Modern Mathematical Methods And Computerized Tools Of Artificial Intelligence For Solving Problems Of Identifying The Energy Quality Of Electrical Systems

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***Abstract* — A comparative review of computer calculation algorithms for known and new electric power quality factors for the main types of voltage quality disturbance (distortion, asymmetry, oscillations, subsidence, interruptions, impulse overvoltages, flicker and combinations thereof) is presented in this paper. Methodes: Fourier transform, wavelet transforms, Hilbert-Huang transforms, S-transforms, and methods using neural networks are compared as algorithms for detection and classification of voltage distortion types. The possibilities of realization are considered. The result of the paper is the identification of the most optimal methods for detection and classification of the factors of the quality of electrical energy for mass equipment. A conclusion is made about the prospects of hardware neural networks for solving these problems.**

Keywords — power quality factors, electrical energy quality factors, wavelet transform, Fourier transform, S-transform, Hilbert-Huang transform, support vector machine, expert systems, neural networks, genetic algorithm.

I. INTRODUCTION

The term "quality of electrical energy" is usually applied to a wide range of electromagnetic phenomena occurring in the electrical network system. The ability of the power system to deliver signals with undistorted voltage, current and frequency is called power quality. Unexpected changes in voltage or current can damage or disable important electrical components. According to the IEEE 1159-1995 standard, energy quality factors cover the characteristics of a wide range of phenomena such as transient (impulse and oscillatory), short-term changes (interruptions, sag and swell), frequency changes, long-term changes (stable at voltage failures and overvoltages), as well as oscillations of the steady state (harmonics, flicker) with a time interval lying in the range from nanoseconds to a constant state. Their quantitative values are characterized by a set of known [1], [2] and new [3] factors of the quality of electrical energy.

II. AUTOMATIC EE QUALITY CLASSIFIER

Before 1990, certain configurations of classifiers with manual control were used to monitor and control the quality of power supplies. The decision was based on the intuition of the operator to maintain the quality in certain ranges. The technology developed and the technique of intelligent signal processing (such as pattern recognition, data collection, artificial intelligence), which uses tools such as computers, digital signal processors, memory devices, replaced the previous one. The basic block diagram of the automatic EE quality classifier is shown in Fig.1

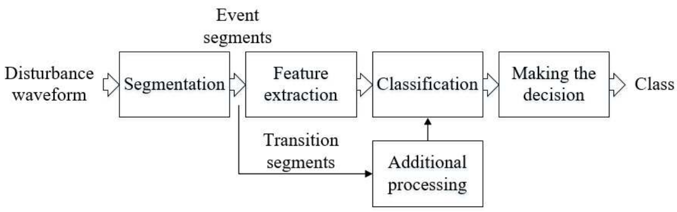

Fig.1. Structure of automatic power quality event classifier

A. Segmentation

Segmentation divides the data sequence into stationary and non-stationary parts (segments). Events are segments in between transition segments. Then the properties are extracted from the event segments, because the signal is stationary and usually contains information unique enough to distinguish the disturbance type. To capture the disturbance period, point-wise comparison of the adjacent cycle is used or point-to-point comparison of the effective values of the distorted signal with its corresponding undistorted signal and / or frequency domain transformation. Modern methods proposed for this purpose are classified into parametric (model-based) and non-parametric (transform based). Parametric methods include techniques such as the Kalman filter, autoregressive models, while nonparametric methods use a fast Fourier transform and wavelet transform.

B. Features Extraction

The extraction of features from the disturbances of EE quality is also called the detection of perturbations. The extracted features are used to classify the events of the EEQ. The classified information is used to make the final decision in the post processing block. The selection of suitable features of the EEQ is very important for classification. Recent developments regarding feature extraction techniques are discussed in the sections below.

1) Methods based on the Fourier transform

The most known method of analysis with frequency transforms is the Fourier transform (FT), which allows to represent the signal as a sum of harmonic oscillations of different frequencies. The FT is suitable for stationary signals and for extracting the spectrum at certain frequencies, however, it is not suitable for extracting any temporal information associated with fluctuations. One of the variants of the FT is the fast Fourier transform (FFT), which divides the signal into small segments, where each segment is assumed to be stationary. Therefore, the FFT determines the frequency of the sinusoid, the phase of the local section of the signal over time. It also extracts several sliding windows that move with time. With the moving window, the ratio of the frequency and time changes can be determined. It is very difficult to analyze non-stationary signals with the help of FFT, but it was applied to non-stationary signals when working with a fixed window size. Discrete FT is used for time-frequency analysis of non-stationary signals. It decomposes the time-varying signals into time-frequency components. Discrete Fourier transform (DFT) represents the discrete signals that repeat themselves in a periodic fashion from negative to positive infinity whereas fast Fourier transform (FFT) gives exactly the same result as the DFT in much less time

The Fourier transform of the signal f(t) is defined as

$$F(w) = \int_{-\infty}^{\infty} f(t) e^{-jwt} dt \tag{1}$$

Discrete Fourier Transform

$$F(k\Delta\Omega) = \sum_{i=-\infty}^{\infty} f(\mathrm{i}\,\Delta\mathrm{T})\, \mathrm{e}^{-jik\Delta\Omega\Delta T} \tag{2}$$

In these equations $\Delta\mathrm{T}$ defines the window of the fast Fourier transform [4].

2) Methods based on S-transform

The S-transform is a time-frequency tool, generated by combination of wavelet transform and FFT. It creates a time-frequency representation which uniquely combines the frequency-dependent solutions and simultaneously finds the real spectrum. The base functions of the S-transformation are the Gaussian modulated cosine wave. In the case of non-stationary disturbances with noise, the S-transformation provides patterns that are very close to perturbation types and therefore have a simple classification procedure.

The S-transform of the function h (t) is defined as the wavelet transform with a definite maternal wavelet (4) multiplied by the phase coefficient (3). Parameter d determines the width of the wavelet w(d, t).

$$S(\tau, f) = e^{j2\pi f\tau} W(d, \tau) \tag{3}$$

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{j2\pi ft} \tag{4}$$

Then the S-transform can be written as (5) and as the Fourier spectrum H (f) of the function h (t) (6):

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{j2\pi ft} dt \tag{5}$$

$$S(\tau, f) = \int_{-\infty}^{\infty} H(\alpha + f) e^{-\frac{2\pi^2\alpha^2}{f^2}} e^{j\pi\alpha\tau} d\alpha \tag{6}$$

Using (6), we can obtain an S-transform from the discrete time sequence h (kT), taking into account that τ → kT, f → n / NT. H[n/NT] is discrete Fourier transform of h (kT).

$$S(kT, \frac{n}{NT}) = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-\frac{2\pi^2 m^2}{n^2}} e^{\frac{j2\pi mk}{N}} \tag{7}$$

where k,m=0,1, …, N-1 and n=1,…, N-1.

The S-transform localizes the phase spectrum and the amplitude spectrum. For the analysis of the EE factors, an amplitude matrix is used $A(kT, f) = \left| S\left[kT, \frac{n}{NT}\right] \right|$, whose strings are the frequencies, and the columns are the time values. Each row displays the amplitude of the S-transform with all frequencies, each column displays the amplitude with time varying from 0 to N-1 at the same frequency, where n = 0,1, .., N / 2-1.

The amplitude of the fundamental frequency can be determined according to formula (10), and the harmonic coefficient according to formula (11).

$$M_{f_i} = \frac{2}{N} \sum_{k=0}^{N-1} A(kT, f_i); \tag{10}$$

$$HR(f_i) = \frac{M_{f_i}}{M_{f_1}} \tag{11}$$

The classifying methodology that is based on S-transform is presented in [5].

3) The Hilbert-Huang transform

In this transform, the signal decomposes using empirical decomposition (ED) into a function that contains instantaneous frequencies and amplitudes. ED decomposes the signal in the function in such a way that they are sorted from the highest frequency to the lowest. When the signal is already decomposed into functions, the Hilbert transform can be applied to them. This allows to extract instantaneous amplitudes and frequencies from the time curve. The combination of ED and the Hilbert transform is also known as the Hilbert-Huang transformation (HHT).

Initially, it is necessary to decompose the signal S (t) into empirical modes using empirical decomposition and to calculate the intrinsic mode function $P_{mf1}(t)$ [10].

Next, for the intrinsic mode function (IMF), it is necessary to apply the Hilbert transform (HT), which can be defined as:

$$H|x(t)| = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{12}$$

where P is the main value of the Cauchy integral.

It can be shown that the Hilbert signal transform effectively creates an orthogonal signal that is phase-shifted by 90 degrees from the original signal independent of the signal frequency.

The signal z (t) is defined as

$$z(t) = x(t) + H|x(t)| = x + jy = a(t)e^{j\theta(t)} \tag{13}$$

The instantaneous amplitude of z (t):

$$a(t) = \sqrt{x^2 + y^2} \tag{14}$$

Phase (15), frequency (16):

$$\theta(t) = \arctan\left(\frac{y}{x}\right) \tag{15}$$

$$w(t) = \frac{d\theta}{dt} \tag{16}$$

Thus, the HT of signal x (t) makes it possible to obtain the instantaneous amplitude, frequency and phase. However, this is only true if the IMF is a pure sinusoid with a single frequency. However, when the original signal S (t) contains frequencies close in value, the ED process can output a IMF that contains a mixed frequency. Therefore, the Hilbert transform does not always allow us to obtain the correct instantaneous amplitude, frequency and phase of the signal.

To solve this problem, the Hilbert-Huang transform (HHT) can be used. In this method, only the first IMF is used to find the instantaneous amplitude, frequency and phase. Once it is received, the function is considered a pure sinusoid with the calculated amplitude, frequency and phase. The IMF can then be subtracted from the original signal, and the process is repeated. Any error received during the calculation in any of these IMFs can be restored at subsequent iterative steps.

1) Wavelet transform

The wavelet transform (WT) is the same mathematical tool as the Fourier transform, which decomposes the signal into different scales with different resolution levels by extending the signal of the function prototype. WT is based on the quadratic integral function and the group theory. WT provides a local representation (both frequency and time) of the signal, so it is suitable for analyzing a signal that requires a time-frequency resolution, such as a transient event in the case of a violation of the quality of the EE.

Daubechies wavelet is widely used. To construct wavelet data the stretch equation (17) and the wavelet equation (18) are used:

$$\varphi(\mathrm{t}) = \sqrt{2}\sum_k h_k \varphi(2t-k) \tag{17}$$

$$\psi(\mathrm{t}) = \sqrt{2}\sum_k g_k \varphi(2t-k) \tag{18}$$

The compactness of the support of the functions φ , ψ can be achieved if a finite number $h_n \neq 0$ is chosen in such a way that the orthogonality and smoothness of the wavelet is attained, or that the moment condition is satisfied. For the Fourier region, the orthogonality and smoothness condition is as follows:

$$|m_0(w)|^2 + |m_0(w+\pi)|^2 = 1, \tag{19}$$

where $|m_0(w)| = \sum_n \frac{h_n e^{-inw}}{\sqrt{2}}$ - trigonometric polynomial under the condition of moments (20).

$$\left.\frac{d^l \psi w}{dw^l}\right|_{w=0} = 0 \tag{20}$$

To find the coefficients h_n, it is necessary to obtain m_0, separating the polynomial P from the orthogonality condition and the condition of zero moments:

$$P(y) = (1-y)^{-N}(1-y^N P(1-y)) \tag{21}$$

By factorization, we can extract the roots m_0 from P:

$$m_0(w) = const\left(\frac{z+1}{2}\right)^N \prod_{j=1}^{N-1}(z-z_j) \tag{22}$$

The required coefficients of the wavelet $h_j/\sqrt{2}$ will be the coefficients of z_j. The squares of the coefficients of the wavelet transform determine the smoothness of the shape of the voltage. Different EE quality factors have different conversion factors, as illustrated in [6].

III. Comparison of Methods of Extracting Features

In the paper [7], as well as in Tables I and II, a comparison between different methods of extracting EE quality factors is presented. Analyzing the data of the table, It can be concluded that there is no universal mathematical tool that would be suitable for tracking the entire range of EE quality factors.

TABLE I. COMPARISON OF FEATUE EXTRACTION METHODS

№	Disturbance	Percentage efficiency of PQ detection techniques			
		HHT	***ST***	***WT***	***FFT***
1	Sag	100	100	98.67	95
2	Swell	100	100	99.33	98
3	Harmonic	95	100	99.33	100
4	Flicker	100	100	98.67	89
5	Notch	100	83	97.33	-
6	Spike	95	77	-	-
7	Transient	98	100	98.67	100
8	1+3	98	100	98.18	-
9	2+3	89	100	98.18	-
10	1+7	-	-	96.36	-
11	2+7	-	-	98.18	-

TABLE II. ADVANTAGES AND DISADVANTAGES OF FEATURE EXTRACTION METHODS

Method	Advantages	Disadvantages
FFT	Successfully used for stationary signals. Simple in implementation	Not suitable for non-stationary signals
HHT	Useful in feature extraction of distorted waveform	Limited only for narrow band conditions
ST	Fully convertible from time domain to 2-D frequency translation domain and then to Fourier frequency domain	Based on block processing manner and doesn't satisfy real-time requirement, incorrect measurement of harmonics
WT	Provides local representation in both time and frequency.	Strongly influenced by noise present in the signal, suffering from spectral leakage

If we compare these methods in terms of computational efforts, then we can conclude that they are comparable in this parameter [8], [9], [10], [11], [12]. As a rule, fast variants of methods have computational complexity O(N log2(N)), under some particular conditions it can be less - O(N); Slow variants O(N^2). Of course, fast methods impose additional restrictions on the accuracy of the results. When choosing the extraction method, it is useful to check whether it refers to a particular, faster, case of one of the methods.

TABLE III. CALCULATION COMPLEXITY OF FEATURE EXTRACTION METHODS

№	Method	Fast calculation	Particular cases
1	FFT	N*log2(N) [11]	
2	HHT	неизвестно [9]	N [10]
3	ST	N*log2(N) [8]	
4	WT	N*log2(N) [12]	N [12]

IV. METHODS OF CLASSIFICATION USING ARTIFICIAL INTELLIGENCE

A. Neural networks

The neural network is a direct calculation tool based on the so-called artificial neurons organized into a network. Currently, the most commonly used type of artificial neuron is a formal neuron, described by the formula

$$y = Fa(\sum_{i=1}^{N} w_i\, x_i + b) \tag{23}$$

where w_i, b – weights, x_i – input arguments (N - number of input arguments of the neuron), Fa – activation function (sigmoidal, stepwise, piecewise linear, etc.)

The generalized structure of a neural network, as a rule, contains one or several hidden layers, characterized by the same activation functions within the layer. Networks of direct propagation transmit the results of the work of neurons in one direction, from the entrance to the exit; recurrent networks transmit information in the opposite direction, which gives the network the dynamic properties. To analyze and predict the time series a time delay line is created, which forms the data for the time window at the input of the neural network (Fig.2).

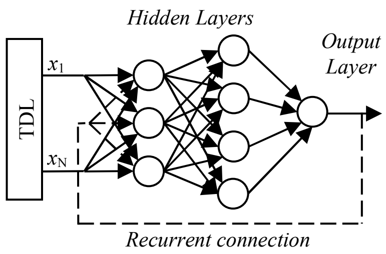

Fig.2. Example of ANN

In order to adjust the weights (f.e. for approximation, classification and forecasting time series), a pre-prepared set of input and output data or current input data is used. An example of the use to classify the distortion of the shape of the voltage is given in [13].

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B. Support vector machine

The support vector machine is a universal tool with one output, which is based on the theory of statistical learning. This SRM framework formally summarizes the empirical principle of risk minimization, which is commonly used for training a neural network (NN)[14]. The number of hidden layers is equal to the number of so-called support vectors, which are the points of the learning data closest to the separating hyperplane.

The training set is described by the formula (24):

$$Tr = \{(x_i, y_i)\}_{i=1}^{l} \tag{24}$$

X_i –real n-dimensional input vector

Y_I –label defining class x_i

The hyperplane is defined by the orthogonal vector w and the bias b, which satisfies the expression (25).

$$w^T x + b = 0 \tag{25}$$

When finding a hyperplane that maximizes the separation boundary *p*, the classifier will have better generalization possibilities. The hyperplane with the largest margin on the training set can be completely determined by the closest points to the hyperplane.

A study devoted to classification models of SVM are presented in [14][13], are called support vectors, since the hyperplane (that is, the classifier) entirely depends on them.

Neural network training functions:

$$f(x) = sign(w^T x + b) \tag{26}$$

$$f^*(x) = sign(g^*(x)) = sign\left(\sum_{i \in SV} \alpha_i^* y_i \langle x_i, x \rangle + b^* \right) \tag{27}$$

C. Expert systems

The expert system is a computer system that is capable of partial replacement of an expert in solving a problematic situation. Modern expert systems began to be developed by researchers of artificial intelligence in the 1970s, and in the 1980s they received commercial reinforcement.

Expert systems are considered together with knowledge bases as models of behavior of experts in a certain field of knowledge using the procedures of logical inference and decision making, and knowledge bases as a set of facts and rules of logical inference in the chosen subject area of activity.

Fuzzy logic is a generalization of the usual Boolean logic. While Boolean logic operates with binary numbers that correspond to the concepts of truth and false. In fuzzy logic, these concepts are generalized to all intermediate states between truth and false. In accordance with this, fuzzy logic operates with numbers from the interval [0,1], which reflects the degree of truthfulness of the statement.

Initially, using the wavelet transform, coefficients are obtained and features are extracted. Then they are formed into a vector.

In general, there are four classification models using fuzzy logic [15]:

- Fuzzy product aggregation reasoning rule (FPARR)
- Fuzzy explicit (FE)
- Fuzzy maximum likelihood (FML)
- Fuzzy k-nearest neighbor (Fk-NN)

As an example, consider the FPARR.

This technique uses three steps. Firstly, the input vector of the characteristics and the undefined values are taken. The pi-type membership function is used to determine whether a particular attribute belongs to different classes. A matrix of attribute's belonging to F(x) is created, which determines the belonging of different characteristics of D to different classes C. Its elements are respectively equal to $f_{d,c}(x_d)$. x_d is the pattern of characteristics.

$$F(x)=\begin{bmatrix} f_{1,1}(x_1) & f_{1,2}(x_1) & \dots & f_{1,C}(x_1) \\ f_{2,1}(x_2) & f_{2,2}(x_2) & \dots & f_{2,C}(x_2) \\ \dots & \dots & \dots & \dots \\ f_{D,1}(x_D) & f_{D,2}(x_D) & \dots & f_{D,C}(x_D) \end{bmatrix} \tag{28}$$

Then the undefined values of features are combined with the help of the multiplication theorem. The output vector:

$$F'(x)=\left[F_1(x),F_2(x),\dots,F_C(x)\right]^T \tag{29}$$

$$F_c(x)=\prod_{d=1}^{D} f_{d,c}(x_d) \tag{30}$$

The last step is a rigid classification made by the operation of determining the maximum to eliminate uncertainty.

D. Genetic algorithm

The genetic algorithm is an optimization tool based on the mechanism of natural selection and natural genetics. It combines the survival between string structures with a structured but randomized information exchange to form a search algorithm with some innovative stream of search. The genetic algorithm is considered an excellent intellectual paradigm for optimization using a multipoint, probabilistic, random and controlled search mechanism. In general, it is used as a classifier in combination with other methods [16].

V. COMPARISON OF CLASSIFICATION METHODS

A comparison of the methods for classifying EE quality factors is presented in [7], and is also presented in Table III. Different techniques manifest themselves in various ways in the presence of noise and with several types of voltage distortion.

TABLE IV. COMPARISON OF CLASSIFICATION METHODS

Method	Advantages	Disadvantages
Neural networks	High classification accuracy for mixed PQ disturbances	Less efficient under noisy conditions
Support vector machines	Is able to operate with many features, provide stable solution to quadratic optimization, high learning abilities	Poor classification accuracy when training samples are minimum
Expert systems	Can be used with or without limited data	Expensive, slow in execution, it is difficult to draw conclusion if assumptions and actual situations do not match
Genetic algorithm	Accurately classifies PQ disturbances generated due to dynamic performance of power system	High computational time, is used in combination with other methods

VI. POSSIBILITIES OF IMPLEMENTATION

Possible implementations of the power quality classifier are divided into two main categories: software and hardware implementations, as well as their combination.

The software implementation is performed on general-purpose microcontrollers or on a computer, all methods are described as program code. The advantage of this method is the ease of use, primarily due to the wide availability of hardware. The limiting complexity of the network's realization depends on the used microcontroller, and limited mainly by the microcontroller speed. In terms of speed, software implementation is inferior to hardware, although for numerical methods this solution is often optimal. The implementation of ANN slows down the operation of the classifier due to the activation function.

Nowadays the largest manufacturers of microcontrollers are STMicroelectronics and Atmel. Both companies have a significantly wide range of solutions for different tasks. Among the high-performance microcontrollers there are solutions performed on the ARMCortexM7 core [18]. These are microcontrollers with a core that has 200-300 MHz of operating frequency and 1-2 MB of flash memory. Also, controllers have up to 24 ADCs, which can be convenient when embedding them in an analog system. In this case, all microcontrollers have an affordable price, up to several tens of dollars.

Hardware implementation of EEQ can be implemented on digital or analog components. Digital implementation is widespread, on FPGAs in combination with a signal processor [19]. It is easier to design than analog ones, because typically they use standard components. However, digital implementation of mathematical methods is much more complicated than the software one. ANN that is implemented in the form of a digital circuit have the advantage of parallel operation. Modern FPGAs are produced mainly by two companies: Altera and Xilinx. Top models have up to 5 million logical cells, up to several hundred MB of memory and several thousand multipliers, which is required for the neural network, the price of one scheme can reach $ 10,000.

The main difficulty in developing analog solutions is that their mass production is possible on discrete components or with creation of integrated circuits for a special purpose. Programmable analog integrated circuits (PAIS), unlike their digital analogs FPGA, have not received wide distribution, and nowadays there are very limited versions of PAIS only. The advantage of analog realizations is compactness, speed of operation. An example of analog realization of ANN is [20].

VII. Discussion

If we generalize the methods for extracting the features considered above, then all of them are a convolution that requires sufficiently large computational costs for the period of the frequency of the supply network to ensure the required accuracy; while the algorithms themselves are relatively simple. These computational efforts can lead to the fact that the efforts of implementation of such methods will be too high when creating mass devices for monitoring the quality of electrical energy. At the same time, there is a computational tool that provides the computation of such convolutions with a predetermined accuracy in a time which is independent of the accuracy of the implementation, or of the size of the time window, or (within reasonable technological limits) from the sampling frequency of the signal being processed. This is hardware (analog or digital) implementation of artificial neural networks (ANN), which provides high speed due to the simultaneous independent operation of specialized calculators - formal neurons. If we talk about the classification of identified features, then this task is less computationally expensive, and also has distinct decisions based on the ANN. Thus, we can make a preliminary conclusion that the hardware implementation of ANN is a promising tool for a mass device for monitoring the quality of electrical energy.

VIII. Conclusion

The most common and effective methods for identifying features of power quality factors are Fourier transforms, wavelet transform, S-transform and Hilbert-Huang transform. Their performance depends on the type of distortion of the waveform, the presence of noise, as well as combinations of factors. Therefore, to ensure accurate and fast operation of the detection system, a combination of mathematical tools takes place. At the same time, the most widely used EE quality classifiers include neural networks, a support vector machine, genetic algorithms and expert systems. It should be noticed that all the classifiers are used in combination with a neural network, since it can compensate for the slow action of various methods for determining the class of EE quality factors.

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