the nature of patterns

in training set. The recognition is performed considerably faster, the time is comparable to time which is necessary for data reading from computer memory.

At present time the investigations on application of adaptive techniques in vibro-acoustic monitoring systems are concentrated on the development of effective feature extraction algorithms and on recurrent networks for context-dependent recognition of incoming patterns.

4. Summary of the work done during 93-95 and answers to standard questions

4.1 Brief description of the benchmark data.

The benchmark data in 1993 contained background noise of Superheaters 2 and 3 of PFR mixed with noise of injections with flow rates 1.8 and 3.8 g / c, recorded on the ASB loop (Germany). The benchmark data have been prepared by Japanese experts and consisted from mixtures with signal to noise ratio from -24 up to -12. The benchmark signals were recorded on magnetic tapes in frequency band up to 40 kHz and consisted of 2 series with 4 records in each.

For 1994 benchmark data background noise recorded at Superheater 2 of PFR, from 4 sensors has been mixed with leak simulation noise recorded on ASB loop also from 4 sensors. The signal to noise ratio was from -6 dB down to -24 dB. The data have been prepared by French experts in digital form with sampling frequency of 131072 Hz. Five test sets have been distributed among the participants.

Closest to real situation are the benchmark data 1995, which differ from previous benchmarks and have been recorded without any artificial mixing. The data were recorded by AEA Technology experts during the End - of - Life experiments on PFR. The benchmark data consist of the following records:

- Background noise of Evaporator 3 loop at full power;
- Background noise of Superheater 3 loop at full power;
- Noise of two hydrogen injections;
- Noise of three argon injections;
- Noise of three water injections.

The injections of hydrogen, argon and water were carried out into Evaporator 3, when the reactor was shut down, steam/water side was padded, and with the sodium pump was been operated at reduced speed. The noise of injections were recorded from 4 sensors (waveguides "a ", "b", "c" and "d"), and were chosen from numerous series of experiments so that the flow rates of injected media were different. The records were enumerated from 1 to 8.

The benchmark data were digitized (16 bit) with sampling frequency 160 kHz and 2 MHz with cut off filter of 72 kHz.

The waveguides location on ASB loop and on PFR Superheater and Evaporator can be seen from Fig. 2.

4.2 Standard questions.

For all benchmark data it was required to determine start time of injection and its duration, as well as to evaluate reliability and probability of false alarms. For benchmark data 93 it was desirable to determine signal to noise ratio, and for the data

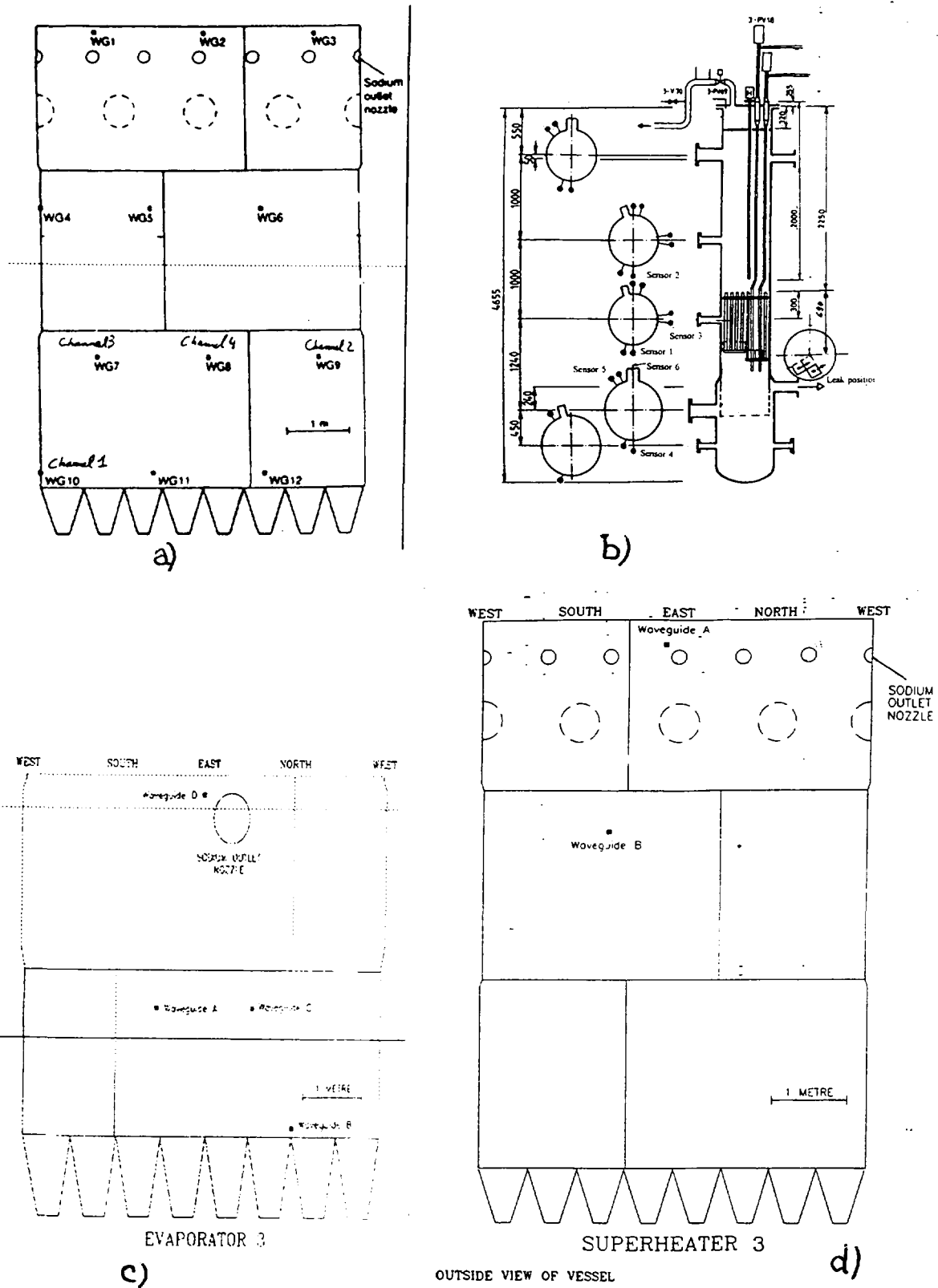


Fig. 2 Location of the waveguides:
 a) PFR SuperHeater 2 b) ASB loop
 c) PFR Evaporator 3 d) PFR SuperHeater 3

94 and 95 to perform leak location. The data 94 could serve for evaluation of advantages of multichannel processing in comparison with processing of signals from one channel. For benchmark data 95, in addition, is offered to determine type of injected media and give opinion about possibility of background noise recognition recorded at different units of SG at full power.

4.3. The results obtained by the moment.

Due to non coincidence of heads on recording and replaying tape recorders only part of 93 benchmark data has been processed, namely, 4 benchmark records with flow rate of 0.8 g/s with different signal to noise ratios. The benchmark data have been analyzed in frequency band up to 4 kHz because it was assumed that in this band the amplitude-frequency characteristics of the sensor is closest to linear. The results of detection of leak start time and duration are represented in Table 1. The applied method has allowed to detect leaks with signal to noise ratio, close to -24 but just for most powerful pulses local in time. Start time and duration were determined using the first and the last patterns identified as leak. The results for each records are represented in the Table 1 under the order, accordingly to deterioration of signal to noise ratio, that was estimated by comparison of patterns for each record. There were no false alarms for all benchmark data. The quantitative evaluations of probability of false alarm and leak missing were not carried out due to insufficient amount of data.

Table 1

	Leak Start , sec	Leak End , sec	Duration , sec
Record 2	15.05	18.43	3.38
Record 4	19.81	21.15	1.34
Record 1	12.54	13.11	0.57
Record 3	12.54	15.05	2.51

The processing of the benchmark data 94 has shown, that patterns from different sensors, recorded at the same moment can be recognized differently. That is if a pattern from one sensor is identified as leak, the pattern from the other sensor can be identified as background noise. Therefore the leak start and leak end were determined separately for each sensor. The reliability of method was determined by evaluation of quality of the recognition, for that it was necessary to identify the leak start and leak end, closest to real. A start of injection has been identified when the first pattern has been identified as leak. End of injection was fixed from the moment of absence of the messages about leak during recognition of several patterns on each sensor separately.

The quality of recognition of background noise was evaluated in a percentage on such parameters, as:

- Correctly recognized background noise;
- The background noise, recognized as leak (false alarm);
- Non recognized background noise (relearning is necessary).

The quality of leak recognition was evaluated similarly on such parameters as:

- Leaks recognized as background noise;
- Correctly recognized leaks;
- Non recognized leaks.

The results of detection of leaks start and their duration along with quality of recognition are summarized in Table 2. The applied method allowed to detect a leak at signal to noise ratio down to 24. Judging by averaged patterns of background and leak noises the numbers of records can be ordered according to deterioration of signal to noise ratio in the following order: 3, 0, 2, 1, 4.

The absence of false alarms during background noise records is provided by impose this condition during training. The obtained results testifies that it is possible to use insignificant volume of data, necessary for training, under condition of availability of the most characteristic examples of background noise. It is necessary to note, that the more examples of different background noises is used during training the lower probability of false alarms.

At the end of leak in the 2-nd record a short-term pulse takes place, which would be identified as leak. However, this pulse should be classified as abnormal background noise, because it was recognized as non recognized. In examples of pure background noise the similar powerful pulses were absent.

The location of leak was not carried out in view of small time delay at registration of pulses in the readings of several sensors.

For benchmark data 95 leak start and duration were determined as separately for each sensor, so for all sensors. Adaptive filtering was not applied, patterns were formed by a new way, that will be in more detail considered further.

In the first case the reliability of method was evaluated similarly to the previous benchmark data (see Table 3). To increase reliability of a leak detection algorithm of issue of the alarm message taking into account result of recognition of several patterns was in addition applied. Times of issue of the alarm messages in the Table 3 are not presented. It should be noted, that in spite of some false recognition of separate patterns, the false alarm messages were absent while processing as leak noise so background noise at full power.

In records of 1-st and 2-nd injections leak noise was not recognized for all sensors. One pattern from waveguide "d" was not recognized as background which means that further learning is necessary. During injection 8 only some patterns from "c" and "d" waveguides were recognized as leak but without issue of the alarm messages about leak. Obviously, the leak was not detected because of the small flow rate of injected media at low pressure. Some patterns from sensors "c" and "d" were identified as requiring training probably due to insufficient training.

Record 4 proved to be the most difficult for recognition. During the 1-st second and further low frequency pulses took place, which are absent in background noise, on which training had been made. Simultaneously with low-frequency effects there was no high-frequency noise, characteristic for injections. However the contribution of low-frequency (up to 800 Hz) components has appeared to be enough, for the neural network to recognize some patterns as leak being not trained on such background noise. If to assume, that the injection begins at 5-th second, when the patterns simultaneously on all the sensors were recognized as leak, the background noise before injection 4 is characterized by a smaller of level high-frequency components in comparison with background noise, on which the training had been

Table 2

N Inject ions	N sensors	Start of Injection, sec	Duration of injection, sec	% background noise recognized as leak	% rightly recognized background noise	% non recognized background noise	% leak noise recognized as background noise	% rightly recognized leak noise	% non recognized leak noise
	1	1.8906	5.4532	0	100	0	13.33	86.40	0.27
	2	1.8906	5.4532	0	100	0	9.33	89.87	0.8
	3	1.8906	5.4532	0	100	0	6.16	93.33	0.51
0	4	1.9063	5.4375	0	100	0	36.53	58.67	4.9
	1	2.0469	3.9219	0	100	0	97.60	2.16	0.24
	2	1.2344	4.7344	0	100	0	94.96	4.08	0.96
	3	1.2500	4.7188	0	100	0	80.58	15.11	4.31
1	4	2.1250	3.8438	0	100	0	98.32	1.68	0
	1	2.0313	5.375	0	99.6	0.4	40.98	54.64	4.38
	2	2.0313	5.375	0	99.6	0.4	25.41	71.31	3.28
	3	2.0313	5.375	0	99.6	0.4	8.47	90.71	0.82
2	4	2.0469	5.3437	0	99.6	0.4	68.85	27.05	4.1
	1	1.6250	5.4844	0	100	0	10.2	89.54	0.26
	2	1.6250	5.4844	0	100	0	10.2	89.8	0
	3	1.6250	5.4844	0	100	0	10.2	89.8	0
3	4	1.6250	5.4844	0	100	0	11.22	88.78	0
	1	4.6563	1.5781	0	100	0	98.14	1.15	0.71
	2	2.2969	3.5781	0	100	0	97.99	1.43	0.58
	3	2.6875	4.0625	0	100	0	87.97	8.31	3.72
4	4	2.6875	4.1094	0	100	0	98.57	1.15	0.38

Table 3

N injections	N sensors	Start of injections, sec	Duration of injections, sec	% background noise recognized as leak	% rightly recognized background noise	% non recognized background noise	% leak noise recognized as background noise	% rightly recognized leak noise	% non recognized leak noise
1	a,b,c,d	-	-	-	-	-	-	-	-
2	a,b,c,d	-	-	-	-	-	-	-	-
3	a	7.89	2.09	0	100	0	5	85	10
	b	7.89	2.09	0	100	0	5	90	5
	c	7.58	2.40	1.57	93.15	5.48	0	100	0
	d	7.78	2.20	0	97.33	2.67	9.52	80.95	9.52
4	a	6.04	3.94	3.45	93.1	3.45	52.63	34.21	13.6
	b	6.04	3.94	0	91.38	8.62	71.05	21.05	7.89
	c	5.43	4.55	9.62	76.92	13.46	29.55	40.91	29.55
	d	5.84	4.14	55.36	26.79	17.86	22.5	60	17.5
5	a	2.87	7.11	0	96.3	3.7	2.9	88.41	8.7
	b	2.77	7.21	0	100	0	17.14	70	12.86
	c	2.77	7.21	0	100	0	0	100	0
	d	2.77	7.21	0	100	0	1.43	97.14	1.43
6	a	5.53	4.45	0	100	0	4.65	95.35	0
	b	5.53	4.45	0	100	0	0	100	0
	c	5.53	4.45	0	100	0	0	97.67	2.33
	d	5.53	4.45	0	100	0	4.65	88.37	6.98
7	a	4.61	5.37	0	100	0	13.46	59.62	26.92
	b	5.12	4.86	0	95.92	4.08	25.53	44.68	29.79
	c	4.40	5.58	0	95.24	4.76	5.56	64.81	29.63
	d	4.40	5.58	0	92.86	7.14	46.30	35.19	18.52
8	a,b	-	-	-	-	-	-	-	-
	c	6.35	3.63	0	98.36	1.64	94.29	5.71	0
	d	4.51	5.47	0	100	0	96.23	3.77	0

performed (see Fig. 3). From comparison of averaged spectral densities of different background noises, shown in Fig.3 it is clear, that the noticed low-frequency effects consist of excess of a level of background noise at about 5 dB. It should be pointed out, that the differences of background noise in the high-frequency area for the sensor on waveguide "d" are expressed in the least degree.

Nevertheless the heaviest quantity of false leak identification was received for this sensor, which proves the inferiority of training. If the injection begins at 1-st second, then it is not clear why high-frequency components till 5-th seconds are more weak, than at background noise before 6-th injection. The situation would be more clear if analysis of flow rate changes during the injection would be carried out, because along with sound generation its attenuation takes place and these processes are the mostly difficult for hydrogen dissolving in sodium. The finding out of the reasons of background noise changes during a series of injections is important for acquisition of adequate understanding about distinctions between background noise and leak noise.

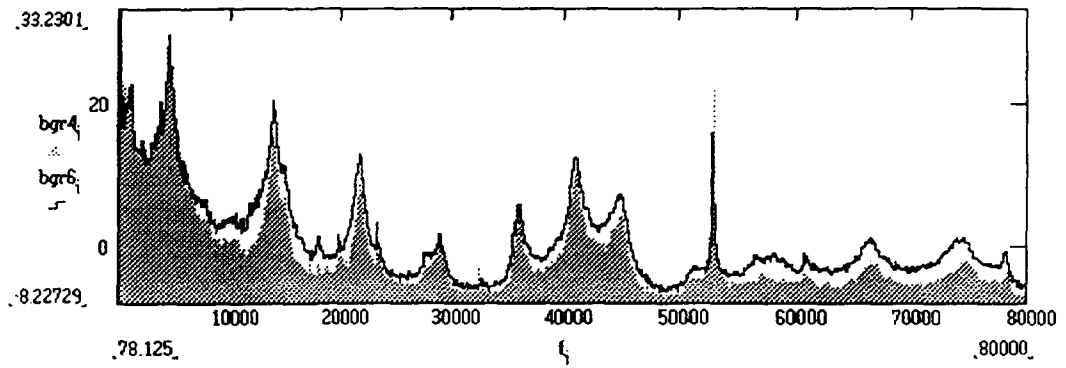
The best results of recognition were obtained for 5-th and 6-th injections, when the prospective quantity of correct leak recognition reached up to 100 % at absence of false alarms. Results of recognition of injections 3 and 7 give variation of correctly recognized leak from 50 up to 100 %.

The researches made on location of noise while have given negative results. Introduction of adaptive methods of localization complicated by the necessity very large computing resources. Thus accuracy of localization and cost of a system can be far from desired.

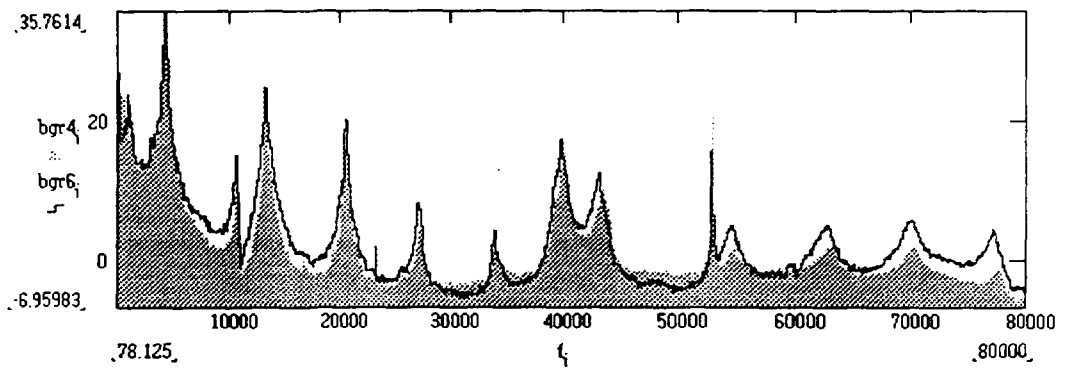
Approximate determination of position of a source of a sound based on attenuation of the amplitude at distance of a source is not acceptable for water leaks in SGU, as far as the effects of attenuation of noise in SGU can appear not unequivocal. The leak noise will be attenuated by different manner passing through sodium, shell and hydrogen bubbles. That is why closest sensor which is shadowed by hydrogen bubbles will register smaller noise than a sensor located at distance from injection place. Use of a principle, based on phase delays, arising at passage by sound of various distances, is complicated by the fact that the useful signal represents broadband noise with varied pulsing activity in accordance with leak escalation and, which is masked by broadband background noise, in which there can be present abnormal pulses because of local sources of a sound. The proliferation of sound waves in SGU has a complex nature because of shielding elements: covers, lattices, tube bundle. The waveguide registers a superposition of acoustic waves, passed through sodium and SGU shell. The additional problems arise because of distribution of sources of noise under leak conditions in the space (oscillations and collapses of hydrogen bubbles). If to be guided only by noise of steam jet, its spectral maximum should be expected in the band, exceeding 80 kHz.

Theoretically, the noise from argon, water and hydrogen injections can be differentiate by different spectra and by character of different components changes in time. In practice these distinctions can be less obvious because of dependence on pressure, size of injection nozzle, injected media and its flow rate. It should be expected, that under equal listed conditions the noise of injection of hydrogen will differ from noise of argon injection, due to greater attenuation on gas bubbles, by lower amplitude of high-frequency components. During water injections the formation of hydrogen bubbles will differ from hydrogen injections by higher intensity and bigger sizes of bubbles. Some water particles can be circled by hydrogen bubbles and react with sodium at some distance from injection place.

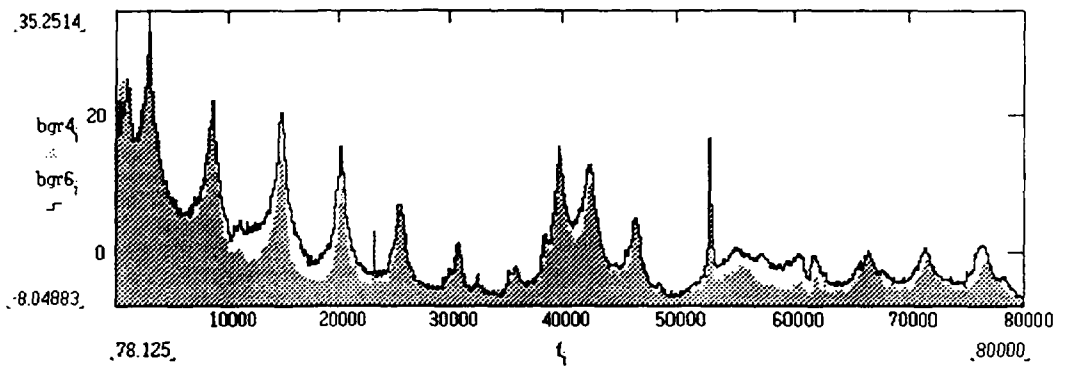
a)



b)



c)



d)

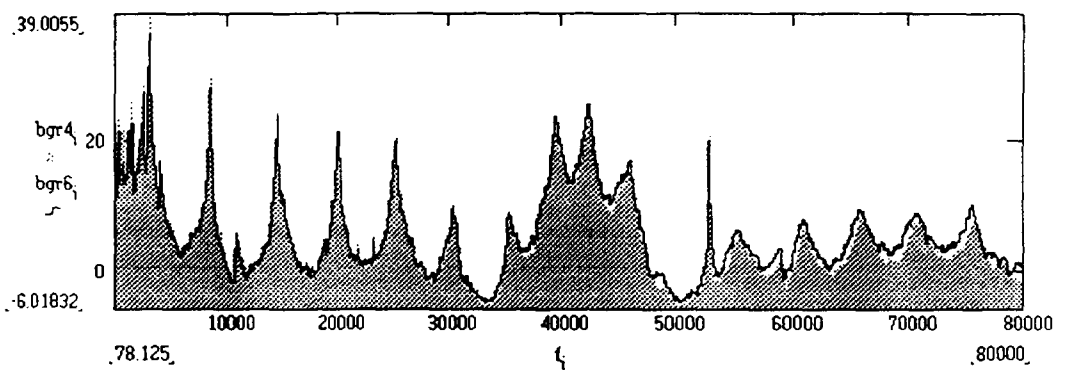


Fig.3 Averaged PSDs of the background noise before injections 4 and 6 for different waveguides - a, b, c, d.

Thus, the noise of water injections can differ from the noise of injection of hydrogen by more intensive impulsing activity (which depends on flow rate) and by larger level as high frequency, so low-frequency components.

As far as the parameters of each injection are unknown for each detected injection, unequivocally to identify a type of injected media is problematic. The analysis of noise changes in time has not allowed to allocate characteristic pulses, which could correspond to a particular type of injected media. To simplify the identification power spectral densities (PSD) for various injections without background noise have been obtained by subtraction from an average spectrum during the injection an average spectrum of noise before the injection. The PSDs are shown in dB relative to a basic level, equal to unity, in Fig. 4.

PSDs of different injections, analyzed separately on each sensor, differ by value of frequency components in the whole frequency range. It proves that even injections of identical media were carried out in different conditions. From the comparison of PSDs of injections 5 and 7 follows, that for sensors mounted on waveguides "a" and "b" high frequency components (>50 kHz) during injection 7 have a greater level than during injection 5, but for sensors "c" and "d" vice versa

Obviously, these injections have been carried out by different media as far as less probably, that the noticed discrepancies are called by difference in flow rates or by difference in other parameters. Judging by relationships of high and low frequencies water has been injected during injection 5 and argon during injection 7.

As was expected, noise even from the same injection differs for different sensors, that it is possible to see from comparison of PSD's of any injection, the plots are represented in Fig. a,b, c and d. Moreover leak noise from each sensors represents a nonlinear superposition of leak noise and background noise.

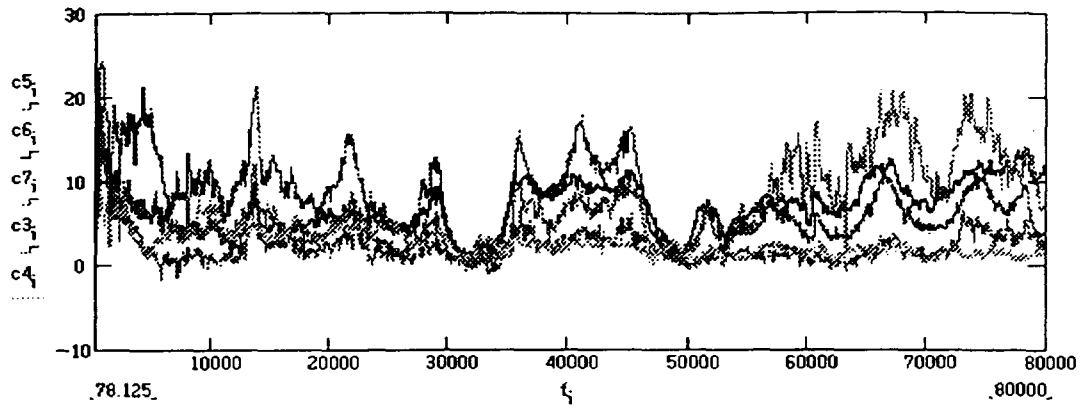
5. Results of verification and improvements of the signal processing techniques using the experimental data

The leak noise in benchmark 93 is characterized by weak medium frequency components and by random occurrence of pulses, that can be invoked by specific character of water injection in conditions of the experimental rig. Maximum of energy of high frequency pulses is concentrated around 30 kHz, that corresponds to sensor's resonant frequency. The low-frequency pulses have a spectral maximum (~2.5 kHz), which is very close to the most powerful spectral peak of background noise (~2.2 kHz). As far as the benchmark data were analyzed in frequencies band up to 4 kHz, the problem of leak detection consisted in recognition of signals, distinguished by occurrence of a weak spectral peak during leak noise overlapped with powerful spectral peak of background noise. During training of adaptive filter a mixture of background noise, and white noise, are entered into input and leak noise was used as a desired signal. After training benchmark signals passed through the filter. The patterns were generated over 4 spectra, calculated consistently.

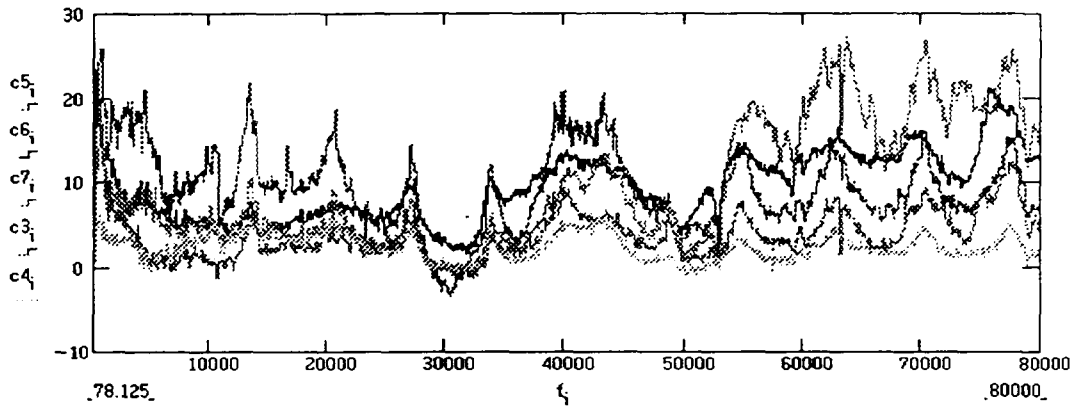
For one cycle of neural network training 4 patterns of pure background noise and 4 patterns of leak noise have been presented. Criterion for completion of training was the absence of false alarms during background noise recognition.

The benchmark data 94 had similar frequency spectra for signals from channels 1 and 3, whereas the signals from channel 2 differed by prevalence of low-frequency components (< 1 kHz) and the signals from channel 4 consisted predominary from frequency components up to 20 kHz. The background noise had smaller differences

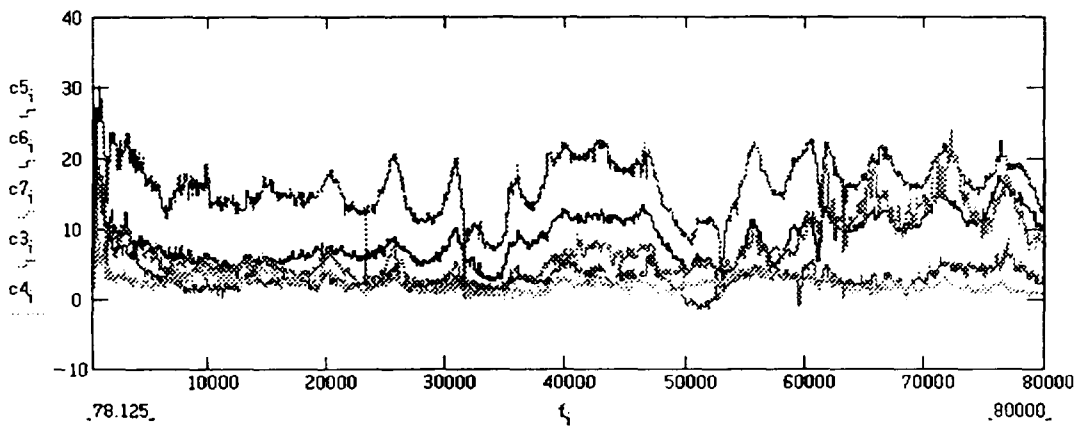
a)



b)



c)



d)

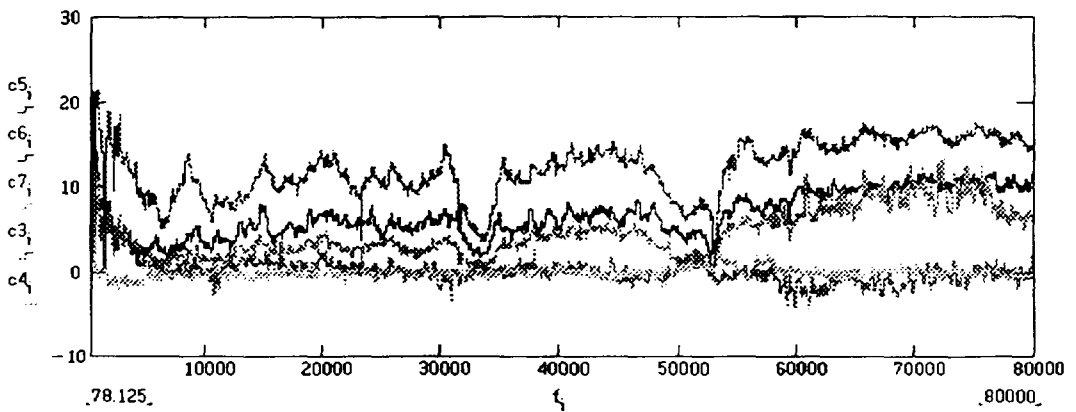


Fig. 4 Averaged PSDs of "pure" injection noise for different injections (without background) for waveguides: a, b, c, d.

between signals from different sensors, and in the spectrum it is possible to allocate about 10 peaks in the frequency band up to 40 kHz. Thus, the problem of leak detection was more difficult and consisted in recognition of broadband background noise and linear superposition of broadband background noise with broadband leak noise. In difference from the previous data, new version of an adaptive linear filter permanently learned new signals of background noise and benchmark data. This filter did not require reference leak signals, and a delay was used to get reference signal from the signal to be processed.

As far as the architecture and parameters of the filter were not optimized, the best results were received only for high frequency components of noise, whereas the useful information in the band of low frequencies after filtering has appeared insignificant and different for each sensor. Therefore, power of the useful signal on output of the filter was not proportional to real power of leak noise in the whole frequency band. Neural network was trained on patterns of background noise and patterns of background noise mixed with leak noise. For different sensors the same network was used but with different initial weights. It was assumed, that the decision on issue of an alarm will be accepted by operator based on the analysis of recognition results separately on each sensor.

In benchmark 95 there are no records of pure background noise before injection and pure leak noise but neural network training requires characteristic examples of background and leak noise. Therefore to get these reference signals a record with injection was taken, where the presence of injection can be identified by spectral analysis and by signal's RMS changes. Such injection was found with number 6.

The pattern generation is based on revealing frequency components, which the most informative from the point of view of leak detection. For correct realization of such a choice the analysis of the whole varieties of background and leak noise is necessary.

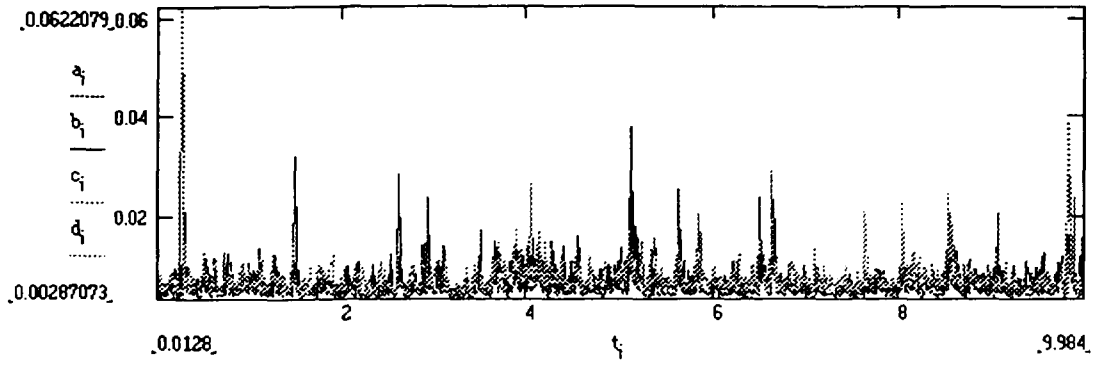
Before processing and recognition of benchmark data root-mean-square value of signals (RMS) over 2048 samples with subtraction of mean value of sample to exclude zero drift was calculated. Plots of RMS changes are shown in Figs. 5 and 6, from which it is obvious, that determination of a leak start time by RMS changes is quite difficult for the majority of injections because of background noise variation and abnormal pulses which present in it. After patterns generation their average values were calculated, which are shown in Figs. 7 - 8.

Comparing the plots of RMS changes and averaged patterns, it is possible to conclude that in some cases the pattern generation has allowed to exclude influence of abnormal pulses of background noise.

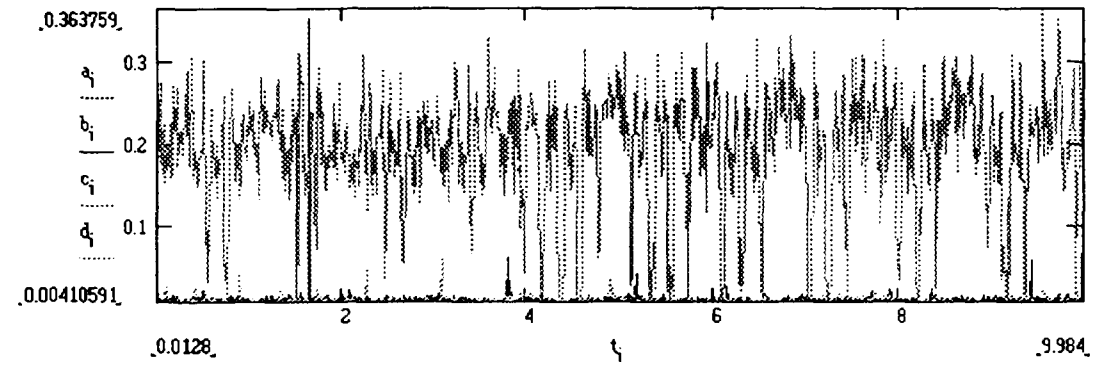
As far as the useful signal from remote sensors can be very small, that will deteriorate network's ability to recognize leak using the data from all sensors, the network was trained on patterns from each sensor separately. Thus one neural network was used, but with different weights depending on a particular sensor. Such approach permits to watch dynamics of recognition on each sensor, but complicates a decision making about leak occurrence if there is weak signal on some sensors. For issue of the alarm message an algorithm is used, which takes into account result of recognition and dynamics of patterns on all sensors.

With the purposes to bring system closer to practice it is purposewise to learn network on leak simulations with quickly growing leak rates and stable maximum flow rate, or on patterns from several simulations with the different flow rates. And it is highly desirable to train on patterns from injections with the minimum flow rates,

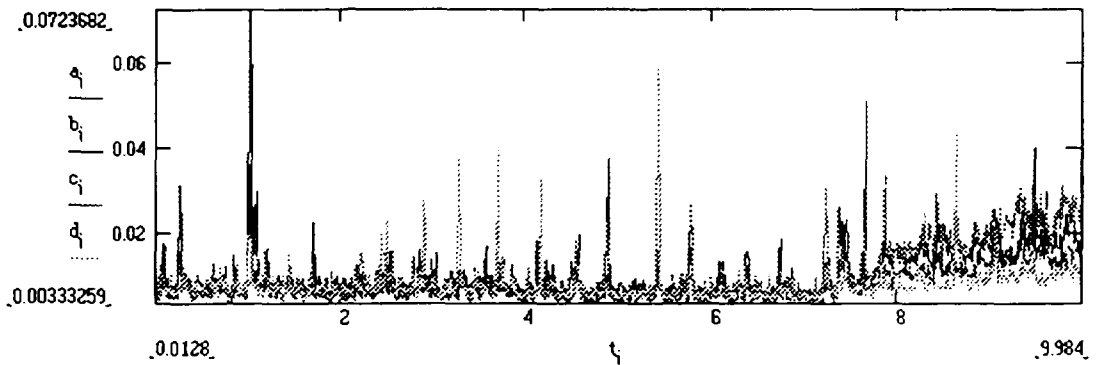
a)



b)



c)



d)

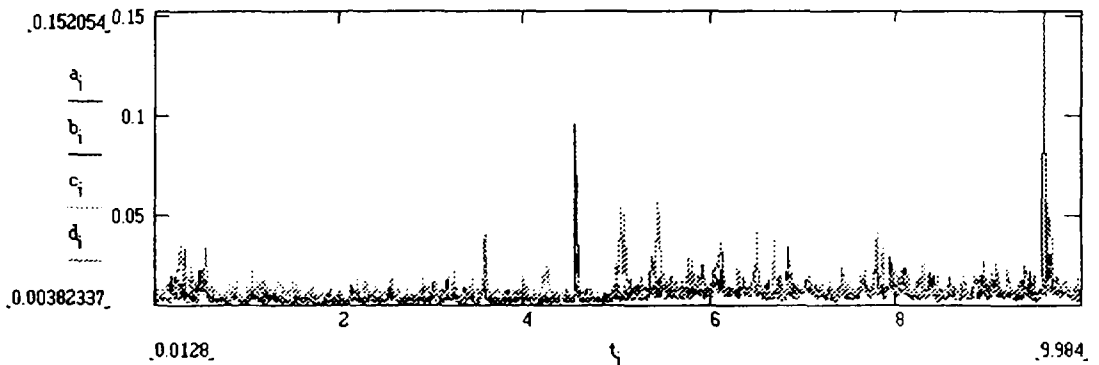
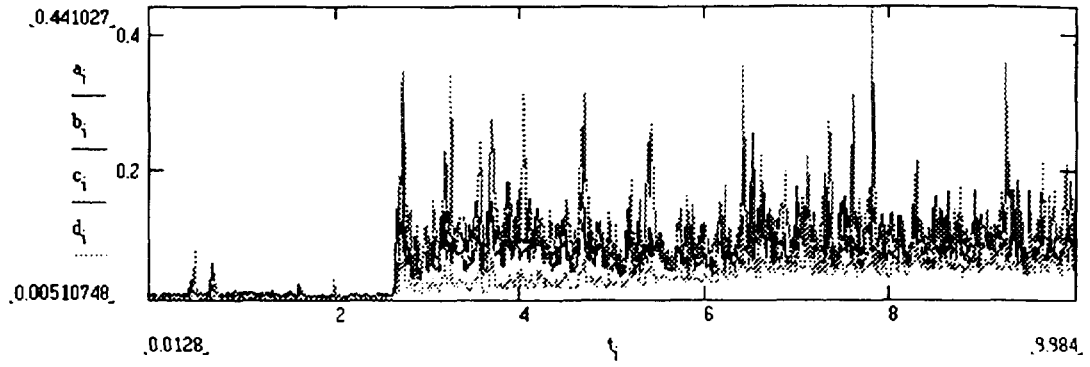
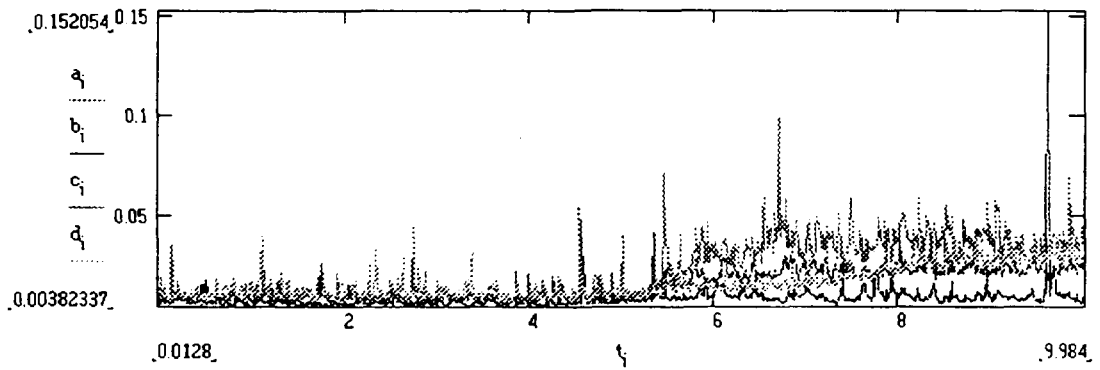


Fig 5 Behaviour of RMS (g) in time (sec) for injections 1-4.
a) - 1, b) - 2, c) - 3, d) - 4

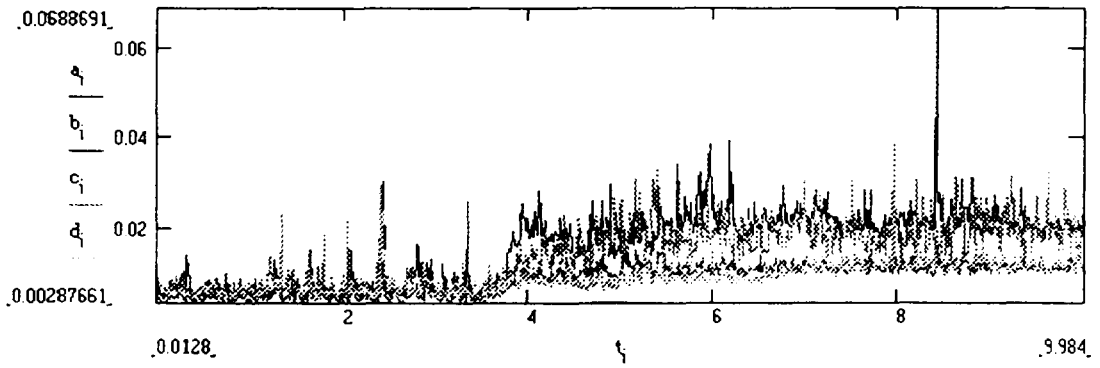
a)



b)



c)



d)

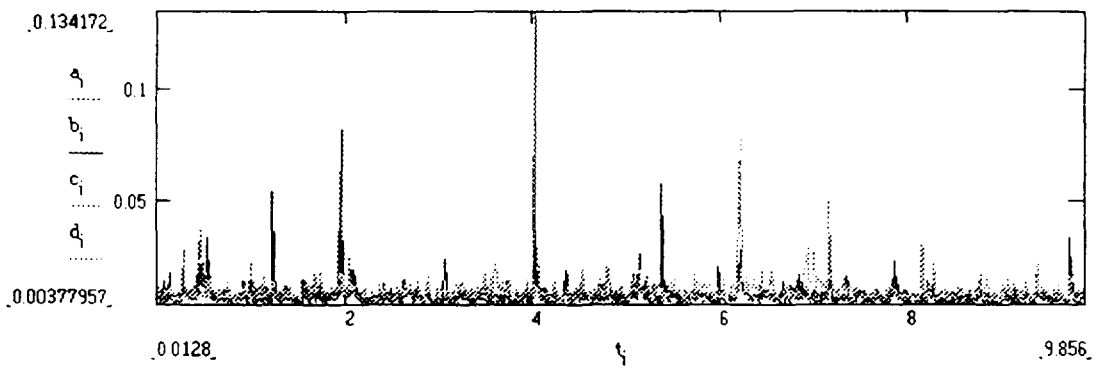


Fig. 6 Behaviour of RMS (g) in time (sec) for injections 5-8:
a) - 5, b) - 6, c) - 7, d) - 8

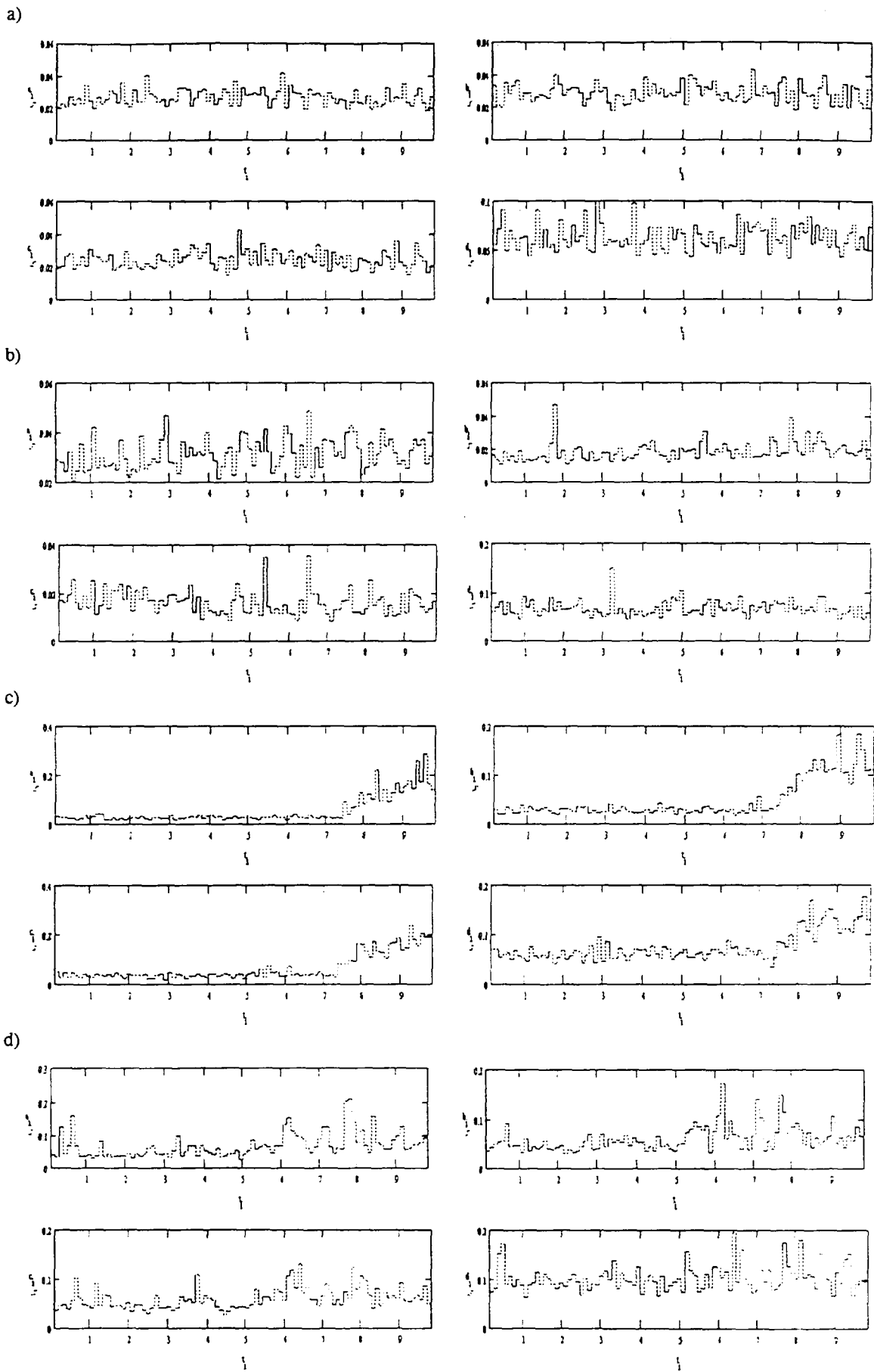


Fig.7 Behaviour of the averaged patterns in time for different waveguides: a. b. c. d
a) Injection 1 b) Injection 2 c) Injection 3 d) Injection 4

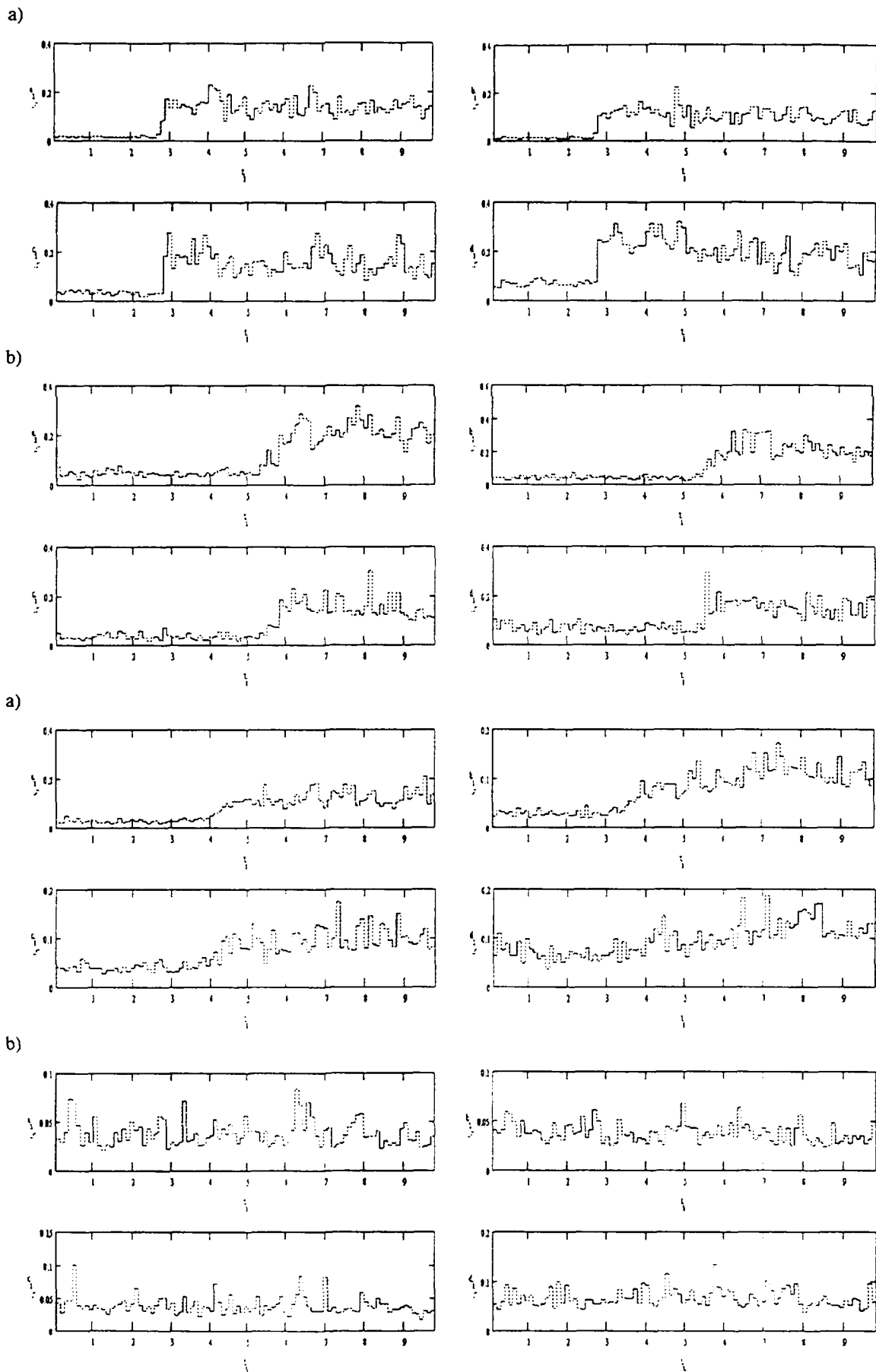
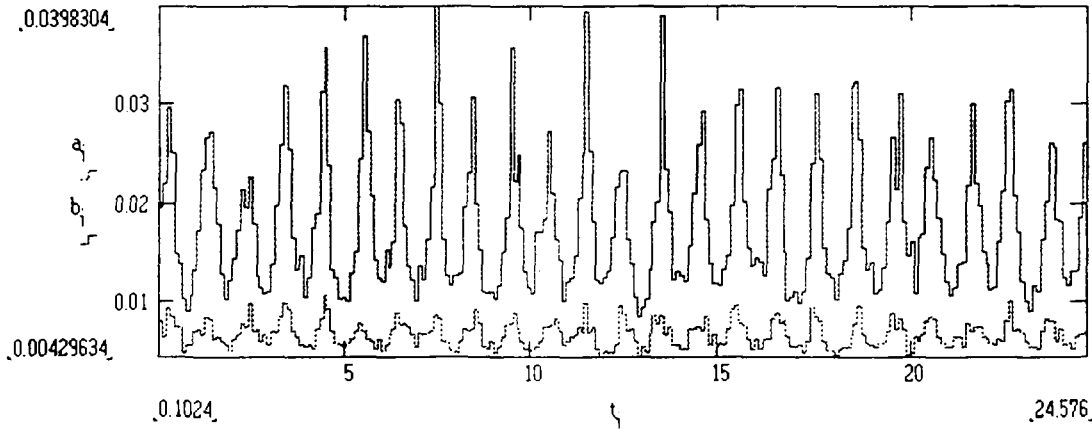
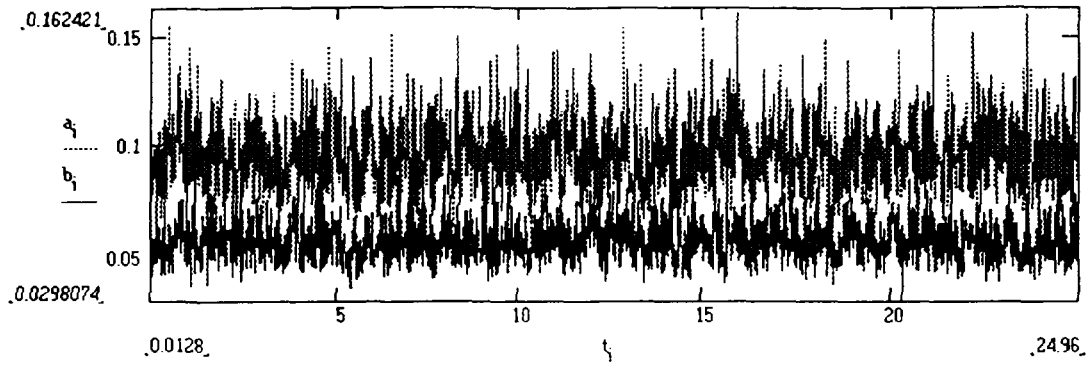


Fig.8 Behaviour of the averaged patterns in time for different waveguides: a. b. c. d
a) Injection 5 b) Injection 6 c) Injection 7 d) Injection 8

a)



b)

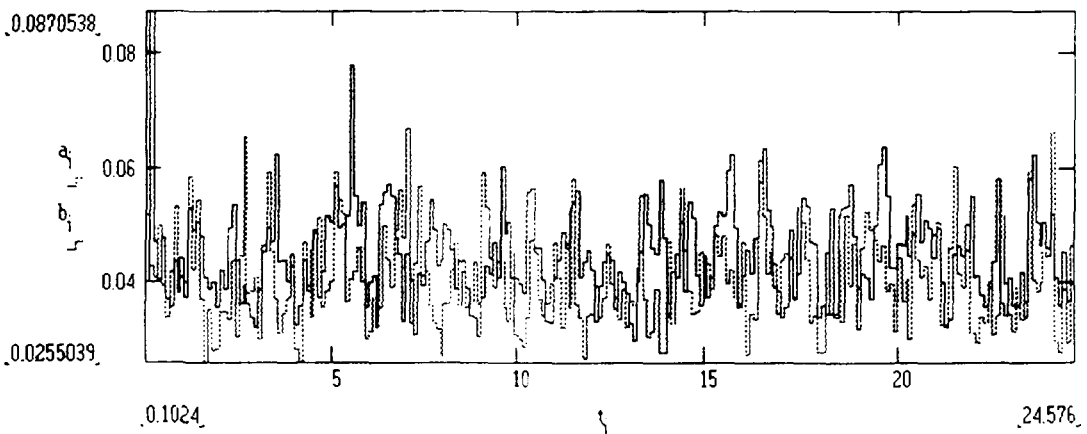


Fig. 9 Behaviour of RMS and averaged patterns in time for signals from waveguides A and B at full power. a) SuperHeater. b) Evaporator

which need to be detected by acoustic method. The specific character of pattern generation and neural network performance is that being trained on an injection with particular flow rate the network will reliably recognize injections with larger flow rates, but reliable recognition of leaks with smaller flow rates will be problematic.

Due to the fact that with removal from injection place the signal is attenuated some additional difficulties arrives for each separate sensor training. A problem is complicated by variation of background noise recorded at different sensors. For example, sensor mounted on waveguide "d" registers background noise, possessing more complex character, than other sensors, and more weak leak noise. Being trained on patterns from this sensor, the network will recognize leaks with smaller flow rates in comparison with other sensors. On the other hand, to exclude false alarm in connection with more complex character of background noise it is necessary to perform training on greater quantity of its patterns. For ideal training from the point of view of achievement of maximum sensitivity it is desirable to have examples of injection noise, carried out in different SGU places. It is related to possible nonlinear effects during sound propagation generated by leak and its superposition with background noise.

The peculiarities of patterns generation allow recognition of leak noise and background noise in SGU, possessing other geometry than that in conditions of which training was performed. However, amplitude - frequency characteristics of sensors along with waveguides, should be identical or as close as possible to that ones on which the training had been carried out. At transition to new conditions it is purposewise to perform additional learning on background noise and on a linear combination of leak patterns without background noise with patterns of new background noise. Additional learning is vital in case of specific noise, stipulated by design features of new SGU, because these noises can be permanently present at background noise or appear for some regimes, and only for some sensors.

It should consider separately the case, when the characteristic examples of background noise were recorded only at one power level but leak should be detected at different power levels.

Probably, that at a higher power levels it is possible to detect leaks with larger flow rates on comparison with leaks at lower power levels irrespective of a way of signals processing. It is necessary to specify, that the important role is played by not mean value of the background noise, but by its variation which can depend on power level. Strictly speaking, correct recognition of background noise at different power levels not yet means successful leak recognition.

The used way of patterns generation will be the most effective, if sensor's signal is directly proportional to noise power in all working band of frequencies or this dependence will be identical for all frequency components.

In spite of the fact that the conditions listed above were not satisfied, recognition of background noise at full power was carried out without any false trips. RMS changes and averaged patterns are shown in Fig. 9. Preliminary estimations show, that without additional learning it would be possible to detect a leak at this power level with acoustic noise which two times exceeds the noise of injection on which the training has been performed (at minimum power level).

6. Recommendations for further activity in the subject area

To obtain a robust estimation of probability of false alarms for acoustic leakage detection an approbation on background noise, registered during transients from one

power level to another is necessary. It is not less important to perform testing of methods on abnormal background noise, when additional sources of noise can be loose parts, vibration of various constructional elements check valves operations, etc.. For evaluation of probability of the leak missing the mostly unfavorable situation is the leak occurrence during fast decrease of power level.

The leak detection in practice means issue by a system of a justified signal of alarm, for which a special algorithms of decision making are necessary which take into account the whole situation in SGU and not only acoustic noise.

A general problem of vibro-acoustic diagnostics is registration of reference noise which characterizes abnormal situation. Making use of linear model, discovered by experiments, does not allow to take into account the whole varieties of real situations. For example, the noise of leak simulation recorded at minimum power, will differ from noise recorded at maximum power due to differences in background noises and nonlinear superposition of background noise and leak noise.

Besides, the noise from the same injection, registered by waveguides of one type, will be problematic to predict using linear relations and other waveguides mounted in other places. One more problem is getting pure leak noises and their utilization for adaptation of the system to SGU with other characteristics. The leak simulations is not the best way due to economical and safety reasons.

Thus, nonlinear mathematical models of leak noise should be developed, using real background noise to get simulated noise, closest to real one. The experience of development of such models would be useful for getting reference noise signals, describing various abnormal situation in NPP.

7. Conclusions

The problem of leak detection in SGU of LMFBR is a problem of acoustic noise recognition. In fact acoustic leakage detection is not a problem even for quite small leaks (0.5-2 g/s). The problem is to discriminate between leak noise and other noises which are generated by SGU.

With the purposes of improvement of signal to noise ratio, investigations on nonlinear filtering are purposewise. Neural networks application for recognition of noisy acoustic signals has shown that it is a prominent approach for plant monitoring. It was confirmed, that the additional advantage of neural network consists in ability to adapt to changing environment and to generalize the unknown earlier information.

For fast and robust training optimal pattern generation and feature extraction is necessary. The first positive results were obtained for power invariant pattern generation.

The first experience of application of recurrent networks has been gained along with recognition of multichannel patterns

To obtain a robust estimation of probability of false alarm and leak missing it is necessary to carry out processing of the noises recorded during transients.

Further research should be concentrated on recognition of other types of abnormal acoustic noises and on the development of nonlinear mathematical models of these noises.

On the basis of experimental data, recorded during PFR End-of-Life Experiments it is purposewise to investigate different leak location techniques.

References

1. D.C. Gabatz, E.L. Gluekler, F. Fletcher, T. Claytor On-line low and high frequency acoustic leak detection and location for an automated stem generator protection system // Report for IAEA Working Group on Fast Reactors Specialists' Meeting on "Acoustic Ultrasonic Detection of In-Sodium Water Leaks", Aix-en-Provence, France, October 1 - 3, 1990.
2. J.A.McKnight, R.Rowly, M.J.Beesly Acoustic surveillance techniques for SGU leak monitoring // IAEA IWGFR Specialists' Meeting on "Acoustic Ultrasonic Detection of In-Sodium Water Leaks", Aix-En-Provence, France, October 1 - 3, 1990.
3. R.P.Lippmann An Introduction to Computing with Neural Nets // IEEE ASSP Magazine, April 1987, pp.4-22.

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