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Optimized Wavelet Transform for the Development of an Algorithm Designed for the Analysis of Digital Substation Electrical Equipment Parameters

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Abstract: This study emphasizes the urgent need for systems that monitor the operational states of primary electrical equipment, particularly power transformers. The rapid digitalization of and increasing data volumes from substations, coupled with the inability to retrofit outdated equipment with modern sensors, underscore the necessity for algorithms that analyze the operational parameters of digital substations based on key power system metrics such as current and voltage. This research focuses on digital substations with Architecture III and aims to develop an algorithm for processing digital substation data through an appropriate mathematical tool for time-series analysis. For this purpose, the fast discrete wavelet transform was chosen as the most suitable method. Within the framework of the research, possible transformer faults were divided into two categories by the nature of their manifestation. A mathematical model for two internal transformer fault categories was built. The most effective parameters from the point of view of the possibility of identifying an internal fault were selected. The proposed algorithm shows its effectiveness in the compact representation of the signal and compression of the time series of the parameter to be monitored.

Keywords: digital substation; wavelet transform; signal processing; time-series analysis; monitoring and diagnostics; fault detection algorithms

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1. Introduction

The constantly increasing demand for energy and integrating renewable energy sources (RESs) with stochastic generation increases the load on the equipment of power stations and substations. It is possible to avoid accidents by detecting defects in early stages [1]. Digital substation (DS) technology allows the assessment of the technical state of the electrical equipment. DSs have moved from the pilot project stage to the category of solutions implemented everywhere on the scale of the electric power system and have firmly established themselves as a standard [2,3]. The current pace of digitalization of the electric power industry, including not only the power grid sector but also generation companies, is fast [4,5]. However, existing methods of equipment diagnostics do not cover all categories of electrical equipment. An additional detail is the fact that the overwhelming majority of the most capital-intensive electrical equipment was manufactured before the introduction of standards requiring that sensors be equipped for monitoring at the production stage. Their implementation without interference in equipment design is not possible.

The combination of the above features necessitates the development of analysis and monitoring methods based on the analysis of primary quantities. Current trends in the development of the electric power industry are characterized by the "3 Ds of the Low Carbon Economy": decarbonization, decentralization, and digitalization. The energy sector was one of the first to implement digital technologies. Since the 1970s, energy companies have used these technologies at an unprecedented pace to optimize not only the operation of facilities but also their operating modes [6–9]. The assessment of the technical state and diagnostics of electrical equipment plays a crucial role in this case.

Electrical equipment diagnostic methods can be divided into destructive testing methods and non-destructive ones.

1. The purpose of this study is to develop an algorithm for processing DS data using OWT. To achieve this goal, the following tasks are defined:
2. The analysis of existing methods for the diagnostics of the substation electrical equipment state and operating parameters in order to identify key trends.
3. The selection of a mathematical apparatus for time-series analysis and review of existing methods.
4. The creation of a transformer mathematical model for simulating different faults.
5. The analysis, transformation, and selection of the most informative parameters.
6. The optimization of the wavelet transform (WT) application based on [7].

The development of an algorithm and its testing on data obtained from a real object. The contribution of the present research is as follows:

- A novel method for determining the operating parameters of substation electrical equipment is developed;
- The use of wavelet transform is substantiated, and optimal parameters for time-series analysis are determined, which lead to optimized wavelet transform use;
- Generalized algorithms for analyzing the operating parameters of substation electrical equipment in real time are proposed.

The presented research is structured as follows. The Introduction presents current trends in the field of digital signal processing and lists the goals and objectives of the study; Section 2 provides a literature review devoted to different methods of electrical equipment operating parameter analysis; Section 3 is devoted to the mathematical apparatus for the processing and analysis of time series and to the development of an algorithm for analyzing the operating parameters of transformers for the purpose of the diagnostics of internal faults; Section 4 discusses the results of the study and their areas of application; and the Conclusion presents the main findings.

2. Literature Review

Non-destructive testing methods are of primary interest for the diagnostics of DSs' electrical equipment. The methods for each type are classified according to the features determined by the nature of the interaction of the monitored phenomenon with the object of observation and to informative parameters obtained during the application of the method.

Most diagnostic methods that can be applied to electrical equipment require its shutdown, which leads to additional costs. In view of this, the most promising methods for research are those that allow the equipment condition to be determined in real time.

An analysis of the methods shows that the greatest scientific interest is centered on methods based on processing signals of certain physical disturbances (electromagnetic and electrostatic fields, infrared and ultraviolet radiation, acoustic and low-frequency mechanical vibrations, etc.). A summary of the studies devoted to non-destructive methods is given in Table 1.

References [10,11] describe the development of a method for analyzing the electromagnetic field. A large volume of time series is considered, and statistical methods are used to identify the main resonant frequency spectra characteristic of the autotransformer during operation. Regularities between the geometry of the transformer components and the spectrum of emitted frequencies are revealed. A further continuation of the work in this direction is given in [12], where the faults characteristic of this type of equipment are considered in more detail, the classification is determined, and the technical condition of a number of special cases of the considered autotransformers is assessed. Another physical principle and methodology are presented in the article [13], where the issue of recognizing transient overvoltages and further determining the insulation condition of TLs is considered. This method is based on measuring capacitance.

The paper [14] presents a method for analyzing vibration characteristics of SF6 circuit breakers (CBs). In the course of developing the method, a sample of signals during normal operation and breaking was formed and processed. The received signals were analyzed in the frequency and time domains, using time-series processing methods based on Fourier analysis. It is worth mentioning that approaches related to processing signals of certain physical disturbances during SF6 CBs making or breaking circuits have to be associated with taking not only the contact separation curve, the signal from the opening solenoid, and the current transformer into account, but also the complex physical processes that occur in the interrupters [15].

Table 1. Features of the implementation of DS architectures.

Ref.	Research Object	Problem	Non-Destructive Method Used
[10]	autotransformer	identifying the main resonant frequency spectra in operating mode	based on analyzing the electromagnetic field
[11]	autotransformer	prediction of the residual life	based on analyzing the electromagnetic field
[12]	autotransformer	faults characteristic classification	based on analyzing the electromagnetic field
[13]	TLs	recognizing transient overvoltages and further insulation condition assessment	based on measuring the capacitance
[14]	SF6 circuit breaker	a sample of signals from normally operating and faulty equipment of the same type was formed and processed	based on analyzing vibration characteristics
[16]	HV insulator	determining the most informative frequency in electromagnetic and acoustic spectra	based on registration of electromagnetic disturbances to determine the parameters of PD
[17]	HV electrical equipment	eliminating noise in on-site PD signals	based on registration of electromagnetic disturbances to determine the parameters of PD
[18]	power transformer	localizing the sources of acoustic emission	acoustic monitoring
[19]	DS	acoustic monitoring of the noise environment of a substation	acoustic monitoring
[20]	electromagnetic drive power and commutation mechanisms	irradiating eddy currents in the microwave range using analytical calculations	based on the analysis of the obtained parameters of eddy currents in electromagnetic mechanisms
[21]	electrical equipment	processing the obtained images in the IR spectrum using a segmentation algorithm for images obtained from thermal imaging devices	optical diagnostics
[22]	electrical equipment	processing the obtained images in the IR spectrum using a segmentation algorithm for images obtained from thermal imaging devices	optical diagnostics in combination with robotic systems
[23]	TLs	analyzing the ultraviolet spectrum emitted by corona discharges of TLs	using UAVs
[24]	electrical equipment	implementation of a cascade model of deep learning to analyze images and video data	robotic systems

An approach using the registration of electromagnetic disturbances to determine the parameters of partial discharges (PD) in equipment and their acoustic emission is presented in [16]. The most informative frequencies in electromagnetic and acoustic spectra for registering PDs were determined. The result of this research is a working prototype of a device for detecting damaged outdoor high-voltage (HV) insulators. Along with the problem of PD parameters' determination, the issue of eliminating noise in on-site PD signals from HV electrical equipment has to be addressed [17]. In the paper, a novel denoising method of PD signals based on improved singular value decomposition (SVD) and variational mode decomposition (VMD) is proposed. SVD allows the elimination of periodic narrowband interference in the Fourier transform (FT) power spectrum through the determination of the number of singular values of periodic narrowband interference.

Another method, which can be attributed to the acoustic type of non-destructive testing, is described in [18]. The emphasis is on sound signal processing technologies. The essence of the method lies in localizing the sources of acoustic emission of the power transformer. Mathematical calculations are given for converting the original acoustic signal into an array of data containing the necessary information.

The work [19] also describes a method for acoustic monitoring with the main emphasis on pre-processing the signal. The result is a prototype of a monitoring system for the acoustic background of detached substation equipment.

The paper [20] describes a method based on eddy current parameters analysis in the electromagnetic mechanisms (EMMs) through irradiating them in the microwave range. Analytical calculations for parameter processing are given.

The use of various means of statistical and analytical processing of the obtained data allows us to automate and improve the diagnostic methods. The work [21] improves the method for image processing in the infrared (IR) spectrum, which can be attributed to optical diagnostics methods. The proposed method describes the use of a segmentation algorithm for images obtained from thermal imagers to determine the most informative parts (patterns) and their processing.

A comparative analysis of software for segmenting images obtained from a thermal imager is given in [22]. The use of robotic systems significantly expands the scope of the diagnostic application.

The article [23] covers the practical aspect of using unmanned aerial vehicles (UAVs) to determine the state of TLs by analyzing the ultraviolet spectrum emitted by corona discharges.

The analysis of images and video data obtained from robotic systems by means of methods based on the cascade model of deep learning is examined in [24].

The prospects for development and the current relevance of the issue addressed in the present research are confirmed by the ongoing method development for analyzing the parameters of a transformer's operation. For example, in the review paper [25], an analysis of patents in the field of monitoring and diagnostics of transformers is carried out, most of which are methods and techniques for analyzing primary quantities.

In order to implement diagnostic methods on the power-system scale, they must be properly tested and introduced at the level of state or corporate standards. The existing ones today do not cover all categories of electrical equipment.

Developing and manifesting equipment defects change the equipment's main electrical parameters. For example, a special case which is addressed in the present research is the turn-to-turn short circuits (TTTSCs) of a power transformer, resulting in a change in the transformation ratio, winding resistance, and as a consequence, currents and voltages.

3. Methods and Materials

3.1. DS Technology

The main difference between the DS and traditional substations is the transfer of the information exchange processes used for monitoring, analysis, and management to a digital format. This leads to the big data paradigm that can be used to develop methods for monitoring the current state of equipment, predictive analysis, and adaptive protection because of the data retrospect potential.

At the moment, that transition mainly affects secondary circuits of relay protection and controls (RPC). However, one of the serious problems arising from the fact that a significant number of primary equipment units' operation is beyond their standard service life remains unsolved. The additional challenge to that transition for, for example, such primary equipment as power transformers, is devoted to collected data preprocessing [6] due to the difficulty of finding a balance between data quality and quantity. Thus, there is a need to develop and implement monitoring systems for the normal and operating states of the substations' primary electrical equipment.

High rates of digitalization and the collected data growth, combined with the lack of the ability to equip outdated equipment with modern sensors, determine the feasibility of algorithm development for analyzing the DS electrical equipment operating parameters.

The specifics of the existing solutions' application in terms of the DS electrical equipment monitoring do not affect the methods of diagnostics data interpretation. The changes affect mainly the devices for collecting and processing information that receive it from sensors close to the equipment under monitoring.

The operation of the sensors and the process of data transmission to the devices for collection and processing remains virtually unchanged due to a number of reasons:

(1) Devices that record a particular physical or chemical parameter will require significant revision and complication to comply with the digital model of IEC-61850;
(2) The structure of the facility's local area network (LAN) will require significant complication;
(3) Compliance with the requirements for electromagnetic compatibility will significantly complicate the design and increase the cost of sensor production.

The result of the digital transformation is data aggregation from all the measurement, monitoring, and control systems at different levels of the facility's LAN (process bus, station bus), which opens up broad prospects for analysis including big data and artificial intelligence (AI)-based approaches.

According to the mentioned above, the following are promising areas:

(1) Development of digital twins of substation equipment [26];
(2) Processing of time-dependent currents and voltages from the process bus, which are highly discretized measurements of instantaneous values;
(3) Application of statistical methods, machine-learning (ML) algorithms, and neural networks for information analysis [27].

It is worth noting several important research articles devoted to digitalization aspects for solving technical condition tasks.

The paper [28] outlines the features of using the analysis of digitized values of currents and voltages for monitoring and detecting contingencies in a power system which is the electrical infrastructure of railway tracks.

The work [29] proposes a comprehensive approach to the methodology for compiling digital twins of substation electrical equipment with a special case of compiling a digital twin for an HV circuit breaker.

The articles [30,31] highlight the practical aspect of using digital twins of substation electrical equipment for the purpose of determining its technical condition.

An integrated approach to the research and development of an RPC digital model based on digital twins is well described in [32].

The study object in the present research is the DS which has Architecture III and has measured digitized currents and voltages obtained from current transformers (CTs) and voltage transformers (VTs). The methods used in the present study are those for analyzing the operating parameters of DS electrical equipment and based on an optimized wavelet transform (OWT) [8].

3.2. DS Description

The parameters of information interaction, model descriptions and requirements for the DS are established by the provisions of the IEC-61850 standard. The information model is described using a configuration file written in the SCL language.

The description levels are scalable, starting from factory configurations of intelligent electronic devices (IEDs) to a complete description of the DS, including configuration files which are used for interacting with substation equipment and devices, including intersystem communications [5]. The types of files describing the DS information model are following ones:

(1) The ICD (IED Capability Description);
(2) The IID (Instantiated IED Description);
(3) The System Specification Description (SSD);
(4) The Substation Configuration Description (SCD);
(5) The Configuration Description (CID);
(6) The SED (System Exchange Description).

In order to organize communication channels in a DS, LAN based on Ethernet technology is used, and the protocols described by the IEC 61850 standard [3] are used as transmission ones.

An important advantage of a DS is the placement of devices for collecting discrete and analog signals, implementing control close to the equipment. The subsequent transmission of all the data required for the RPC devices is carried out in digital form. This allows the overall length reduction in cables and secondary circuits, which, in its turn, leads to a reduction in the damage likelihood and the increase in the observability of secondary systems.

Within the framework of the substation's secondary system, the IEC 61850 standard defines the use of the following data transmission protocols:

(1) SV (Sampled Values);
(2) GOOSE (Generic Object-Oriented Substation Event);
(3) MMS (manufacturing message specification);

Depending on how widely digital data transmission technologies are implemented at the substation, three architectures can be distinguished. The main difference between them is the presence of a separate level of the LAN, the so-called "process bus" (PB).

The main features of the implementation of Architectures I, II, and III in terms of the applied technical means and protocols are given in Table 2.

Table 2. Features of the implementation of DS architectures.

Functions	Architecture I	Architecture II	Architecture III
Using the MMS protocol	yes	yes	yes
Using the GOOSE protocol	no	yes	yes
Using the Sampled Values protocol	no	no	yes
Application of IEC 61850-enabled equipment at the substation level	no	yes	yes
Application of IEC 61850-enabled equipment at the connection level	yes	yes	yes
Field-level application of IEC 61850-enabled equipment	yes	yes	yes
Using the DSC	no	yes	yes
Using the ASC	no	no	yes
Using DCT, DVT, working on the SV protocol	no	no	yes

Architecture III for the development of an algorithm designed for the analysis of DS electrical equipment parameters is considered in the present research.

3.3. Applied Methods of Time-Series Analysis

The main parameters characterizing the operating mode of electric power facilities are the currents and voltages obtained from CTs and VTs.

The data are time series to which various methods of signal conversion and processing can be applied. The main tasks that arise in this case can be reduced to the following:

- Reliable determination and localization of disturbances in the signal, characteristic of the detected and analyzed phenomenon;
- Noise removal, determination of the signal informative component;
- Identification of correlations and dependencies between the nature of the signal and changes in the system parameters for issuing a control action or further use in processing algorithms.

One of the "classical" methods used for frequency analysis of signals is the Fourier transform (FT).

$$F(f) = \int_{-\infty}^{+\infty} f(x)e^{-\iota\omega x}dx, \quad (1)$$

where $e^{-\iota\omega x}$—complex representation of trigonometric functions that form an orthonormal basis.

Due to the fact that signal processing is currently performed mainly by means of computer technology, the discrete Fourier transform (DFT) is used, namely a more advanced type of DFT in terms of speed—the fast Fourier transform (FFT).

To improve the implementation of localization in the time domain, the windowed Fourier transform (WFT) is used:

$$F(f) = \int_{-\infty}^{+\infty} f(x)g(x - x_0)e^{-\iota x\omega}dx, \quad (2)$$

where $g(x - x_0)$—time-localized window function.

There are many different window functions (Blackman, Bartlett–Hann, Hanning, Bohman, etc.), where the main differences are determined mainly by the type of the specified function and the level of distortion introduced by the use of windows.

Let us consider the non-stationary signal. The spectrum of a discrete time series of 1000 samples obtained with the STFT, using the Blackman window, the width of which is 50 points, and the overlap parameter of which is 20 points, will look as follows (Figure 1).

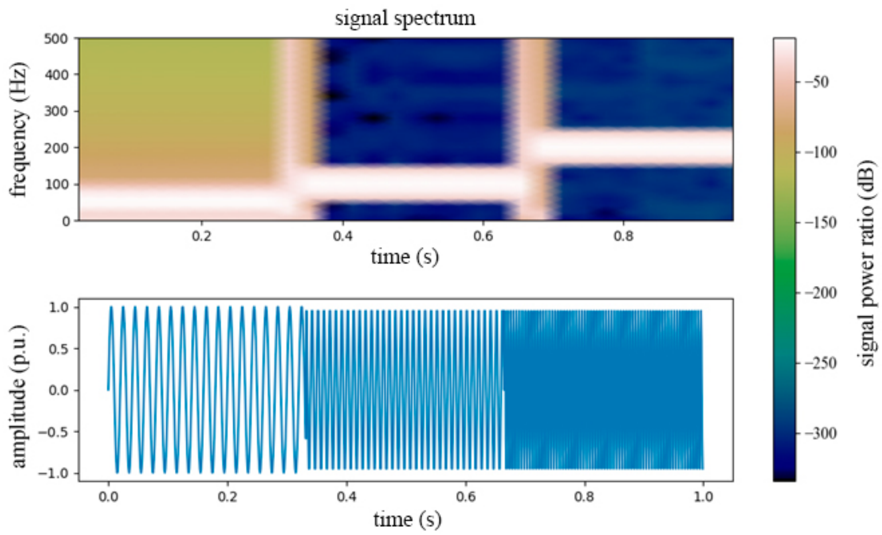

Figure 1. Spectrogram of the signal after the STFT.

As can be seen, the spectrum areas showing the presence of frequencies and the localization of changes in time are not clearly defined. This effect is due to the choice of the window, the setting of its width, and the methods used for overlapping windows. They are of decisive importance for the implementation of the STFT. The wider the window, the higher the frequency resolution of the signal, but the worse the representation of the signal in the time domain.

It is impossible to obtain a good resolution simultaneously in the time and frequency domains due to the Heisenberg uncertainty principle [33].

One of the main disadvantages of the WFT is the fact that the window parameters are fixed and cannot be changed in accordance with the local features of the signal under consideration. This moment complicates the analysis of time series dynamically changing in the frequency spectrum.

3.4. Wavelet Transform

The WT will help solve the above-described problems of the STFT. The main difference between the WT and the FT is the choice of the analyzing function. The so-called wavelets are used as such, which are short functions limited in time and frequency and formed from the original (parent) wavelet:

$$\psi_{ab}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \tag{3}$$

where $\psi_{ab}(t)$—resulting wavelet; a—scaling factor; ψ—“parent” wavelet; b—shift coefficient.

These functions, due to changes in the coefficients a and b, have the properties of scaling and time shift.

There are many wavelet functions with different types of transformation, methods of definition, and properties of the formed basis:

- Functions that perform discrete or continuous wavelet transformation;
- Functions that have an orthogonal, semi-orthogonal, or biorthogonal basis;
- Functions that have the properties of symmetry, asymmetry, or non-symmetry;
- Functions that are defined analytically or iteratively.

The requirements for functions that are used as wavelets for signal decomposition can be reduced to the following:

1. Boundedness—the square of the norm of the function used for the transformation must be finite:

$$\|\psi\|^2 = \int_{-\infty}^{+\infty} |\psi(t)|^2 dt = 0, \tag{4}$$

2. Localization—the wavelet function must be localized in the time domain:

$$\begin{cases} |\psi(t)| \le C(1+|e|)^{-1-\varepsilon} \\ S_\psi(\omega) \le C(1+|\omega|)^{-1-\varepsilon}, \end{cases} \text{if } \varepsilon > 0 \tag{5}$$

3. Zero mean—the function must be alternating, have at least one transition through the zero point, and have zero area:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{6}$$

4. Self-similarity—wavelets of different levels of decomposition are obtained by transforming the mother wavelet using a scaling and shifting coefficient.

It is worth noting that the disadvantage inherent in the windowed FT, which is the fixed window size, is successfully solved using the WT. The defining moment is the fact that the wavelet functions are scaled, for high-frequency components they are narrowed, and for low-frequency ones they become wider. At the same time, an erroneous choice of window in the OFT and the resulting values due to spectrum spreading can mask high-frequency signal distortions, which will affect the accuracy of the analysis.

The scalability properties of the WT allow a more detailed analysis of the signal on all frequency spectra.

The WT, by the nature of the actions with the coefficients, can be divided into the following:

- Continuous (integral);
- Discrete;
- Batch.

3.5. Selecting the Type of WT for Analyzing Time Series from the DSP Process Bus

Since the time series obtained from the DS process bus are discrete samples, the use of a continuous WT requires large computational costs and therefore it is impractical. In the present research, the fast wavelet transform (FWT) that is the part of the DWT is used.

Discretization of the basis functions is required, while maintaining the properties of signal synthesis from the expansion coefficients. For these purposes, the DWT is used. The most common variant of discretization is by a power of two.

The formation of the basis ψ_{mk} in this case is described as follows:

$$a = 2^m, b = k \cdot 2^m, \psi_{mk} = \frac{1}{\sqrt{2}} \psi\left(\frac{t-b}{a}\right) = \frac{1}{\sqrt{2}} \psi\left(2^{-m} t - k\right), \tag{7}$$

where m and k—integers. The parameter m, in this case, performs scaling.

This method results in a partition of the plane a, b into a grid with a step along the axes m and k, respectively. This method has been called a dyadic transformation in a number of sources.

The signal decomposition in this case is given below:

$$c_{mk} = (S(t), \psi_{mk}(t)) = \int_{-\infty}^{+\infty} S(t) \psi_{mk}(t) dt, \tag{8}$$

The signal synthesis is defined as follows:

$$S_t = \sum_{m,k} c_{mk} \psi_{mk}(t). \tag{9}$$

where c_{mk}—expansion coefficients.

For the analyzed signal, which is a series of samples, the provisions of Kotelnikov's theorem [34] are fulfilled. They determine the fact that a continuous signal $S(t)$, having a frequency spectrum not higher than f_{max}, can be determined with a sufficient degree of reliability by a sequence of instantaneous values with a sampling frequency at least 2 times higher. For digital streams having the format of the corporate standard FGC (288 samples per period), the sampling frequency of the signal is 14,400 Hz, respectively—the maximum frequency, information about which is contained in this signal, is 7200 Hz.

If the number of discrete values in the signal under consideration is $N = 2^{n0}$, then the maximum scaling coefficient m is equal to $n_0 - 1$. The maximum value of the shift coefficient for the current scaling coefficient is determined by $k = 2^{n_0 - m} - 1$. In particular, for the smallest scale, when $m = 0$, the number of wavelet shifts will be equal to $2^{n_0} - 1 = N - 1$. Increasing the coefficient m "expands" the wavelet $\psi_{mk}(t)$ by two times, and the number of shifts decreases accordingly.

If the SV-stream of the FGC corporate profile with a sample of 288 instantaneous values for a period of 1 s is considered, then the maximum level of decomposition m_{max} will be equal to $\log_2 14,400 - 1 = 13.808 \approx 13$.

The wavelet coefficients c_{mk} can be found using the fast wavelet transform (FWT) procedure, which is a type of discrete wavelet transform. The essence of the method is reduced to the sequential decomposition of the results obtained at the previous iteration.

The signal can be represented as two components—approximating $A_m(t)$ and detailing $D_m(t)$:

$$S(t) = A_m(t) + \sum_{j=1}^{m} D_j(t). \tag{10}$$

The components are refined by an iterative method, each step corresponding to the scale a^m. In practice, this method is called multiple-scale analysis (MSA).

At the zero level of decomposition, the initial signal $S(t)$ can be represented as a sequence of coefficients a_k obtained during the WT, with scaling functions $\varphi_{0k}(t)$:

$$S(t) = A_0(t) = \sum_k a_{0k}\varphi_{0k}(t), \tag{11}$$

where $a_{0k} = a_k = (S(t), \varphi_{0k}(t))$—approximating coefficients at the level $m = 0$.

The signal is decomposed into two components $A_1(t)$ и $D_1(t)$:

$$S(t) = A_1(t) + D_1(t) = \sum_k a_{1k}\varphi_{1k}(t) + \sum_k d_{1k}\psi_{1k}(t). \tag{12}$$

The length of the coefficients is reduced by half.

Then, the decomposition process continues along $A_1(t)$, as a result of which the decomposition of the signal into an approximating $A_2(t)$ and a detailing $D_2(t)$ component is obtained.

The functions $\varphi(t)$ and $\psi(t)$ that form the basis can be uniquely determined by the coefficients h_l.

$$\varphi(t) = 2\sum_l h_l \varphi(2t - l), \tag{13}$$

$$\psi(t) = 2\sum_l (-1)^l h_{l-1}\varphi(2t - l) = 2\sum_l g_l \varphi(2t - l), \tag{14}$$

where h_j, g_l—coefficients of the functions that form the basis.

These coefficients are determined as follows:

$$h_l = (\varphi(t), \varphi(2t - l), \tag{15}$$

$$g_l = (-1)^l h_{2n-1-l}, \tag{16}$$

where $l = 0, 1, \ldots, l_0 = 2n - 1$, n—wavelet order.

The search for the approximating a_{mk} and detailing d_{mk} coefficients is performed using the following formulas:

$$a_{mk} = (S(t), \varphi_{mk}(t)) = \sum_l h_{l-2k} a_{l,m-1}, \tag{17}$$

$$d_{mk} = (S(t), \psi_{mk}(t)) = \sum_l g_{l-2k} a_{l,m-1}. \tag{18}$$

The process of signal synthesis based on its wavelet coefficients is described as follows:

$$a_{m-1,k} = \sum_l (h_{k-2l} a_{ml} + g_{k-2l} d_{ml}). \tag{19}$$

The algorithmic complexity of a direct FWT signal of length N is $2LN$, where $L = 2n$. Similarly, this is true for signal synthesis.

The sequence of the decomposition process can be represented in the form of a block diagram, shown in Figure 2.

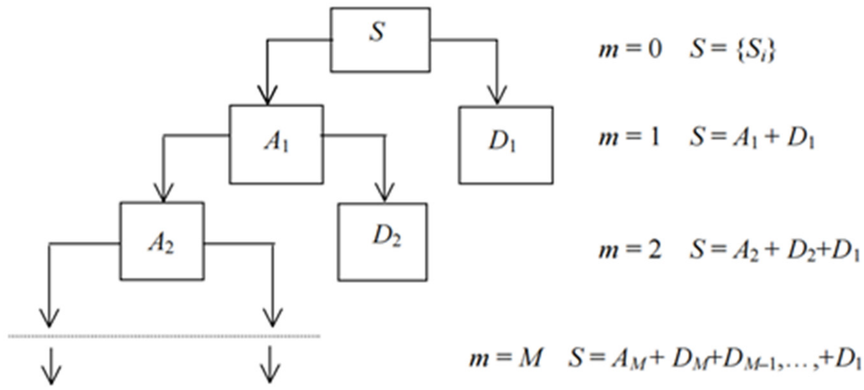

Figure 2. Multiple-scale analysis.

In practice, the approximating branch of the decomposition A_m plays the role of a low-pass filter (LPF), and the detailing D_m acts as a high-pass filter (HPF).

Considering a signal which consists of three sections of a sinusoidal signal with a frequency of 50, 100, and 200 Hz and approaching implementation on a DSP, it is represented as a signal sampled with a frequency of 14,400 Hz. The decomposition levels, which will contain the target frequencies to a greater extent, can be determined by the empirical formula:

$$level = \log_2\left(\frac{F_s}{f}\right), \tag{20}$$

where F_s is the sampling frequency and f is the target frequency.

To construct the decomposition levels, the MATLAB 2023b package with the Wavelet Toolbox module was used as shown in Appendix A (Figures A1–A3). The total length of the coefficients of these decomposition levels is 869 samples, which is significantly less than the initially specified 14,400 and, as can be seen, the signal is reproduced with a sufficient degree of accuracy. The compression ratio, in this case, is more than 16.

3.6. Definition of a Substation Equipment Group and Conditions for Developing an Algorithm

To develop an algorithm designed for the analysis of DS electrical equipment parameters, such important HV equipment as power transformers is considered.

In this paper, for modeling and developing algorithms, a group of three autotransformers is considered. The failure of one entails the occurrence of an incomplete phase state, which is the contingency and affects the power system stability. The economic aspect represents significant costs in the form of large capital and time expenditures for repairs, as well as energy not supplied.

The most frequent causes of failure of transformer equipment are failures associated with a malfunction of the windings, which can be conditionally divided into the following:

(1) Rapidly developing and manifesting faults, usually of an electrical nature of occurrence (various types of breakdowns and short circuits);
(2) Faults, the development and manifestation of which is stretched out over time.

Common examples of these categories of failures are TTTF [35].

These types of faults are considered in the present research for compiling mathematical models and developing an algorithm for analyzing the operating parameters of substation electrical equipment.

The development of models is carried out in MATLAB 2023b Simulink software.

3.7. Development of an Algorithm for Determining TTTSC

3.7.1. Creation of a Mathematical Model for TTTSC Simulation

Modern algorithms and methods for detecting TTTSC, mainly longitudinal differential protection of the transformer, react to short circuits of more than 10% of winding turns.

Statistically, this type of fault most often occurs on the low voltage (LV) side, due to the fact that the currents on the LV side are significantly higher. The range of necessary data that must be obtained from the model is determined by the APDU format defined by IEC 61850-9-2 and applied by ASC on the transformer LV and HV sides. The frame must contain instantaneous values of phase currents and voltages, as well as those in the neutral, which are the values of the zero-sequence parameters multiplied by 3.

In the present research mathematical model for simulation, TTTSC consists of the following:

(1) A source with superimposed noise and a spontaneously changing frequency in the range from 49.5 to 51 Hz;
(2) A spontaneously changing load in the range from 40 to 200 percent of the rated power of the transformer;
(3) Functional blocks of an autotransformer with a split secondary winding, for simulating a short circuit of an arbitrary number of turns within 10% of the total number;
(4) A block simulating the spontaneous occurrence of a TTTSC;
(5) A block for measuring current and voltage on the LV and HV sides;
(6) A block in which the calculation of zero sequences of current and voltage is carried out.

The sampling frequency of the model calculation was selected in accordance with the digital stream format defined by the corporate profile of FGC, namely 14,400 Hz. The simulation duration was set to 10 s. The number of samples was correspondingly equal to 144,000.

For the given parameters of duration and sampling frequency, the maximum degree of signal decomposition is $\log_2 144,000 \approx 17$. The randomly selected number of turns for TTTSC is 6% of the total number. Analysis showed that the most informative data are the zero-sequence currents on the HV side.

The time series of the TTTSC occurrence and HV winding zero-sequence currents is shown in Figure 3.

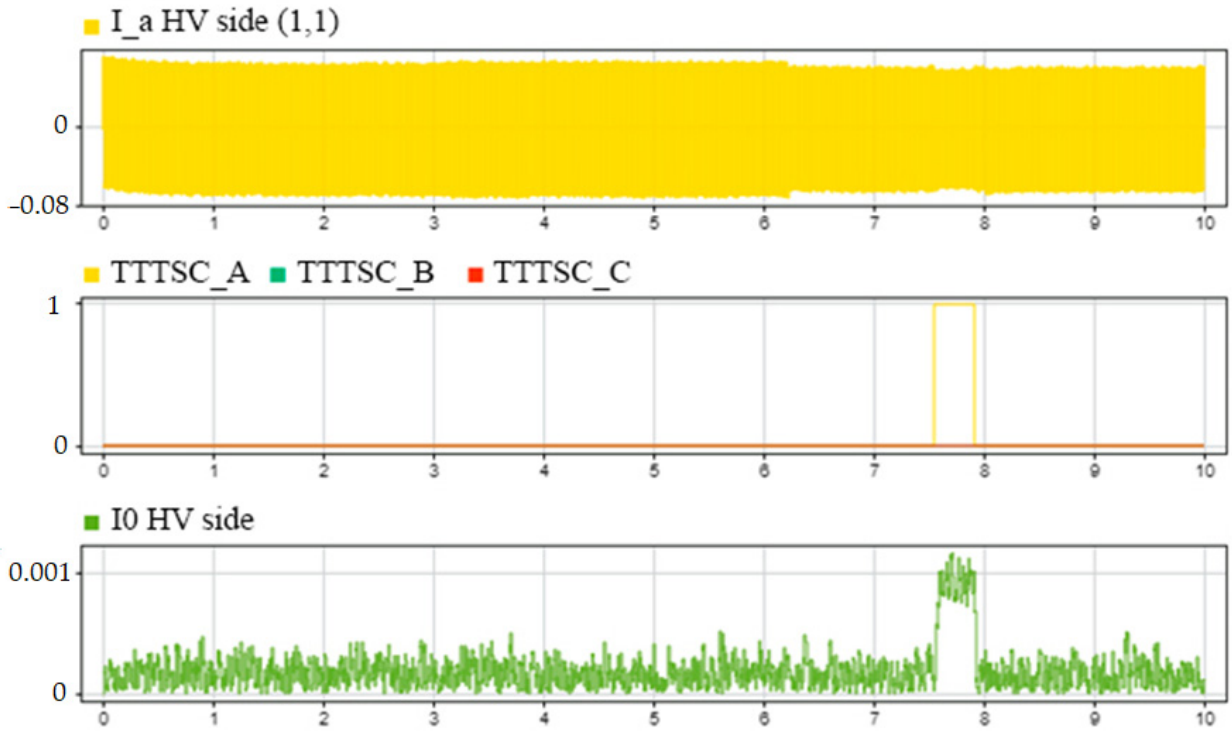

Figure 3. The moment TTTSC starts.

As can be seen, the signal has both high-amplitude sections that determine the moment of a sharp change in the signal, and a "plateau", which can be detected at a lower frequency.

Also, a section with a reduced current value at the moment of failure is clearly defined. This is due to a change in the transformation ratio at the fault occurrence moment. The magnitude of the resulting zero-sequence current is significantly less than in the case of ground faults, which can also be used to identify the TTTSC by introducing threshold values.

The result of signal decomposition into the maximum possible number of levels to determine the most informative ones shows that the moment of TTTSC occurrence is most pronounced at decomposition levels from 9 to 14. These levels correspond to frequencies in the range of 3–28 Hz. This moment is illustrated in Figure 4.

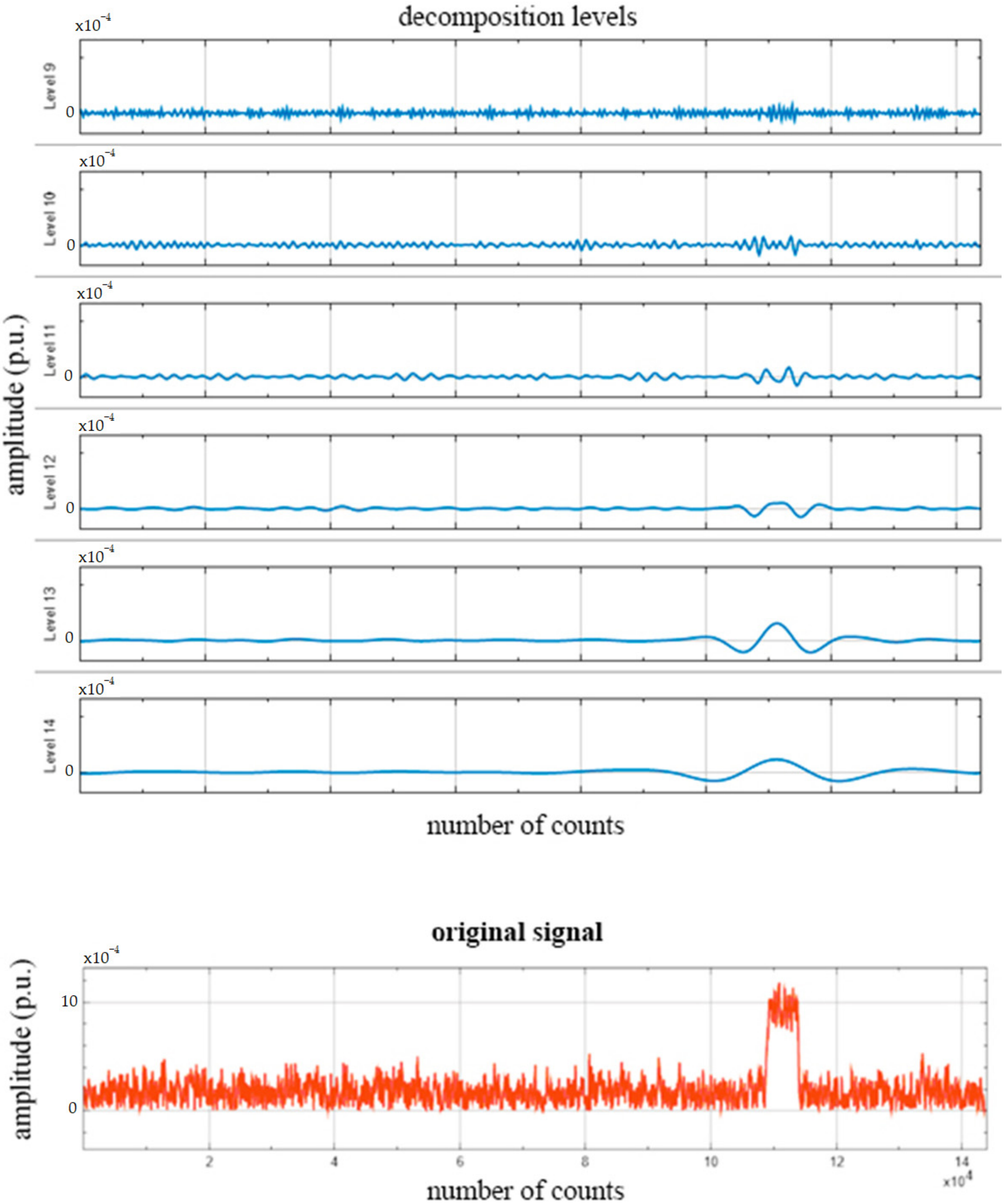

Figure 4. Levels zero-sequence current signal decomposition.

In this case, to synthesize the most informative component of the signal, the approximating coefficients of the 9th level of decomposition are used. This is illustrated in Figure 5.

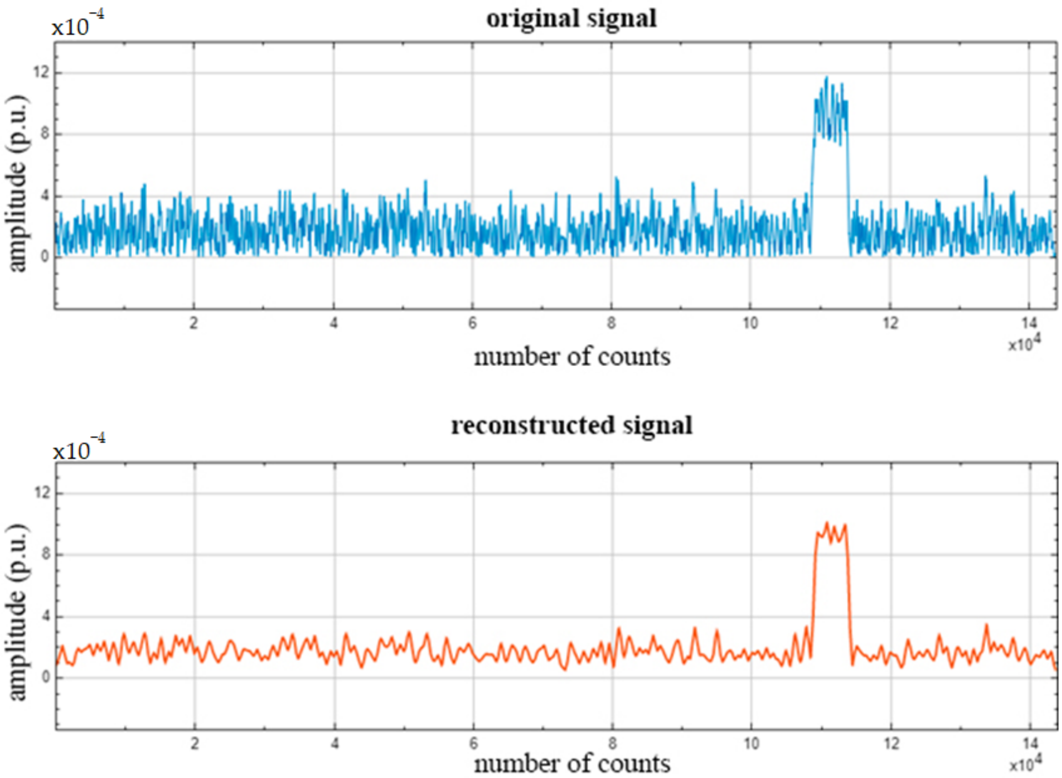

Figure 5. Original and synthesized signals I0.

Due to the fact that for determining this type of fault, it is necessary to respond to the amplitude values by introducing threshold values, by analogy with the "classical" methods of RPC, this paper proposes an analysis of the coefficients' integrated values of the approximating branch of zero-sequence currents at the HV side.

The physical meaning of integration for a discrete signal of length N is the sequential sum of the values counts.

$$S = \frac{1}{N}\sum_{i=1}^{N} s_i. \quad (21)$$

The integrated values of the approximating branch coefficients of the expansion is shown in Figure 6, according to which the section with the manifestation of the TTTSC is clearly visible.

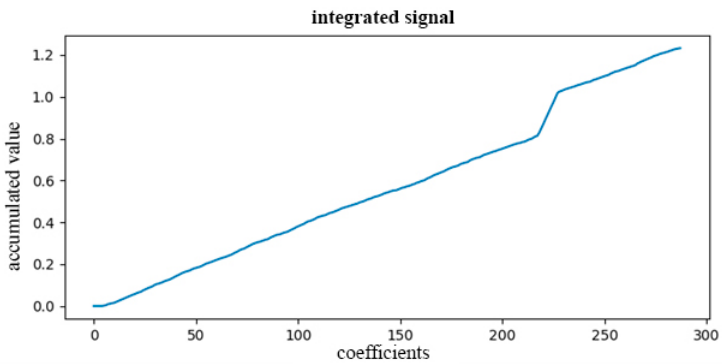

Figure 6. Integrated expansion coefficients.

As can be seen, as of the malfunction, the angle of inclination is changed, which is due to the increase in the value of the zero-sequence currents. This parameter can be considered as a qualitative indicator of the equipment state.

To determine the angle of inclination, it is proposed to use methods of the linear approximation of signal sections, namely the least squares method (LSM).

Also, the resulting coefficients of the approximating branch of the 9th level of decomposition are supposed to be transferred to upper-level systems for analysis using machine-learning (ML) methods and the use of artificial intelligence (AI).

3.7.2. Development of the Algorithm for Determining the TTTSC

For the algorithm to work in real time, it is supposed to use the sliding window method, the essence of which is that the incoming values form a window, which will then be analyzed. After the current window is filled, the formation of the next one should begin without losing samples.

Due to the fact that at least $2^9 = 512$ samples are required to obtain the approximating coefficients, the window width is taken to be significantly larger than this value. In the algorithm being developed, this parameter will be 14,400 samples, which corresponds to the number of values of one parameter of the SV stream in 1 s.

The occurrence of a malfunction will be determined by calculating the slope of the straight line obtained as a result of the linear approximation of the signal recorded in the window. If the value changes by 10% relative to the previous one, then it can be concluded that there is a malfunction in this equipment. To approximate the signal of integrated values of the 9th level of decomposition, the least squares method is used, the essence of which is reduced to minimizing the sum of squares of the deviations between counts. The function to be minimized is described as follows:

$$S = \sum_{i=1}^{n} (y_i - (kx_i + b))^2, \tag{22}$$

where n—signal length; y_i—dependent variable; x_i—independent variable; k—weight coefficient; b—free coefficient.

This method is reduced to solving a differential equation of two variables. The solution to this equation will be a system of the following form:

$$\begin{pmatrix} n & \sum\limits_{i=1}^{n} x_i \\ \sum\limits_{i=1}^{n} x_i & \sum\limits_{i=1}^{n} x_i^2 \end{pmatrix} \begin{pmatrix} b \\ k \end{pmatrix} = \begin{pmatrix} \sum\limits_{i=1}^{n} y_i \\ \sum\limits_{i=1}^{n} x_i y_i \end{pmatrix}. \tag{23}$$

The values of the coefficients are found as follows:

Weight coefficient:

$$k = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}, \tag{24}$$

Free coefficient:

$$b = \frac{\sum_{i=1}^{n} x_i - k\sum_{i=1}^{n} x_i}{n}. \tag{25}$$

As a result, a straight line equation is obtained, where the weighting coefficient will act as a qualitative indicator, by the nature of the change in which a conclusion will be made about the presence of a TTTSC.

The damaged phase will be determined after the TTTSC has been identified, by calculating the effective values of the phase currents over a period of 100 ms, and then comparing the values to identify the damaged winding.

To calculate the currents values, the method of finding the root mean square (RMS) is used:

$$S_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} s_i^2} \tag{26}$$

where n—number of counts; s_i—signal meaning.

The algorithm in the form of a block diagram is presented in Figure 7.

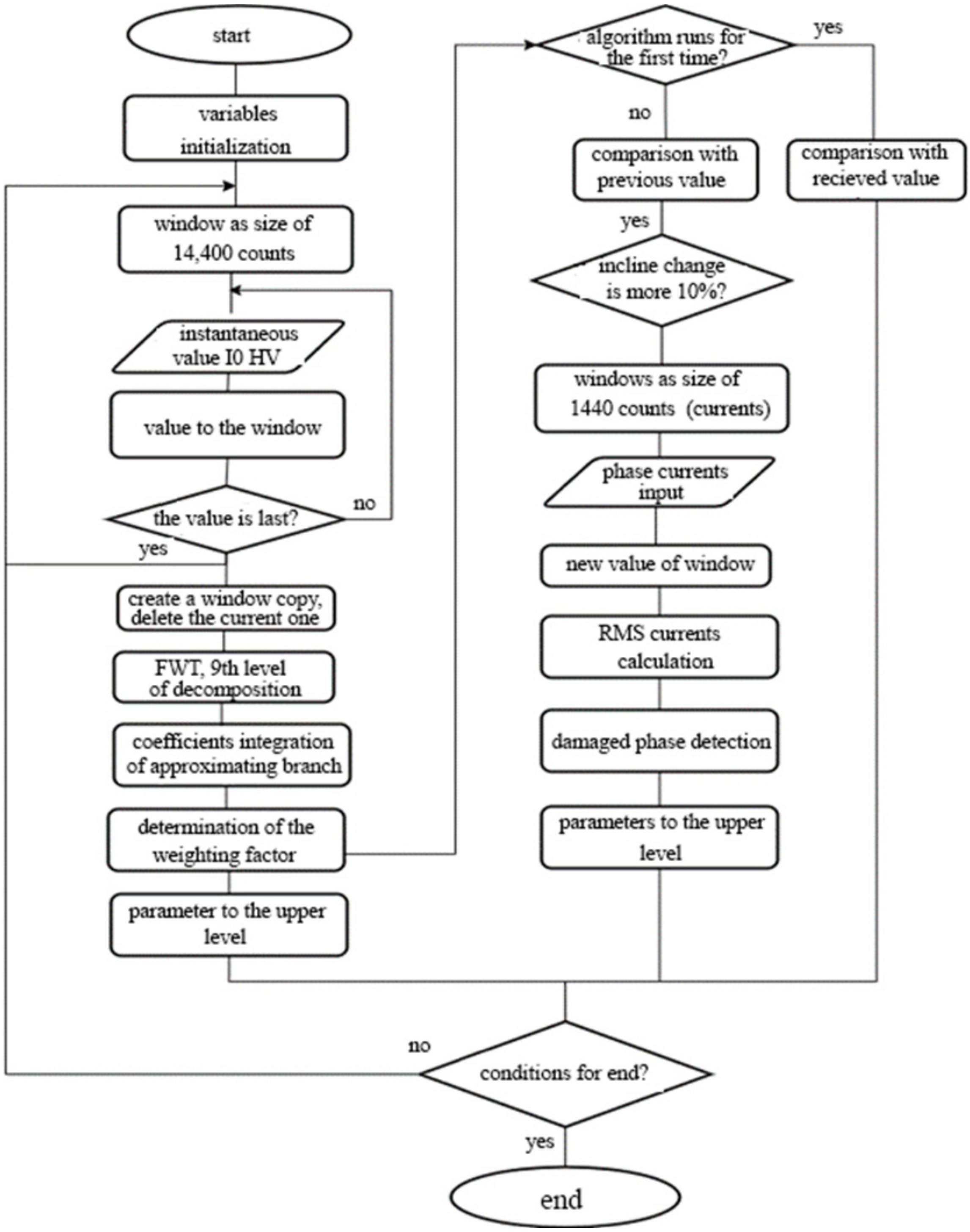

Figure 7. Algorithm for determining the TTTSC.

3.7.3. Development of the Mathematical Model for Determining the TTTSC Based on the Algorithm

This type of fault does not manifest itself with the same speed as, for example, short circuits and breakdowns and is the cause of their occurrence. The difficulty in determination is due to the low dynamics of development in combination with the absence of a clear manifestation in currents and voltages.

According to [36], the parameters of the total short-circuit resistance z_{SC} increase up to 20% with deformations of the windings. This value is taken as the maximum range of changes when model developing.

3.7.4. Development of the Algorithm for Receiving and Transmitting a Signal for Analyzing Internal Transformer Faults

The required window width is selected since the result in the form of the approximating coefficients' series of the 13th decomposition level will be given to the upper level once per minute. The analysis and output of the result must be continuous and not contain missing data parts.

As input data, the values of the zero-sequence voltages of the HV and LV sides are used, which must be integrated and divided by each other. The division result will then form the filling of the window for the subsequent FWT with the Daubechies db4 wavelet and the formation of a frame consisting of the 13th decomposition level approximating coefficients.

The algorithm in the form of a block diagram is shown in Figure 8.

Because at the initial and final sections there are distortions caused by the boundary conditions of the FWT and the small initial values of the quantities, the first and last 6 values of the series of decomposition coefficients were taken as uninformative. The required minimum signal overlap is 10%. The last 10% of the counts of the ratio values that have the initial sampling frequency are added to the beginning of the new window.

It should be noted that, to comply with the continuity condition, the output period is also reduced by 10%. For the coefficients to be output once per minute, it is necessary to increase the window size by 86,400 values. After creating a new window, the values calculated using the integration and ratio value finding operations are gradually added. When the window is filled, the integrated values are reset to zero and the result of subsequent operations will be added to the new window.

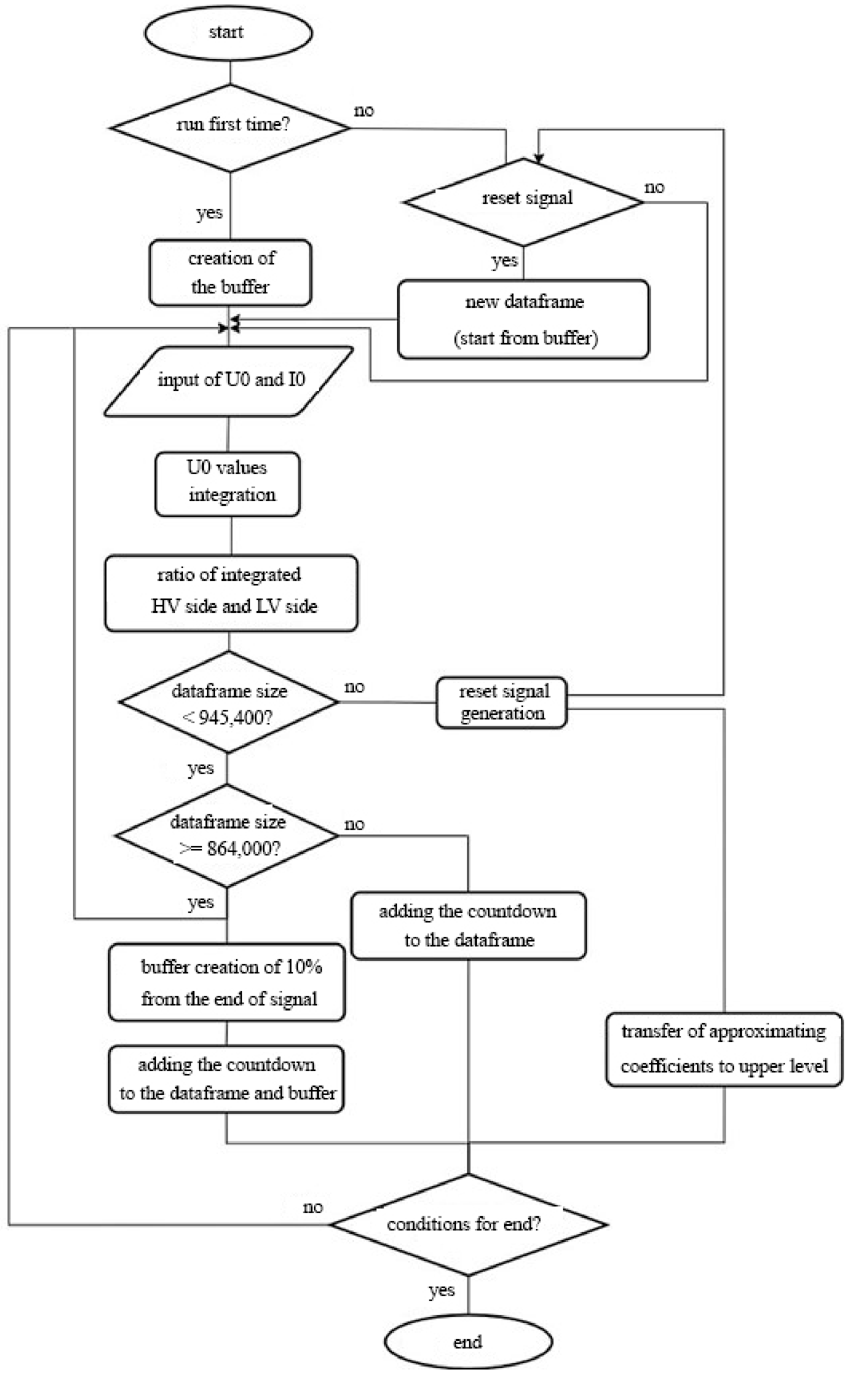

Figure 8. Signal acquisition and transmission algorithm for analyzing internal transformer faults.

4. Results

4.1. Results of the Developed Algorithm

In order to determine the most informative parameters that are available in the digital stream, a sharp change in parameters by 20% was simulated. The simulation duration is set to 1 min.

In this case, changes in the transformer parameters are reflected in the values of the zero-sequence currents and voltages of both LV and HV sides.

The manifestation of the TTTSC allows us to conclude that the calculated instantaneous values of the zero-sequence power will be more informative. The signals of these values are shown in Figures 9 and 10.

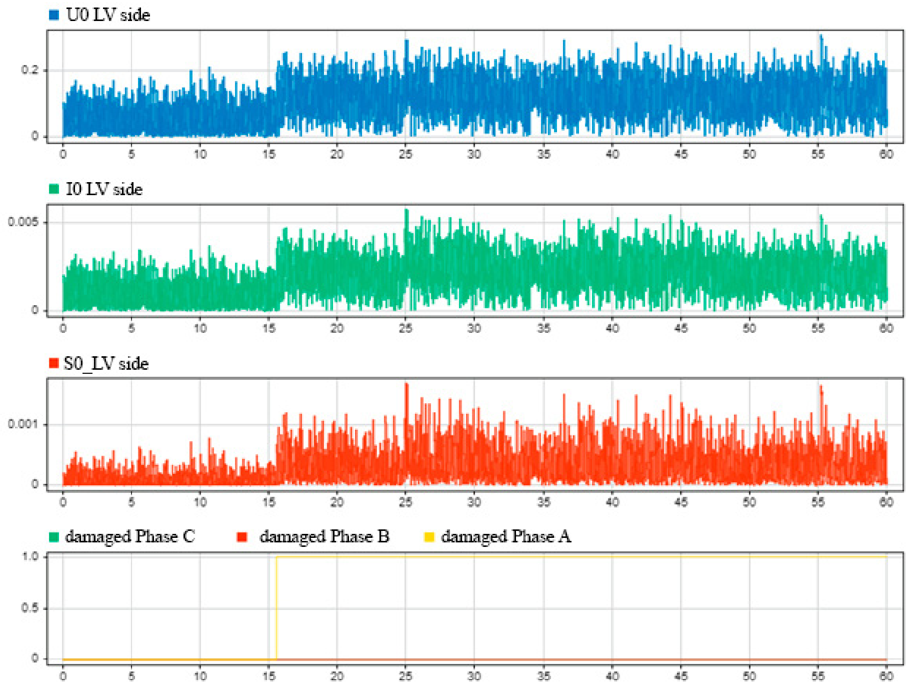

Figure 9. I0, U0, S0 of the LV side when TTTSC occurs.

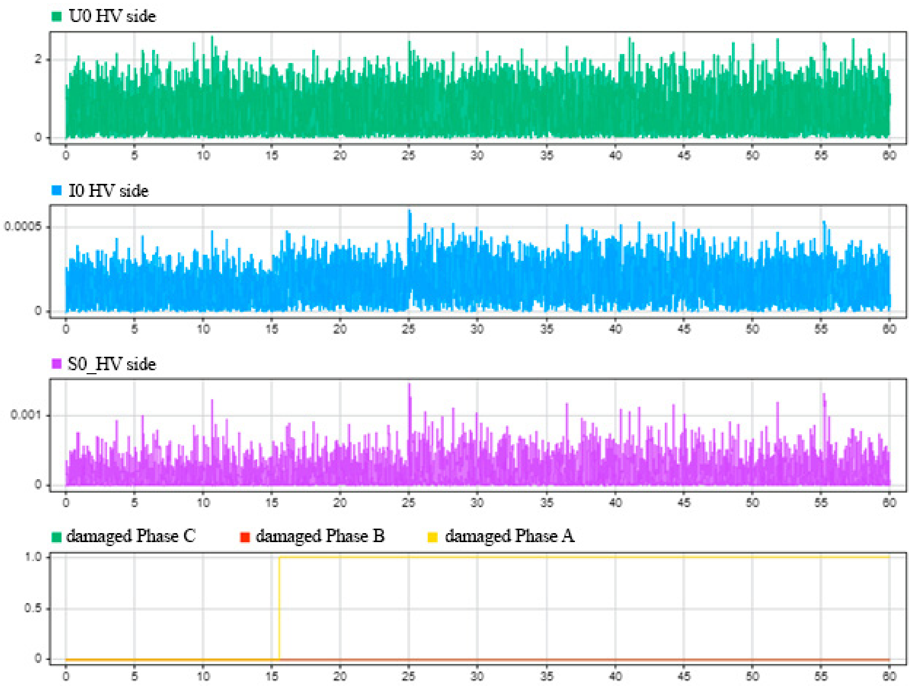

Figure 10. I0, U0, S0 of the HV side when TTTSC occurs.

As can be seen, in the zero-sequence power signal for the HV side, no obvious correlation with the fault was found.

By analogy with the algorithms for determining the TTTSC, since the fault is determined by amplitude analysis, the integrated values of the above parameters will be more indicative.

In this case, the zero-sequence values directly received as part of the digital stream and the result of their product will be integrated.

The changes in the values for the LV and HV sides are shown in Figure 11.

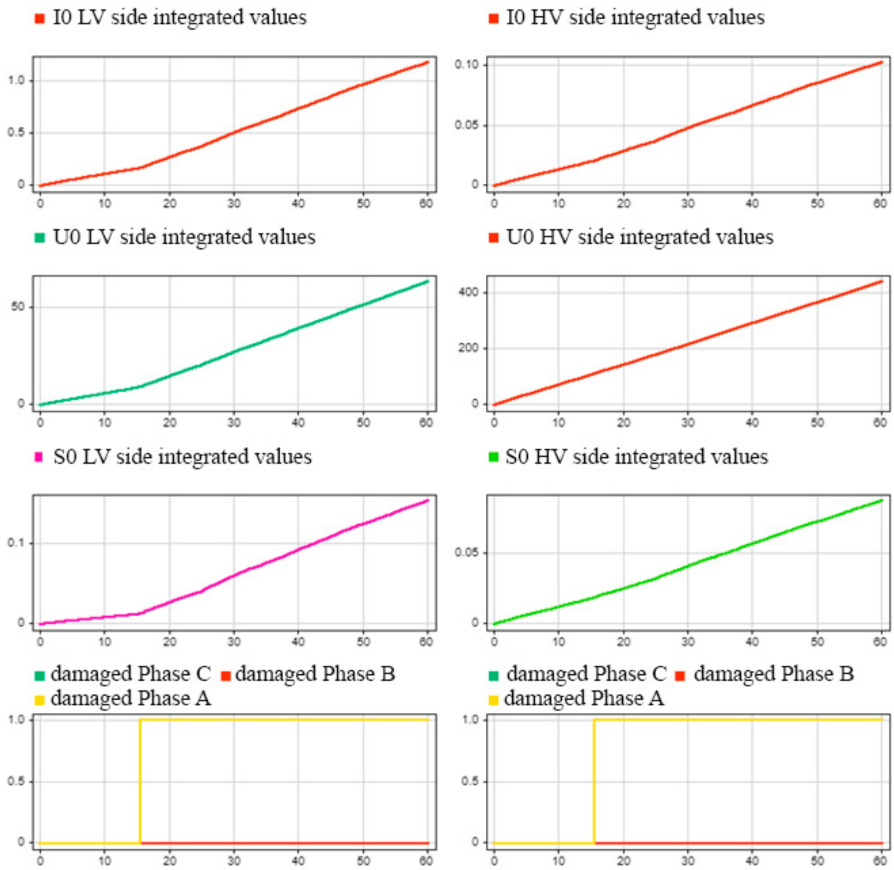

Figure 11. Integrated I0, U0, S0 of the LV and HV sides.

The figures above clearly show that the integrated values represent a linear trend, the slope of which changes at the moment of the accident.

The nature of the zero-sequence power manifestation on Figure 11 on the LV side is more pronounced than on the HV side. This is primarily due to the absence of the effect of the emergency situation on the HV level. This fact is used to synthesize a signal that will display internal changes in the transformer.

The parameter that clearly reflects the operating state is the ratio of the integrated value of the zero-sequence power of the HV side to the LV side. The HV and LV ratios have a similar nature. For the case of an instantaneous change, the results are shown in Figure 12.

The moment of changing the transformer parameters is quite clearly shown in the figures above. The peak in the initial sections is due to the small values of the calculated quantities and the results of the division operation. This part of the data is not taken into account for the analysis.

Conducting the experiment of gradually changing the parameters of the transformer and analyzing the signals described earlier, new results are given as shown in Figure 13. The resistance z_{SC} will change once every 4 s by 0.1%.

As can be seen, there is no obvious manifestation of a developing fault. A conclusion about a developing fault can be made based on the nature of the signal trend: the figures clearly show that the integrated values ratios are gradually decreasing. In this case, the magnitude of the change in the parameters was 1.3%.

It can also be noted that zero-sequence voltages integrated values ratios do not contain some discrepancy at the beginning, which can be mistakenly interpreted as a z_{SC} decrease. This fact determines the choice of this parameter for further analysis.

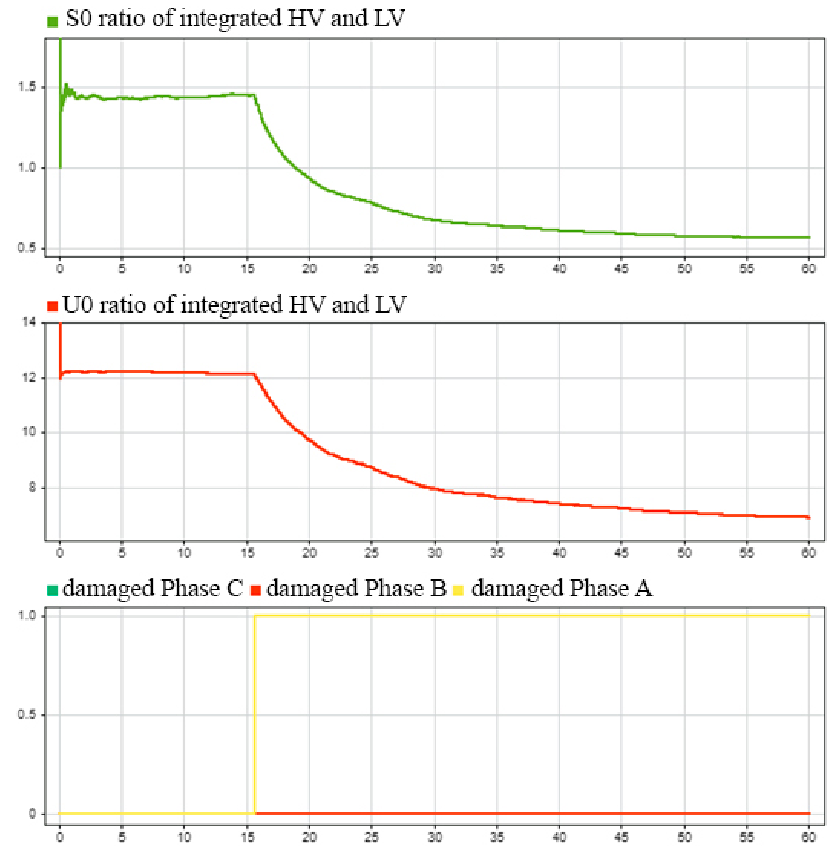

Figure 12. Integrated U0, S0 of the LV and HV sides.

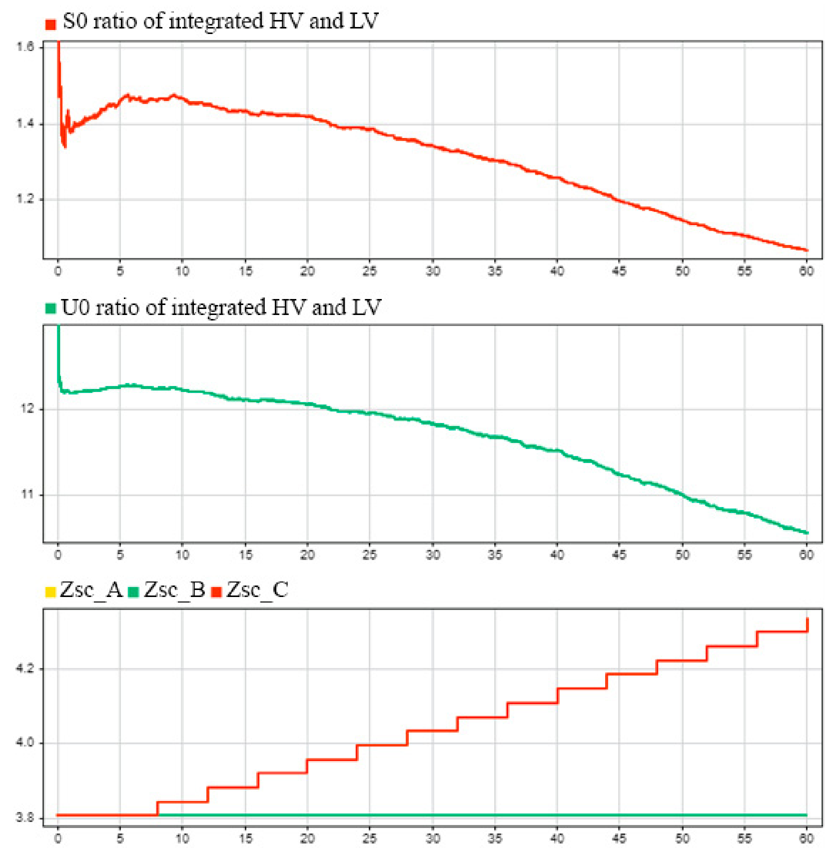

Figure 13. Integrated U0, S0.

4.2. The Role of WT in the Developed Algorithm

The WT of the obtained values is relevant, first of all, as a signal compression method for transmission to the decision support system (DSS) and further analysis using ML, AI, etc.

The maximum level of the FWT for a signal with a sampling frequency of 14,400 Hz and a duration of 1 min is 19. To perform the transformation, the wavelet of the Daubechies db4 family is selected.

Based on the nature of the signal change, which can be defined as a sequential accumulation of values, it allows us to conclude that almost all the energy is contained in the approximating component. But, synthesized from the approximating coefficients of the maximum decomposition level, the signal will not contain information displaying the nature of changes in the electrical equipment operation state. This case is illustrated in Figure 14.

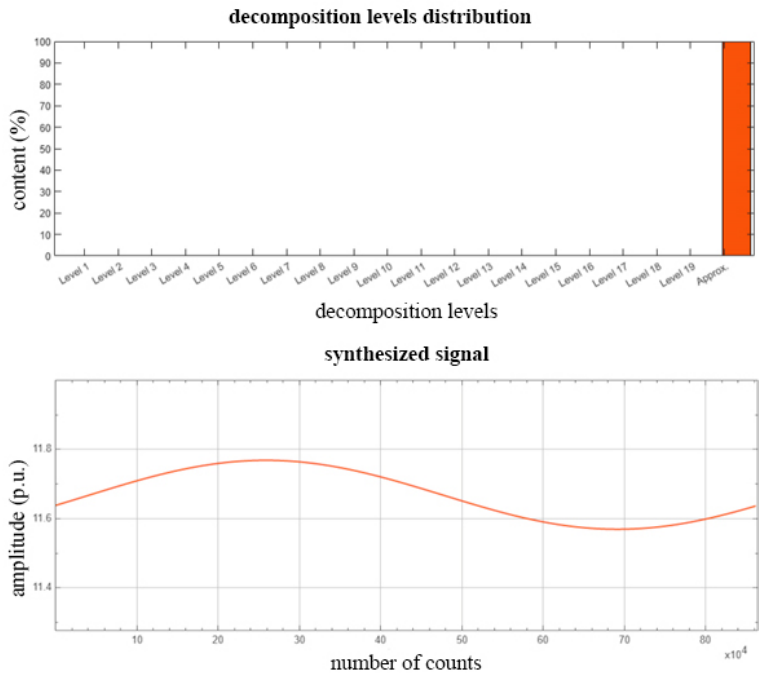

Figure 14. Energy distribution and approximating coefficients of Level 19.

It was determined experimentally that the signal synthesized from the expansion coefficients from Levels 14 to 19, together with the approximating coefficients, describes the behavior of the signal with a sufficient degree of accuracy. They are used for transmission to the upper level.

Considering that all levels starting from 14 are used for signal synthesis, it can be said that the signal will be determined with a sufficient degree of accuracy by the approximating coefficients of 13th-level expansion.

The original and synthesized signals of the LV and HV sides' integrated values of the zero-sequence voltage ratios are shown in Figure 15.

The length of the series of approximating coefficients of the 13th level of decomposition by the Daubechies wavelet db4 is 112 values; compared to the original signal, the number of coefficient values is 7714 times less.

The synthesized signal clearly shows manifestations of data inaccuracy. To cope with that, the window width where the data is unreliable is taken as 5% from the beginning and 5% from the end of the signal. Given the length of the series of coefficients, the six coefficients at the beginning of the series and six coefficients at the end are considered to be unreliable. In order to exclude the influence of this moment on the reliability of the signal, during its synthesis, and to comply with the continuity condition, the method of overlapping windows in the developed algorithm is used, in which data for the subsequent FWT are recorded.

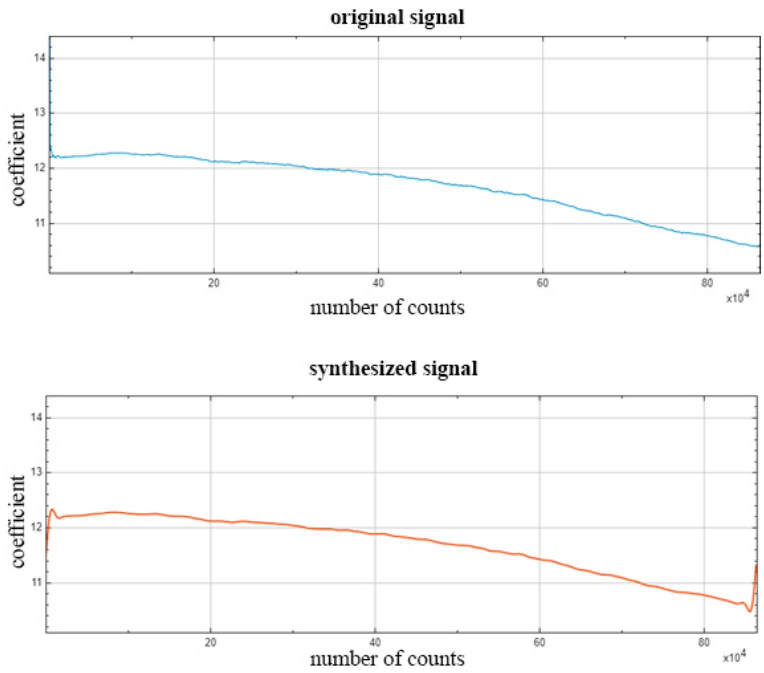

Figure 15. Original and synthesized signals.

5. Discussion

The presented study describes the currently used methods of time-series analysis in order to obtain a representation of the signal in the frequency and time domains.

To solve the problems of the higher-quality analysis of non-stationary signals, the WT apparatus is considered. To analyze the time series obtained from the DS process bus, the most suitable method of FWT with the Daubechies db4 wavelet was chosen.

The strengths of this method include the possibility to represent the analyzed signal in the frequency–time domain, as well as signal compression and filtering. In other words, the method can be used to provide bandpass filters for monitored frequencies or for signal compression and noise removal, for subsequent transmission to upper-level systems and further synthesis.

The proposed algorithm was used to determine the presence or development of an internal fault in the power transformers on the DS. Within the framework of the research, possible transformer faults were divided into two categories by the nature of their manifestation. For each case, a mathematical model was built, computer simulation was carried out, and a characteristic parameter was selected, by which it is possible to identify an internal fault. Algorithms for processing the time series of the obtained values are based on the use of an FWT.

The proposed algorithm works correctly at small values of the number of closed turns and can be used as an additional method to the main types of equipment protection—it can be a part of the DSC.

The work analyzes and proves the effectiveness of the analysis at values of closed turns below 10%. To determine developing faults, the FWT is used primarily for compact representation of the signal and compression of the time series of the parameter, by which it is possible to determine the development of transformer internal faults on a long-term scale. The result of the algorithm is the fact that the length of the expansion coefficients in the synthesized signal is 7714 times smaller than the original signal.

The proposed algorithm based on the FWT with the Daubechies db4 wavelet can be used as an example for various types of DS equipment parameters' analysis.

As the prospects of the present work, the following could be considered:

1. The implementation and verification of the algorithm, for conditions close to real-time systems, at the initial stage has to be carried out in software based on an open-source programming language such as Python, using the Numpy and Pywt libraries.
2. Comparison of the proposed method with commonly used current methods such as the Maximal Overlap Discrete Wavelet Transform (MODWT), singular value decomposition (SVD), Enhanced Phase Locked Loop (EPLL), etc., and even the fast Fourier transform (FFT).
3. The implementation of the algorithm for different important electrical equipment in DS such as SF6 CBs.
4. The development of analysis algorithms based on modern mathematical methods with the subsequent prospect of using big data analysis technologies, AI, ML, etc., [30], for the problem of monitoring parameters of electrical equipment operation, followed by testing and improving the developed algorithms on data from real DSs that take into account various defects of electrical equipment.

6. Conclusions

The following key results were achieved in the presented research.

The relevance and significance of the tasks related to the development of DS equipment monitoring methods was substantiated. Both existing and promising methods of the non-destructive testing of equipment were considered. The need to develop algorithms based on the frequency analysis of time series of current and voltage signals obtained from the DS process buses was confirmed. A detailed analysis of the existing time-series processing methods was carried out, and the use of the FWT method was justified in the context of this problem.

DS equipment requiring the development of algorithms for analyzing operating parameters for a power transformers, was selected. The analysis and identification of the main cause categories of failure was carried out, which served as the basis for the development of corresponding algorithms. Mathematical models for each category of faults were compiled. Methods for processing and extracting qualitative parameters that allow the determination of the presence of a fault, as well as algorithms for analyzing the operating parameters of equipment faults, are proposed.

An algorithm has been created for diagnosing faults characterized by abrupt changes in electrical quantities. This algorithm allows an increase in the accuracy of detecting TTTSC in the range of 5–10%. An algorithm has been developed for diagnosing faults with temporarily extended manifestations, which has demonstrated its effectiveness in a more compact representation of the signal. This allows for analyzing time series on a long-term scale and implementing signal parameter transmission to DSs. The data volume was compressed by 7714 times compared to the original signal.

Author Contributions: Conceptualization, S.A.E. and P.V.M.; methodology, S.A.E. and A.S.E.; software, A.S.E. and P.V.M.; validation, A.S.E., P.V.M. and V.V.P.; formal analysis, S.A.E. and V.V.P.; investigation, A.S.E. and S.A.E.; writing—original draft preparation, A.S.E. and S.A.E.; writing—review and editing, P.V.M. and V.V.P.; visualization, A.S.E. and V.V.P.; supervision, S.A.E. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

PCS	–	process control systems
FWT	–	fast wavelet transform
WT	–	wavelet transform
IED	–	intelligent electronic device
MSA	–	multiple-scale analysis
BC	–	bay controller
LAN	–	local area network
TTTSC	–	turn-to-turn short circuit
IEC	–	International Electrotechnical Commission
LV	–	low voltage
HV	–	high voltage
STFT	–	short time Fourier transform
ASC	–	analog signal converter
DSC	–	discrete signal converter
RPC	–	relay protection and controls
VT	–	voltage transformer
CT	–	current transformer
FGC UES	–	Federal Grid Company of Unified Energy System
DS	–	digital substation
DVT	–	digital voltage transformer
DCT	–	digital current transformer
GOOSE	–	generic object-oriented substation event
MMS	–	manufacturing message specification
SV	–	sampled values
RES	–	renewable energy sources
TL	–	transmission lines
ML	–	machine learning
AI	–	artificial intelligence
DSS	–	decision support system

Appendix A

The construction of the decomposition levels using a MATLAB package (Wavelet Toolbox module) is shown in Figure A1.

As can be seen, the decomposition levels act as frequency filters. Also, at the frequency change boundary at high-frequency decomposition levels, the presence of bursts caused by the nature of the specified signal and the wavelet used can be seen. In this case, the Daubechies db4 wavelet was used.

The degree of contribution of a certain decomposition level can be estimated by finding the ratio of the sum of the squares of the level coefficients to the sum of the squares of all decomposition coefficients, including the final approximation level:

$$C_{\%} = \frac{\sum_{m=1}^{m_{max}} c_{mk}^2}{\sum_i c_{ik}^2} \tag{A1}$$

where *i*—level of decomposition.

This function is also implemented in the MATLAB Wavelet Toolbox package. The results are illustrated in the form of a histogram in Figure A2.

As can be seen, Decomposition Levels 5 through 8 contain the main part of the signal.

It can be concluded that there is another promising use of the WT, namely, in data compression and a more compact representation of time series that can be transmitted as coefficients, with subsequent synthesis.

An example of synthesizing the considered signal using decomposition coefficients from 5 to 8 is shown in Figure A3.

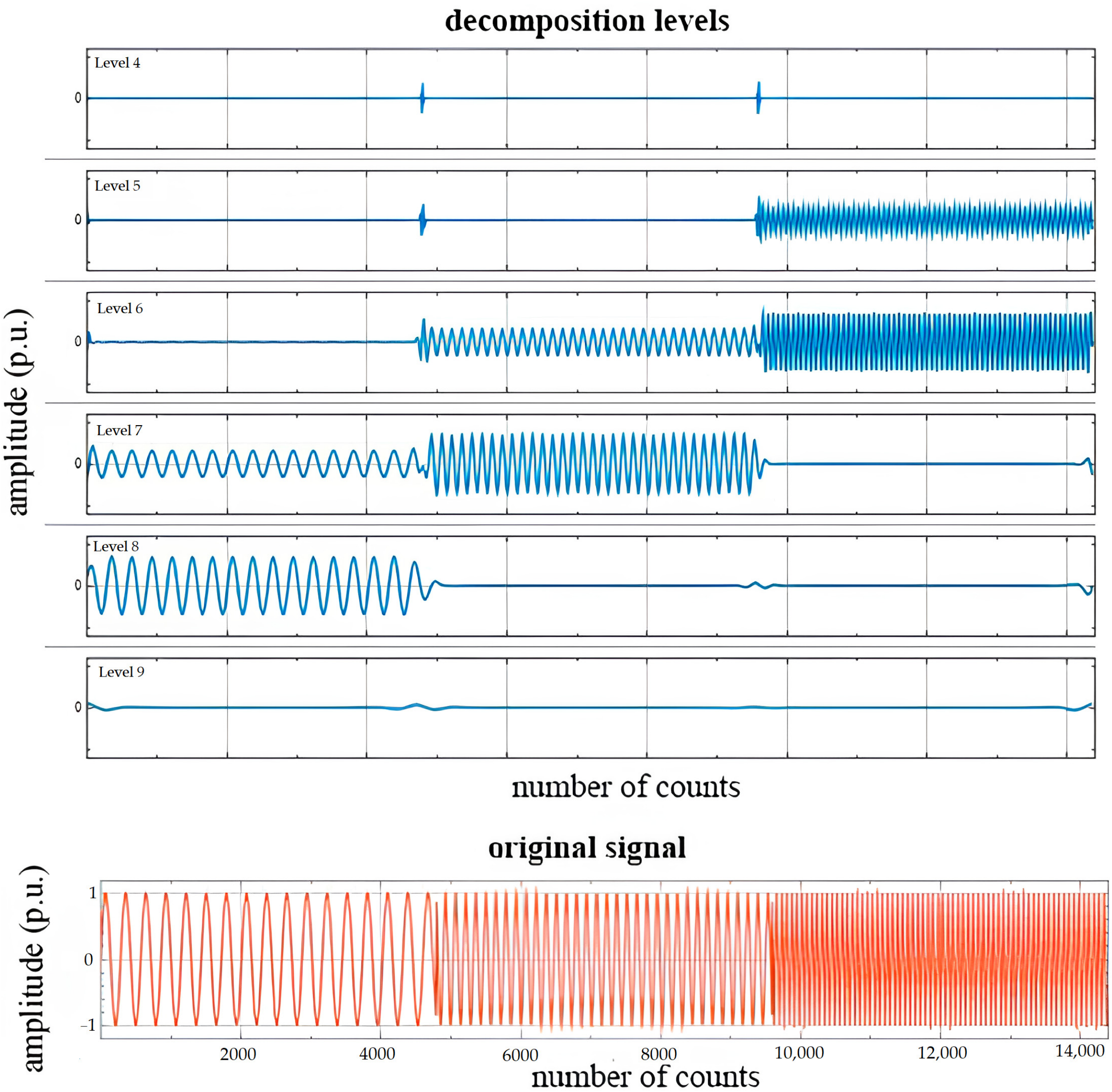

Figure A1. Decomposition levels obtained during signal DWT.

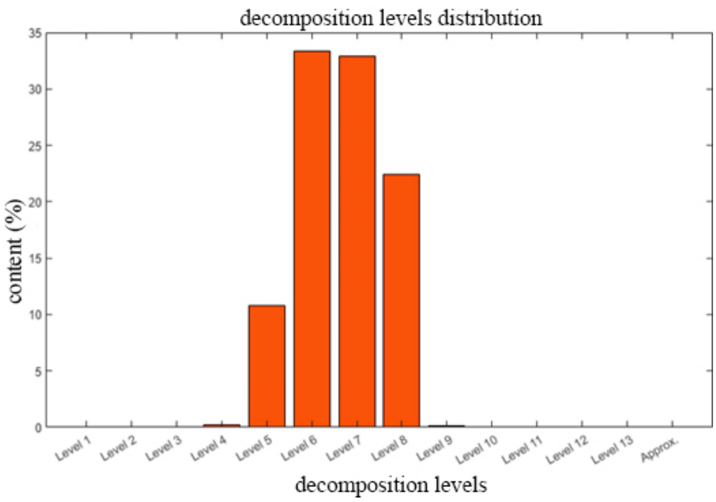

Figure A2. Distribution of energy by decomposition levels.

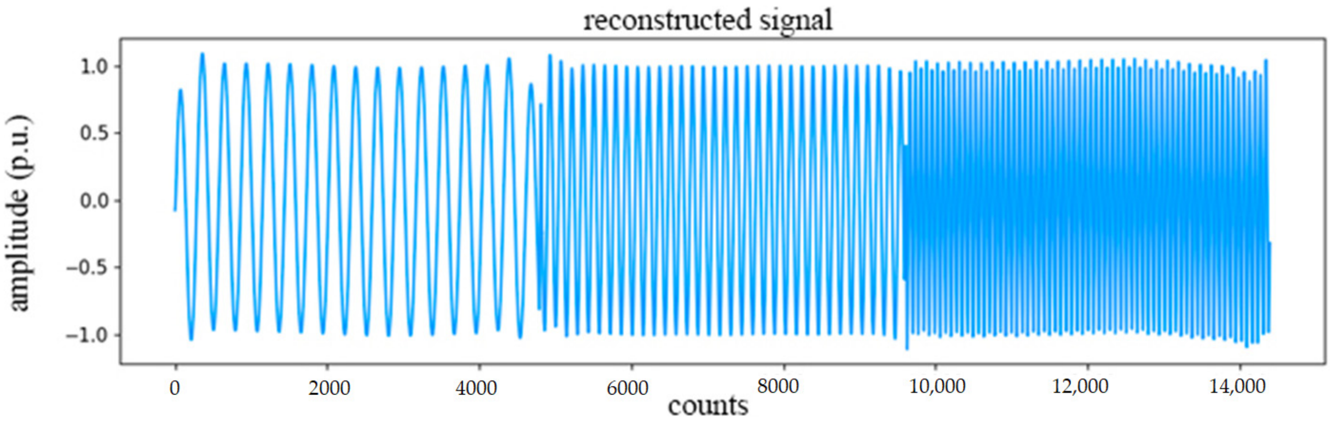

Figure A3. Synthesis of the signal using the required coefficients.

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