УДК 620.9 DOI:10.30724/1998-9903-2024-26-1-128-137

ANALYSIS OF APPLICATION OF ENTROPY METHODS OF VIBRATION DIAGNOSTIC SIGNAL PROCESSING TO ASSESS TECHNICAL CONDITION OF PIPELINES

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Abstract.*The purpose of this article is to review the existing reliability problems of pipeline systems of power complexes. The article considers the existing statistical and logistics systems, which allow to process diagnostic information when assessing the technical condition of pipelines. Modern diagnostic methods are mainly based on the use of vibration, sound, and ultrasonic sensors. The presence of a defect in a pipeline is determined by analysis of the amplitude of a diagnostic signal. Higher efficiency in detecting defects was shown by probability-statistical methods of signal analysis, which are based on chaos theory. One such method is entropy analysis. Analysis of modern signal processing methods has shown that methods based on chaos theory are the most effective. The possibility of using entropy indices as sensitive diagnostic signs is considered. Comparative analysis of signal processing was carried out using entropy methods (Shannon entropy, Kolmogorov entropy) and using known statistical and logistic methods (Fourier Transform, Wavelet Transform, Hilbert-Huang Transform). The analysis results showed that entropy indicators respond to a change in signal structure caused by the presence of a defect in the pipeline or Entropy analysis is a promising method of processing diagnostic signals when assessing the technical condition of pipelines.*

Keywords: *Analysis; application; entropy methods; processing; vibrodiagnostic signals; evaluation; technical condition; pipelines.*

For citation: Gaponenko S.O., Kondratiev A.E., Kalinina M.V., Derbeneva A.A. Analysis of application of entropy methods of vibration diagnostic signal processing to assess technical condition of pipelines. *Power engineering: research, equipment, technology*. 2024; 26 (2): 128-137. doi:10.30724/1998-9903-2024-26-2-128-137.

АНАЛИЗ ПРИМЕНЕНИЯ ЭНТРОПИЙНЫХ МЕТОДОВ ОБРАБОТКИ ВИБРОДИАГНОСТИЧЕСКИХ СИГНАЛОВ ДЛЯ ОЦЕНКИ ТЕХНИЧЕСКОГО СОСТОЯНИЯ ТРУБОПРОВОДОВ

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Резюме: *Целью данной статьи является обзор существующих проблем надежности трубопроводных систем энергетических комплексов. Рассмотрены существующие статистические и логистические системы, позволяющие обрабатывать диагностическую информацию при оценке технического состояния трубопроводов. Современные методы диагностики в основном основаны на использовании вибрационных, звуковых и ультразвуковых датчиков. Наличие дефекта в трубопроводе определяется путем анализа амплитуды диагностического сигнала. Более высокую эффективность при обнаружении дефектов показали вероятностно-статистические методы анализа сигналов, основанные на теории хаоса. Одним из таких методов является энтропийный анализ. Анализ современных методов обработки сигналов показал, что наиболее эффективными являются методы, основанные на теории хаоса. Рассмотрена возможность использования энтропийных показателей в качестве чувствительных диагностических признаков. Проведен сравнительный анализ обработки сигналов с использованием энтропийных методов (энтропия Шеннона, энтропия Колмогорова) и известных статистических и логистических методов (преобразование Фурье, вейвлет-преобразование, преобразование Гильберта-Хуанга). Результаты анализа показали, что энтропийные показатели реагируют на изменение структуры сигнала, вызванное наличием дефекта в трубопроводе* *или Энтропийный анализ является перспективным методом обработки диагностических сигналов при оценке технического состояния трубопроводов.*

Ключевые слова: *Анализ; применение; энтропийные методы; обработка; вибродиагностические сигналы; оценка; техническое состояние; трубопроводы.*

Для цитирования: Гапоненко С.О., Кондратьев А.Е., Калинина М.В., Дербенева А.А. Анализ применения энтропийных методов обработки вибродиагностических сигналов для оценки технического состояния трубопроводов // Известия высших учебных заведений. ПРОБЛЕМЫ ЭНЕРГЕТИКИ. 2024. Т.26. № 2. С. 128-137. doi:10.30724/1998-9903-2024-26-2-128-137.

Introduction

Pipeline systems of energy complexes are considered critical structures, and high requirements are imposed on their safe and reliable operation.

Due to high operating parameters, such as operating pressure, flow rate, length, and increasing age of pipeline systems, there is a complex of problems related to safety, reliability, resource assessment, and risk [1].

The solution to these problems is ensured by timely diagnostics of pipeline systems. According to the results of diagnostics, pipelines are either allowed for further operation or undergo repair or replacement [2].Modern methods of pipeline diagnostics are mainly based on the use of vibration, sound, and ultrasonic sensors [3]. Vibration diagnostic signals are used as diagnostic information. In this case, the presence of a defect in the pipeline is determined by analyzing the amplitude of the diagnostic signal.

To carry out a reliable assessment of the technical condition of the pipeline, it is necessary to properly extract the diagnostic information from the vibration signal [4,5].The following methods are traditionally used for signal processing: wavelet transform, Fourier transform, S-transform, Hilbert-Huang transform. In this article, we will consider the possibility of using probabilistic-statistical methods of signal analysis, which are based on chaos theory.

Fast Fourier Transform

Fast Fourier transform (FFT) [6] is a kind of discrete Fourier transform (DFT), which is calculated by the formula:

$$X(k) = \sum_{n=0}^{N-1} x\,(n) W_N^{nk},\ 0 \leq k\ \leq N-1 \quad (1)$$

where X (k)–k-яcomplex amplitude (component) of the spectrum; x(n)– samples of a discrete signal (periodic with a period N or finite length N); W_N^{nk}– turning factor (or transformation kernel).

Direct calculation of the DFT by formula (1) for large N (when processing audio signals, the length of the audio signal can reach 2^{10}= 1024) is ineffective, a large number of operations does not make it possible to provide real-time. Indeed, to calculate the N-point transformation, it is required to perform $(N\text{-}1)^2$complex multiplications andN(N-1) complex additions, that is, the amount of computation is of the order of N^2operations of addition and multiplication of complex numbers [7].To reduce computational costs, FFT algorithms have been developed based on the periodicity of the transformation kernelW_N^{nk}. The idea of the FFT is to divide the N-point sequence into two, from the DFT of which you can obtain the DFT of the original sequence, and continue this division of each new sequence until there are only two sequences left [8].

The main problem when applying the Fourier transform is the requirement to use only signals whose length must be with a power of two. For example, performing an FFT with an array of 512 or 1024 points of the signal is acceptable, but not with an array of 500 or 1000 points. As a result, a signal with a frequency of 1 kHz, taken at a sampling rate of 10 MHz, cannot be subjected to an FFT at its length of the period, which in these conditions will be 1000 points, then you will have to use a slightly larger area for analysis - 1.024 signal periods and thus distort the signal spectrum because the Fourier transform should be carried out exactly on the segment of the signal period or a multiple of it [9].

Another disadvantage of the FFT is that the Fourier transform does not reveal the peculiarities of the behavior of the spectral components in time. The signal is measured at certain points in time, and there is no information about its state in the intervals between these points.

Wavelet transform

The wavelet transform is similar to the windowed Fourier transform but has a completely different scoring function. The main difference is that the Fourier transform decomposes the signal into sine and cosine components, i.e. functions localized in Fourier space.

The wavelet transform, on the other hand, uses functions localized in both real and Fourier space. The wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\psi^{*}_{(a,b)}(x)\,dx \quad (2)$$

where * - complex conjugacy symbol and functionψ - some function. The function can be chosen arbitrarily, but it must follow certain rules.

The wavelet transform is actually an infinite set of different transformations, depending on the evaluation function used to calculate it [10].

There are many types of classification of wavelet transform options. Consider a division based on wavelet orthogonality. In practice, orthogonal wavelets are used for discrete wavelet transforms and non-orthogonal wavelets for continuous ones. Thesetwotypesoftransformationshavecertainproperties.

Discrete Wavelet Transform (DWT) is an implementation of a wavelet transform using a discrete set of wavelet scales and translations that obey certain specific rules [11]. DWT decomposes the signal into a mutually orthogonal set of wavelets, it is the main difference from the continuous wavelet transform (CWT).

A wavelet can be constructed from a scale function that describes its scalability properties. The limitation is that the scale function must be orthogonal to its discrete transformations, which implies some mathematical constraints on them, namely the homothety equation:

$$\Phi(x) = \sum_{k=-\infty}^{\infty} a_k \Phi(S_x - k) \qquad (3)$$

where S - the scale factor, is usually selected equal to two. The area under the function must be normalized, and the scaling function must be orthogonal to its numerical translations:

$$\int_{-\infty}^{\infty} \Phi(x)\Phi(x+l)dx = \delta_{0,l} \qquad (4)$$

After introducing some additional conditions, we obtain the result of all these equations, i.e. a finite set of coefficients$a_k$that determine the scaling function, as well as the wavelet. The wavelet is obtained from the scaling function as N, where N is an even integer. The set of wavelets then forms an orthonormal basis that is used to decompose the signal.

Continuous Wavelet Transform (CWT) is an implementation of a wavelet transform using arbitrary scales and arbitrary wavelets. The wavelets used are not orthogonal, and the data obtained during this transformation is highly correlated. For discrete-time sequences, you can also use this transform, with the restriction that the smallest wavelet translations should be equal to the data sampling. This is sometimes called Discrete-Time Continuous Wavelet Transform (DT-CWT) and is the most commonly used method for calculating CWT in practice[11].

With CWT, the definition of the wavelet transform is used directly, i.e. calculate the convolution of the scaled wavelet signal. For each scale, a set of the same length N as the input signal is obtained. Using M randomly selected scales, an N × M field is obtained that directly represents the time-frequency plane. The algorithm used for this calculation can be based on forward convolution or on convolution through multiplication in Fourier space, which is called the fast wavelet transform.

The choice of the wavelet for use in time-frequency decomposition is the most important step in determining the time and frequency resolution of the result. You cannot change the basic characteristics of the wavelet transform in this way, but you can increase the overall frequency or time resolution. This is directly proportional to the width of the used wavelet in real and Fourier space. For example, if we use the Morlet wavelet, then one can expect a high-frequency resolution since such a wavelet is very well localized in frequency. Conversely, using the derivative of Gaussian (DOG), we get good localization in time, but poor in frequency.

The reliability of the vibration signal analysis using the wavelet transform largely depends on the choice of the basis function. In this regard, the problem arises of the formation of an adaptive basis of the frequency-time conversion functionally dependent on the content of the vibroacoustic signals themselves.

Hilbert-Huang transform

The Hilbert – Huang transform [12] (HHT) is a transformation based on the assumption that any signal can be represented as a sum of oscillatory processes, each of which satisfies the symmetry condition and some residual, which is a trend.

The implementation of the Hilbert – Huang transform consists of two stages: empirical mode decomposition (EMD) and the Hilbert transform. The EMD method is intended for the analysis of non-stationary and non-linear processes. Unlike Fourier and wavelet analysis, EMD is straightforward, intuitive, and adaptive.

Empirical mode decomposition is implemented in several stages [13].

1. The position of all local extrema is determined in the signaly(k).

2. The upper $u_t(k)$ and lower $u_b(k)$ envelopes of the process are calculated using a cubic spline, respectively.

The function of average values $m_1(k)$ between the envelopes is determined:

$$m_1(k) = \frac{u_t(k)+u_b(b)}{2} \quad (5)$$

The difference between the signal y(k) and the function $m_1(k)$ gives the first sifting component - the function $h_1(k)$, which is the first approximation of the internal mode function:

$$h1(k) = y(k) - m1(k) \quad (6)$$

3. The operations are repeated in stages 1 and 2, in this case, instead of the functiony(k) the functionh$_1$(k) is taken, and then the second approximation to the first function of the internal mode is found::

$$h2(k) = h1(k) - m2(k) \quad (7)$$

The sifting operation can be stopped at a given iteration value or at a given normalized squared difference between two successive iterations.

4. The last value $h_i(k)$ of iterations is taken as the highest-frequency functionc$_1$(k) = $h_i(k)$ of the family of functions of the internal mode, which is directly included in the original signaly(k). This allows us to subtract $c_1(k)$ from the signal and leave the lowest-frequency components in it:

$$r1(k) = y(k) - c1(k) \quad (8)$$

The functionr$_1$(k) is processed as new data using a similar technique with finding the second function of the internal mode – $c_2(k)$, after which the process continues.

So, the signal decomposition in the n-approximation is achieved:

$$y(k) = \sum_{i=1}^{n} c_i(k) + r_n(k) \quad (9)$$

Decomposition is based on the assumption that any data consists of various simple internal mode oscillations. Each internal mode, linear or non-linear, represents a simple wobble containing the same number of extrema and zero crossovers. Moreover, the fluctuations are symmetrical about the local mean. At any moment of time, many internal oscillations can coexist, superimposed on each other [14]. The signal data itself is the sum of all mode waves.

The Hilbert-Huang transform is a time-frequency analysis of data and does not require an a priori functional transformation basis. Instantaneous frequencies are calculated from the derivatives of the phase functions by the Hilbert transformation of the basis functions [15].

S-transform

S-transform [16] (on behalf of the researcher Stockwell) is a relatively recently developed method of time-frequency analysis. The S-transform is a kind of windowed Fourier transform with a Gaussian windowing function of the form:

$$f(x) = ae^{-b(x-c)^2} \quad (10)$$

This operational method is based on the use of polynomial approximation as an operational calculus.

Mathematically, an S-transform is defined as follows:

$$S_x(t,f) = \int_{-\infty}^{\infty} x(\tau)|f|e^{-\pi(t-\tau)^2 f^2} e^{-j2\pi f\tau} d\tau \quad (11)$$

S-transform combines features of FFT and wavelet transforms. The S-transform provides frequency-dependent resolution similar to the wavelet transform, while simultaneously providing a direct link to the linear Fourier spectrum like the short-term Fourier transform. The S-transform procedure is based on the Fourier transform and the use of a sliding window function, which is similar to the short-term Fourier transform; however, the width of the window function in the time domain will be inversely proportional to the frequency of the analysis.So, the window is wider in the low-frequency regions and narrower in the higher-frequency regions. As a result, the S-transform (like the wavelet transform) has a "fine" frequency resolution in the low-frequency region and a "coarse" resolution for the high-frequency components. S-transform is used to analyze short-duration transient signals. Examples of the use of S-transform are described in some engineering and biomedical fields.

Despite its important advantages, the S transform has limitations. First, because the windowing function narrows in time at higher analysis frequencies, the frequency resolution inevitably becomes worse. Poor frequency resolution can lead to poor performance or even erroneous results in practical applications. Secondly, the amplitude of the noise can be increased in the high-frequency region, which can lead to false conclusions when analyzing noisy signals.

Methods for entropy parameterization of diagnostic signals

The above signal processing methods are based on the registration and analysis of vibroacoustic signals. However, such signals have different sources, physical nature, and causes of occurrence.So, the typical methods of processing vibroacoustic signals have significant differences, which forces the use of several parallel mechanisms in diagnostic systems, which complicates these systems[17].At the same time, these mathematical mechanisms often do not allow detecting deviations in the technical state of objects that go beyond the previously described ones, especially at an early stage of the occurrence of these deviations. For example, if there is a vibrodiagnostic signal, the parameters of which do not exceed the set threshold values, but the signal carries information about the deviation of the state of the diagnosed object, then this signal can be ignored[18].

Considering the complexity of dynamic interactions in the presence of defects in pipeline systems, the use of traditional processing methods is insufficient. Equipment and pipelines of power systems and complexes often exhibit chaotic behavior, which is reflected in the nature of diagnostic signals.

Such irregular signal components cannot be effectively identified by traditional methods.

Modern methods of processing useful signals are mainly based on the analysis of the amplitude of the useful signal [19]. However, the amplitude is not a reliable diagnostic sign, since a large number of different factors can affect the change in amplitude, which is extremely problematic to take into account.

Methods of entropy parameterization of diagnostic signals (Shannon entropy, Kolmogorov entropy) can be successfully used to study chaotic oscillations in physical systems. Their use for the analysis of vibroacoustic signals will improve the reliability of the control of pipeline systems of power complexes and, as a result, will significantly increase the reliability of the operation of these facilities[20].

In this case, probabilistic and statistical methods of signal analysis, which are based on chaos theory, show high efficiency. It should be noted that the entropy indicators respond to changes in the signal structure caused by the presence of a defect or leak in the pipeline. At the same time, the entropy indices depend little on the amplitude. Let us consider the possibility of using entropy indicators as sensitive diagnostic signs[21].

Shannon's entropy

Shannon's entropy characterizes the degree of process variability. By increasing the value of Shannon's entropy, one can judge the effect of the defect on the signal under study[22]. The calculation of Shannon's entropy is based on the formula proposed by Claude Shannon to calculate the informational entropy:

$$H = -\sum_{i=1}^{n} p_i log p_i \ , \qquad (12)$$

where p_i is the probability of the value from the sample falling into the i-level.

Shannon's entropy quantifies the deviation of the distribution of the values of the time series by levels from the equiprobable one. If one of the levels is filled with values, the Shannon entropy is $H_{sh} = 0$. When the values are evenly distributed over the levels, Shannon's entropy is maximum and is equal to log n, where n is the number of levels[23, 24].

So, the entropy of event X is the sum with the opposite sign of all the products of the relative frequencies of occurrence of an event i, multiplied by their own logarithms. This definition for discrete random events can be extended to the probability distribution function.

Shannon derived this definition of entropy from the following assumptions:

- the measure must be continuous; that is, a small change in the value of the probability value should cause a small resultant change in entropy;
- in the case when all are equally probable, an increase in the number of options should always increase the total entropy;
- it should be possible to make a choice in two steps, in which the entropy of the final result should be the sum of the entropies of the intermediate results[25].

Using Shannon's entropy, it is possible to quantitatively characterize the distribution of time series values. When the state of the system changes, the distribution of its parameters changes, which leads to a change in the entropy value. So, Shannon's entropy is a function of the state of the system, since it quantitatively estimates the measure of uncertainty in the values of the parameters that characterize the system.

Kolmogorov's entropy

Kolmogorov's entropy or, in other words, approximating entropy (ApEn) is an important characteristic of deterministic chaos. ApEn is defined as the rate at which information about the state of a dynamic system is lost over time[26].

When calculating the Kolmogorov entropy, the time series is divided into a sequence of vectors m, then the distance between two vectors X (i) and X (j) is determined:

$$d\big(X(i), X(j)\big) = \max_{k=1,2\ldots,m}(|x(i+k-1) - x(j+k-1)|) \qquad (13)$$

wherei = 1,2, ... N-m + 1, j = 1.2 ..., N-m + 1 and N is the number of samples contained in the time series.

Then, for each vector X(i) wecalculate$C_i^m(r)$ – a measure describing the similarity between the vectors X(i) and all other vectors:

$$C_i^m(r) = \frac{1}{N-(m-1)} \sum_{j\neq 1} \theta \{r - d[X(i), X(j)]\}, \quad (14)$$

where j = 1,2, ..., N - m + 1; r - the value of the tolerance, which is the parameter of the noise filter.

Next, the average value of the logarithm$C_i^m(r)$is calculated:

$$\varphi^m(r) = \frac{1}{N-(m+1)} \sum_i \ln[C_i^m(r)], \quad (15)$$

wherei = 1,2, ..., N-m + 1.

Then the value of the Kolmogorov entropy:

$$ApEn(m,r) = \lim_{N\to\infty}[\varphi^m(r) - \varphi^{m+1}(r)], \quad (16)$$

In practice, a limited-time series is used, which consists of N reports[27], while the value of the Kolmogorov entropy of the time series is determined as follows:

$$ApEn(m,r,N) = \varphi^m(r) - \varphi^{m+1}(r) \quad (17)$$

Equation (17) shows the similarity between the reconstructed vectors m and m + 1 in the time series. This similarity indicates the regularity of the analyzed time series and affects the corresponding value of the Kolmogorov entropy ApEn[28, 29]The more regularity, the lower the entropy value.

At the same time, the Kolmogorov entropy expresses the regularity of time series in several dimensions and reflects more time information. This makes this parameter an attractive tool for monitoring the dynamics of the system, and information on the development of defects is important not only for diagnosing the current state of the controlled object but also for predicting its behavior in the future[30].

Conclusion

When assessing the technical condition of the pipeline by a specialist, it is important that diagnostic information is efficiently extracted from the signals of diagnostic sensors.

The effectiveness of diagnostic signs is determined, first of all, by the methods of processing the vibrodiagnostic signal. When assessing the technical condition, statistical, spectral and chaotic characteristics of digitized signals are used as primary features.

The choice of entropy parameters is due to the sensitivity of the Shannon entropy Hsh and the Kolmogorov entropy to the chaotic components of the vibrodiagnostic signal accompanying the manifestation of defects.

The results of the analysis showed that the entropy indicators respond to changes in the signal structure caused by the presence of a defect or leak in the pipeline. In this case, the entropy indices depend little on the amplitude. Entropy analysis is a promising method for processing diagnostic signals when assessing the technical condition of pipelines.

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Шифр научной специальности: 2.4.5. «Энергетические системы и комплексы»

Получено ***20.11.2023 г.***

Отредактировано ***11.01.2024 г.***

Принято ***12.02.2024 г.***