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Detection and Classification of Voltage Disturbances in Electrical Power Systems Using a Modified Euclidean ARTMAP Neural Network with Continuous Training

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Abstract—This article presents a method to detect and classify voltage disturbances in electric power distribution systems using a modified Euclidean ARTMAP neural network with continuous training. This decision-making tool accelerates the procedures to restore the normal operation conditions providing security, reliability, and profits to utilities. Furthermore, it allows the diagnosis system to adapt to changes from the constant evolution of the electric system. The voltage signals features or signatures are extracted using discrete wavelet transform, multiresolution analysis, and the energy concept. Results show that the proposed methodology is robust and efficient, providing a fast diagnosis process. The data set used to validate the proposal is obtained by simulations in a real distribution system using ATP software.

1. INTRODUCTION

Users have recently been demanding a best energy supply with quality and reliability, reducing voltage abnormalities and minimizing interruptions caused by disturbances [1, 2]. Among the most common disturbances, emphasis is on voltage sag; caused by, e.g., short circuit, voltage swell; caused by, e.g., capacitor bank switching, and harmonics; caused by, e.g., the presence of non-linear equipment connected to the electric network.

The occurrence of these disturbances degrade the power quality, leading to faulty operation of some equipment connected to the network, conductor superheating, and malfunction of the protection system. Therefore, distribution companies invest in developing new techniques that are able to detect and classify such disturbances quickly, with security and in an efficient manner, contributing to the automation of the distribution systems [3, 4]. Normally, detection of the disturbances is done through the visual inspection of voltage disturbances by the operators, who require some previous experience

Keywords: wavelet transform, Euclidean ARTMAP neural network, continuous training, power quality disturbance, power distribution system
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in analysis and decision making. Because of the dependence on human operators, the diagnosis is susceptible to errors. Thus, the automation of this practice is very important, where techniques based on artificial intelligence assist the operator to classify abnormalities.

The specialized literature contains several proposals aiming to identify voltage disturbances automatically [5, 6, 7, 8].

In [9], a hybrid technique to characterize the power quality disturbances is presented. The hybrid technique uses the Kalman filter with discrete wavelet transform (DWT) to extract the waveform characteristics. Then, based on fuzzy rules, the fuzzy system provides as output the type of the disturbance.

A new approach to classify the power quality disturbances employing the Markov model and wavelet transform (WT) was proposed in [10]. By applying WT, it is possible to calculate the energy distribution coefficients considering each decomposition level of the analyzed disturbances. Therefore, the extracted indexes initialize the training matrix of the Markov model maximizing the precision of the classification. Furthermore, the Dempster–Shafer algorithm [10] is used to obtain qualitative information about the result.

In [11], a classification system based on S-transform and a probabilistic neural network was proposed. The power quality disturbances are analyzed by S-transform; then the characteristics of the time–frequency domain are extracted from the S-matrix to compose the input vector of the neural system, which provides the diagnosis.

In [12], a base rule was employed to classify the power quality disturbance. The disturbances are characterized by multi-layer S-transform, which acts as a singularity extraction tool. The pattern classification algorithm that identifies the disturbances uses linear and parabolic rules, where the decision intervals are defined by heuristics.

In [13], a methodology was proposed to classify power quality disturbances by an intelligent recognition system. The characteristics representing the disturbances are extracted applying WT on the three-phase voltage signals. Also, a support vector machine classifies the disturbance present on the power system.

In [14], a decision-making system was presented for automated classification of power quality disturbances, where the most common types of disturbances, including flickers, harmonics, impulses, notches, outages, sags, swells, and switching transients, were studied. The signal-processing techniques utilized to extract the waveforms features are Fourier and S-transform, and a method based on the binary feature matrix was designed to classify the disturbance type.

Considering the concept of the smart grid, where the distribution systems must be intelligent and with learning capac-

ity, the development of voltage disturbance diagnosis methods must present the above-described characteristics. Self-adaptation is a fundamental characteristic that allows the system to adapt to the changes coming from the expansion and evolution of the electrical system, *e.g.*, new kinds of disturbances, failures, and without the interference of human operators. Considering that several techniques based on artificial intelligence are available, some characteristics in choosing one or other must be observed. For example, none allows activating an automatic learning system without the interference of human operators. Therefore, the ART family neural networks that present characteristics of plasticity and stability can be used to incorporate new information different from those previously acquired, *i.e.*, knowledge.

This study presents an auto-adaptive methodology for voltage disturbance diagnosis in electrical distribution feeders. It is simple, robust, and flexible, using the modified Euclidean adaptive resonance theory mapping neural network, to classify and learn different disturbances [15]. The neural network is based on a new conception where the performance is improved as time goes by; *i.e.*, as new knowledge is presented to the network, it is not necessary to reinitialize the training process. The reinforcement of this knowledge is on-line, automatic and refines the previously acquired knowledge once the network presents parameters that identify the presence of new knowledge. This continuous training module does not require additional computational effort when compared to other neural network configurations, *e.g.*, the backpropagation algorithm.

The continuous training uses data of the acquisition system (supervisory control and data acquisition [SCADA]), data obtained from simulations containing topology changes on the electrical system, and other kinds of voltage disturbance, including other abnormalities, *e.g.*, low- and high-impedance short circuits.

The extraction of the voltage waveform characteristics is realized through the employment of DWT, multi-resolution analysis (MRA), and the energy concept. These characteristics correspond to the input vector of the MECT-ARTMAP neural network. As output, the neural network provides a binary codification previously defined to represent the type of disturbance present on the feeder.

This article is organized as follows. Section 2 shows the structure of the method used. Sections 3 and 4 present the DWT and the MRA, respectively. The voltage disturbance detection module is described in Section 5. Section 6 emphasizes the procedures to extract the voltage disturbance characteristics. Section 7 shows the methodology to process and codify the voltage disturbances. Section 8 presents the classification module. Section 9 highlights the database configuration. The

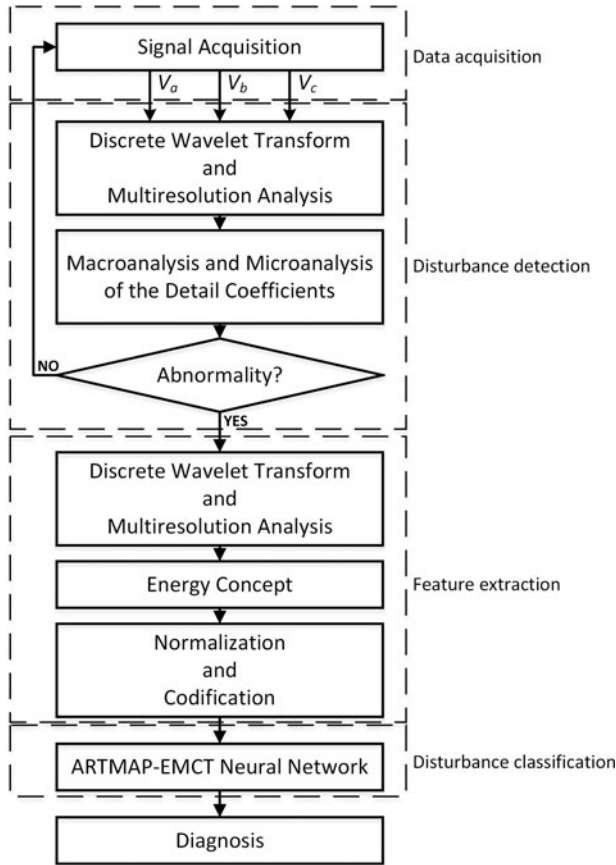


FIGURE 1. Structure of the voltage abnormality diagnosis system.

results and discussions are presented in Section 10 and the conclusion in Section 11.

2. STRUCTURE OF THE PROPOSED METHODOLOGY

Figure 1 presents the modules of the developed system to detect and classify voltage disturbances. This system can be modified to attend the necessities of distribution companies according to the electrical system constant evolution.

3. WT

In most applications, where it is necessary to extract characteristics, the methods employed are based on Fourier transform. Even being a powerful tool for disturbance diagnosis, Fourier transform is inadequate to analyze non-stationary signals. Thus, WT is a concept that surpasses the limitations of techniques based on Fourier transform once it provides the temporal evolution of frequency transients [16].

WT is a linear transform that uses oscillation functions with different frequencies as windowing functions. This base function, called the mother wavelet, must have finite energy and medium value equal to zero. The mother wavelet is defined according to Eq. (1) [17]:

$$\psi_{r,s}(t) = \frac{1}{\sqrt{|r|}} \psi\left(\frac{t-s}{r}\right), \quad (1)$$

where s is a translation parameter and r the scale parameter.

To analyze oscillographs obtained by acquisition data equipment, it is necessary to discretize the wavelet function. Thus, DWT of a sample signal $f(k)$ is defined as follows [17]:

$$DWT_f = \langle f, \psi_{m,n} \rangle = \sum_k f[k] \psi_{m,n}^*[k], \quad (2)$$

where

$$\psi_{m,n}^*[k] = \frac{1}{\sqrt{r_0^m}} \psi^*\left[\frac{k - ns_0 r_0^m}{r_0^m}\right].$$

4. MRA

MRA consists of calculating coefficients ca_m and cd_m determined by Eqs. (3) and (4), respectively. To calculate coefficients ca_{m+1} and cd_{m+1} , it is necessary to perform the discrete convolution of the signal ca_m with a low-pass filter (h ; *i.e.*, discrete scale function) and a high-pass filter (g ; *i.e.*, discrete wavelet function). At the output of each one of the filters, the decomposed signal is subsampled by a factor of 2 [18]:

$$ca_{m+1}[p] = \sum_n h[n-2p] ca_m[n], \quad (3)$$

$$cd_{m+1}[p] = \sum_n g[n-2p] ca_m[n]. \quad (4)$$

The coefficients obtained at the output of the low-pass filter ca_{m+1} are characterized as being the high-scale and low-frequency components of the signal, called approximation coefficients. The coefficients obtained at the output of the high-pass filter cd_{m+1} are the components of low-scale and high-frequency components, called detail coefficients.

5. DISTURBANCE DETECTION MODULE

The voltage disturbance detection module is designed considering the constant evolution of technologies employed at the substations and the natural dynamism of the electric power systems, such as loading, disturbance insertion angle, location, and noise presence in oscillographs, and is aimed to obtain a robust, flexible, and efficient methodology.

The disturbance detection is done by analyzing the voltage oscillographs acquired at the principal substation output. In this step, the signal windowing is defined to be two cycles and the step under analysis to be one cycle. Thus, MRA is applied to decompose the signal of the phase in two resolution levels. Subsequently, calculations of the arithmetic average of the absolute value of the detail coefficients (previously defined in Eq. (4)) of each one of the decomposition level of the oscillograph under analysis are made [16]:

$$\bar{d}_{ij} = \frac{\sum_{k=1}^{N_j} |cd_{ij}^k|}{N_j}, \quad (5)$$

where

i is the oscillograph under analysis, *i.e.*, Va , Vb and Vc ;

j is the decomposition level, *i.e.*, 1 and 2;

N_j is the quantity of the detail coefficients of level j ;

k is the k th detail coefficient of level j referred to oscillograph i ; and

\bar{d}_{ij} is the arithmetic average of the detail coefficients of level j referred to oscillograph i .

Further, the variation in relation to the arithmetic average obtained for each detail coefficient using Eq. (6) is calculated [16]:

$$var_{ij}^k = ||cd_{ij}^k| - \bar{d}_{ij}|, \quad (6)$$

where var_{ij}^k is the variation of the k th detail coefficient in relation to the arithmetic average of these coefficients for level j referred to oscillograph i .

At the same time, the standard deviation of the absolute value of the detail coefficients under evaluation is obtained [16]:

$$\sigma_{ij} = \sqrt{\frac{\sum_{k=1}^{N_j} (|cd_{ij}^k| - \bar{d}_{ij})^2}{N_j - 1}}, \quad (7)$$

where σ_{ij} is the standard deviation of the detail coefficients of level j referred to oscillograph i .

The voltage disturbance detection process is based on the two sets of rules presented in Eqs. (8) and (9), where each rule is divided into two parts: macro-analysis and micro-analysis. The general behavior of the signal is known by the macro-analysis, *i.e.*, comparing the maximal variation of the detail coefficients with a percentage of the standard deviation, which provides major immunity to noise presence in oscillographs under analysis and minimizes the effect of changes in the power distribution system. The micro-analysis allows a point-to-point analysis of the major detail coefficient with a predefined limit

(set by the operator) [16]:

$$\text{if } \max[var_{ij}] > 1.25\sigma_{ij} \text{ or } \max[cd_{ij}] > \mu_j, \text{ then } \tau_{ij} = 1 \quad (8)$$

shows the existence of abnormalities on the system

$$\text{if } \max[var_{ij}] \leq 1.25\sigma_{ij} \text{ or } \max[cd_{ij}] \leq \mu_j, \text{ then } \tau_{ij} = 0 \quad (9)$$

shows the normal operation of the system,

where μ_j is the parameter to be specified based on the protection philosophy of the system and the operator experience, and τ_{ij} is the index of the operation state of the system.

The rate 1.25 is defined after the analyzing the values from Eqs. (6) and (7) and also considering the signals representing the normal operation from the voltage disturbances. Thus, the detection module presented in Figure 1 assures the presence of abnormalities if the rule of Eq. (9) is satisfied, and the normal operation if the rule of Eq. (8) is satisfied.

6. FEATURE EXTRACTION MODULE

Once any abnormality on the system is detected, the classification step is activated. The extraction of the disturbance characteristic indices is realized by DWT, MRA, and the energy concept. These behavioral indices compose the input vector of the MECT-ARTMAP, which classifies the disturbance.

6.1. Energy

The energy concept corresponds to a data fusion tool that can be used to aggregate information extracted from a signal through signal processing techniques. In particular, this concept is used often to aggregate the coefficients extracted using DWT. If the diagnosis procedure considers these features as input, the process can become inefficient once high computational effort is required. Therefore, the application of the energy concept reduces the dimension of the input vector; *i.e.*, the coefficients are aggregated in scalars, leading the procedure to be faster and reliable [19].

The energy can be calculated using the following equation:

$$E = \sum_{n_p=1}^Z |x[n_p]|^2, \quad (10)$$

where $x[n_p]$ is the n_p th sample of signal x , Z is the quantity of points of the analyzed signal, and E is the energy of the signal.

6.2. Characteristic Extraction

The classification model selects two pre-disturbance and two disturbance cycles of the voltage oscillographs. These cycles are decomposed by the MRA into four resolution levels. It is emphasized that DWT is applied again once the cycles are analyzed at this juncture. It is to be noted that these two pre-

disturbance cycles and two cycles with disturbance are different from those used on the detection process.

The characteristics of the system's operation state are based on the detail coefficients of the third and fourth level, and the approximation coefficients of the fourth level [20]. Then the energy of the detail and approximation coefficients of the pre-disturbance cycles, considering each one of the phases, is calculated according to Eqs. (11) and (12):

$$Eca_j^{f,pd} = \sum_{n=1}^{N_j} \left| ca_j^{f,pd}[n] \right|^2, \quad (11)$$

$$Ecd_j^{f,pd} = \sum_{n=1}^{N_j} \left| cd_j^{f,pd}[n] \right|^2, \quad (12)$$

where

pd is the pre-disturbance;

j is the decomposition level, *i.e.*, third and fourth detail level, and fourth approximation level;

f is the phase of the analyzed oscillograph, *i.e.*, *Va*, *Vb*, and *Vc*;

N_j is the coefficients' quantity of level *j*;

ca^{pd}[n] is the value of the *n*th approximation coefficient of the pre-disturbance cycles; and

cd^{pd}[n] is the value of the *n*th detail coefficient of the pre-disturbance cycles.

The same procedure is applied for the coefficients of the disturbance cycles:

$$Eca_j^f = \sum_{n=1}^{N_j} \left| ca_j^f[n] \right|^2, \quad (13)$$

$$Ecd_j^f = \sum_{n=1}^{N_j} \left| cd_j^f[n] \right|^2, \quad (14)$$

where:

f is the phase of the analyzed oscillograph, *i.e.*, *Va*, *Vb*, and *Vc*;

j is the decomposition level, *i.e.*, third and fourth detail level, and fourth approximation level;

N_j is the coefficients' quantity of level *j*;

ca[n] is the value of the *n*th approximation coefficient of the cycles with disturbance; and

cd[n] is the value of the *n*th detail coefficient of the cycles with disturbance.

Thus, the characteristic vectors for the pre and with disturbance cycles are defined.

$$A_{pre-disturbance} = \left[E_{cd3}^{Va,pd} E_{cd4}^{Va,pd} E_{ca4}^{Va,pd} E_{cd3}^{Vb,pd} E_{cd4}^{Vb,pd} \right]$$

$$E_{ca4}^{Vb,pd} E_{cd3}^{Vc,pd} E_{cd4}^{Vc,pd} E_{ca4}^{Vc,pd} \Big], \quad (15)$$

$$A_{disturbance} = \left[E_{cd3}^{Va} E_{cd4}^{Va} E_{ca4}^{Va} E_{cd3}^{Vb} E_{cd4}^{Vb} E_{ca4}^{Vb} E_{cd3}^{Vc} E_{cd4}^{Vc} E_{ca4}^{Vc} \right], \quad (16)$$

Subsequently, the pre-disturbance characteristic vector is subtracted from the characteristic vector under disturbance. This is necessary to obtain a complete analysis of the type of disturbance, incorporating into the methodology system's reference operation, *i.e.*, normal operation [20]:

$$\Gamma = A_{disturbance} - A_{pre-disturbance}. \quad (17)$$

After analyzing the type of disturbance, vector Γ is normalized and codified to obtain more generalization of the project and maintaining the signal information (positive and negative) [20].

7. PROCESSING AND CODIFICATION MODULE

The input vector of the MECT-ARTMAP neural network (**a**) is defined by [20]

$$a = [\Psi \Phi], \quad (18)$$

where

$$\Psi = [\Psi_1 \Psi_2 \dots \Psi_9],$$

with

$$\Psi_i = \frac{|\Gamma_i|}{\Gamma_{\max}},$$

$$|\Gamma_{\max}| = \max \{ |\Gamma_i| \}, i = 1, \dots, 9.$$

The components of vector ϕ are defined according to

$$\begin{cases} \Psi_i > 0 \rightarrow \Phi_i = 1 \\ \Psi_i \leq 0 \rightarrow \Phi_i = 0 \end{cases}, i = 1, \dots, 9, \quad (19)$$

where ψ is the vector of the normalized characteristics, and ϕ is the signal of each normalized characteristic.

This process corresponds to the normalization step presented in Figure 1. This procedure must be executed for each vector to be analyzed to provide a correct distinction among the different disturbances analyzed by the modified Euclidean ARTMAP (ME-ARTMAP) neural network.

The output of the neural network, defined by vector (**b**), provides the type of voltage disturbance present on the system. This output is codified as shown on Table 1.

Voltage disturbance	Output codification
Swell	[0 0 0 1]
Sag	[0 0 1 0]
Interruption	[0 0 1 1]
Harmonics	[0 1 0 0]
Swell with harmonics	[0 1 0 1]
Sag with harmonics	[0 1 1 0]
Oscillatory transient	[0 1 1 1]

TABLE 1. Output codification

8. DISTURBANCE CLASSIFICATION MODULE USING MECT-ARTMAP

The classification of the voltage disturbances is realized by the MECT-ARTMAP, which had been previously training in the off-line mode to improve the acquired knowledge in the on-line mode, *i.e.*, during the diagnosis.

8.1. ME-ARTMAP Neural Network

The ME-ARTMAP is a self-organized system composed of two Euclidean adaptive resonance theory (ART) modules, ART_a and ART_b, interconnected by an associate memory module called inter-ART. This neural network uses the Euclidean distance in the calculus, allowing the neural system responses to binary or analogic input patterns, pertaining to the set \mathbb{R}^+ ($[0, +\infty)$).

The inter-ART module has a self-regulatory mechanism, called match-tracking, that uses the fuzzy operator AND (\wedge) to verify if the matching with the input and output of the neural network happens or not, as well as that at ARTMAP-fuzzy [21]. If there is no matching, then the reset occurs. At the reset, a new category of the ART_a module is chosen to be introduced at the resonance process. Furthermore, a decrease occurs at the parameter ρ_a . The inter-ART vigilance criterion is only activated when no category is created either in ART_a or in ART_b. It is initialized with one active neuron, *i.e.*, the first pattern presented to the network ($W_{1,i}^a = a_{1,i}$ and $W_{1,j}^b = b_{1,j}$). The weights of the inter-ART module are defined as follows: $W_{1,1}^{ab} = 1$ and $W_{1,n}^{ab} = 0$, where $n = 2, 3, \dots, N$. The other weights W^{ab} are set in 1 [22]. The input and output vectors are represented by \mathbf{a} and \mathbf{b} , respectively, and defined according to Eqs. (20) and (21):

$$\mathbf{a} = [a_1, a_2, \dots, a_{Ma}], \quad (20)$$

$$\mathbf{b} = [b_1, b_2, \dots, b_{Mb}], \quad (21)$$

where

$$a_i \in [0, 1], i = 1, 2, \dots, Ma,$$

$$b_j \in [0, 1], j = 1, 2, \dots, Mb,$$

where Ma is the dimension of vector \mathbf{a} (input), Mb is the dimension of vector \mathbf{b} (output), and N is the quantity of input and output patterns.

The training depends basically on choosing the vigilance parameters (ρ_a , ρ_b , and ρ_{ab}), the training rate (β), and the increasing parameter (ε).

The ME-ARTMAP neural network is a conception that provides solutions with quality, precision, and speed. One advantage of this neural network is that the complementary normalization and codification of the input patterns are not required, which consequently doubles the dimension of the input vector. Furthermore, as it uses a quadratic geometry, the formation of classes is more precise when compared to the conventional formulation of the fuzzy ARTMAP (rectangular geometry). Figure 2 presents the flowchart of the ME-ARTMAP neural network.

8.2. MECT-ARTMAP Neural Network

The continuous training to be incorporated at the ME-ARTMAP neural network is presented as follows. With the training in a continuous form, if new patterns are available, *e.g.*, simulations or oscillographs provided by the data acquisition system, the training step does not need to be reinitialized, which is different when compared to other neural network approaches already known in the literature. The incorporation of continuous training, as in the ME-ARTMAP and other ART family neural networks, is possible because of the stability and plasticity characteristic, consisting of an improved neural system when compared to the multi-layer perceptron with the backpropagation algorithm [15, 22, 23].

Continuous training allows inclusion of new patterns to the memory permanently. Thus, the training and analysis (diagnosis) are faster and more efficient procedures. Some new elements were added to the training algorithm of the ME-ARTMAP neural network for a correct run of this mechanism.

The first modification is the inclusion of temporary and definitive weights at the ART_a module. This is necessary to avoid the presence of categories similar to the network memory. Therefore, there are temporary and definitive categories during the process of choosing categories. Further, two choice functions are defined, one for the temporary categories (T_v^t), and other for the definitive categories (T_i^d) [22].

The temporary category is initialized with only one active neuron, *i.e.*, the first pattern presented to the network ($W_1^{at} = a_1$), and the weights of the temporary inter-ART module W^{abt} are set in 1. Definitive weights W^{ad} , W^{bd} , and W^{abd}

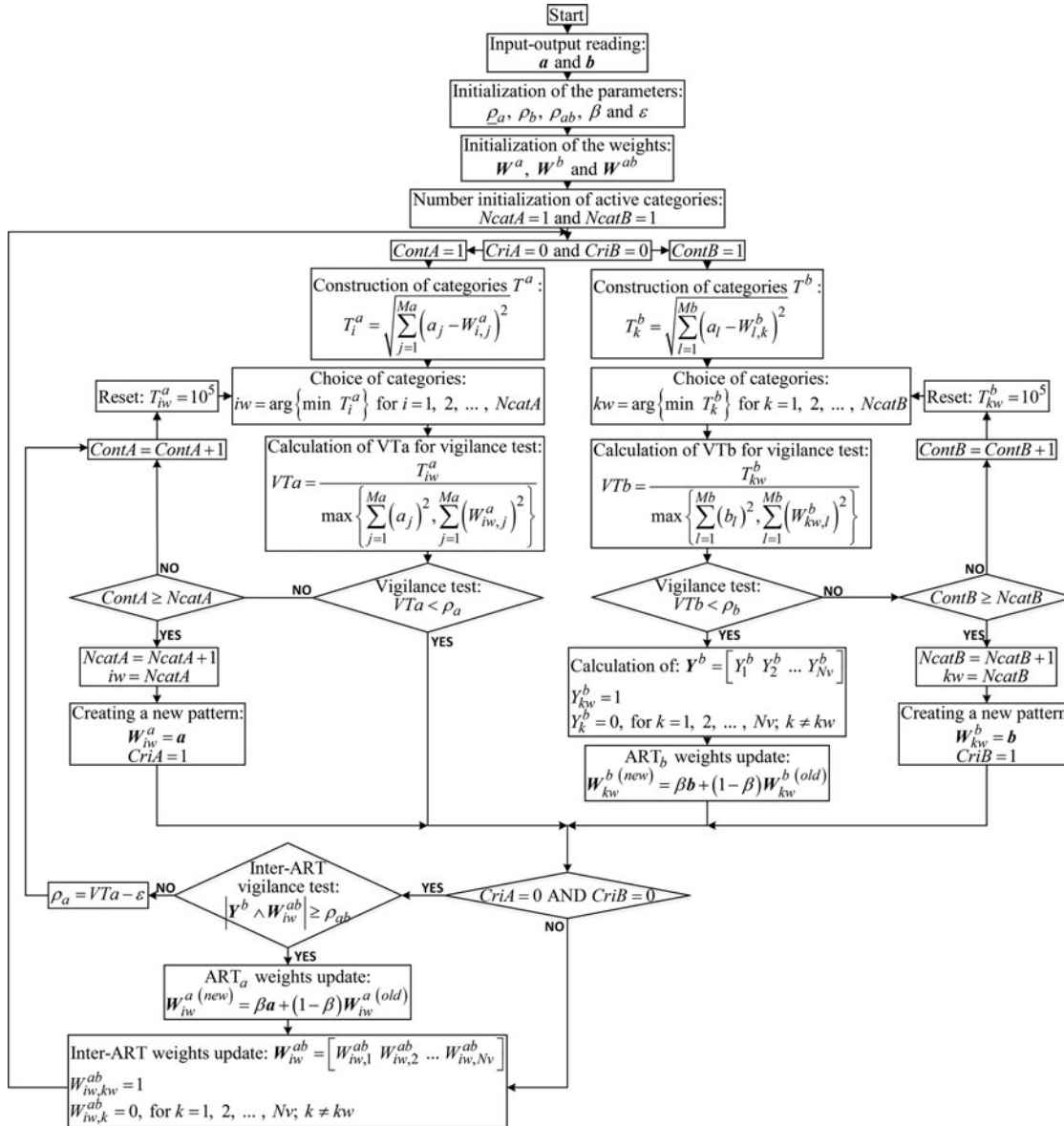


FIGURE 2. Flowchart of the ME-ARTMAP neural network.

of ART_a, ART_b, and inter-ART are equal to weights W^a , W^b , and W^{ab} of ME-ARTMAP trained off-line, respectively.

The second modification is the inclusion of two new patterns: $NMIN$ and η . The parameter $NMIN$ ($NMIN \in \mathbb{R}$, with $NMIN > 1$) refers to the quantity of patterns necessary for a temporary weight to become a definitive one. During the training, similar temporary patterns are counted and filed on vector $ContT$, and when the value attains $NMIN$, it becomes definitive. The parameter η ($\eta > 0$) verifies if it is necessary to update the winner of the definitive category of weights; i.e., the redundant information are undervalued. Thus, classes and similar patterns do not need to be allocated in different

categories, and, moreover, the unnecessary overloading of the memory is avoided [22]. Figure 3 presents the flowchart of the MECT-ARTMAP neural network.

9. TEST SYSTEM

Generally, research centers and distribution companies do not have a consistent data set representing the operation system under disturbance. Considering the lack of these registers, it is necessary to use test systems to simulate the disturbances, leading to the extraction of adequate information and validating the disturbance diagnosis methodology.

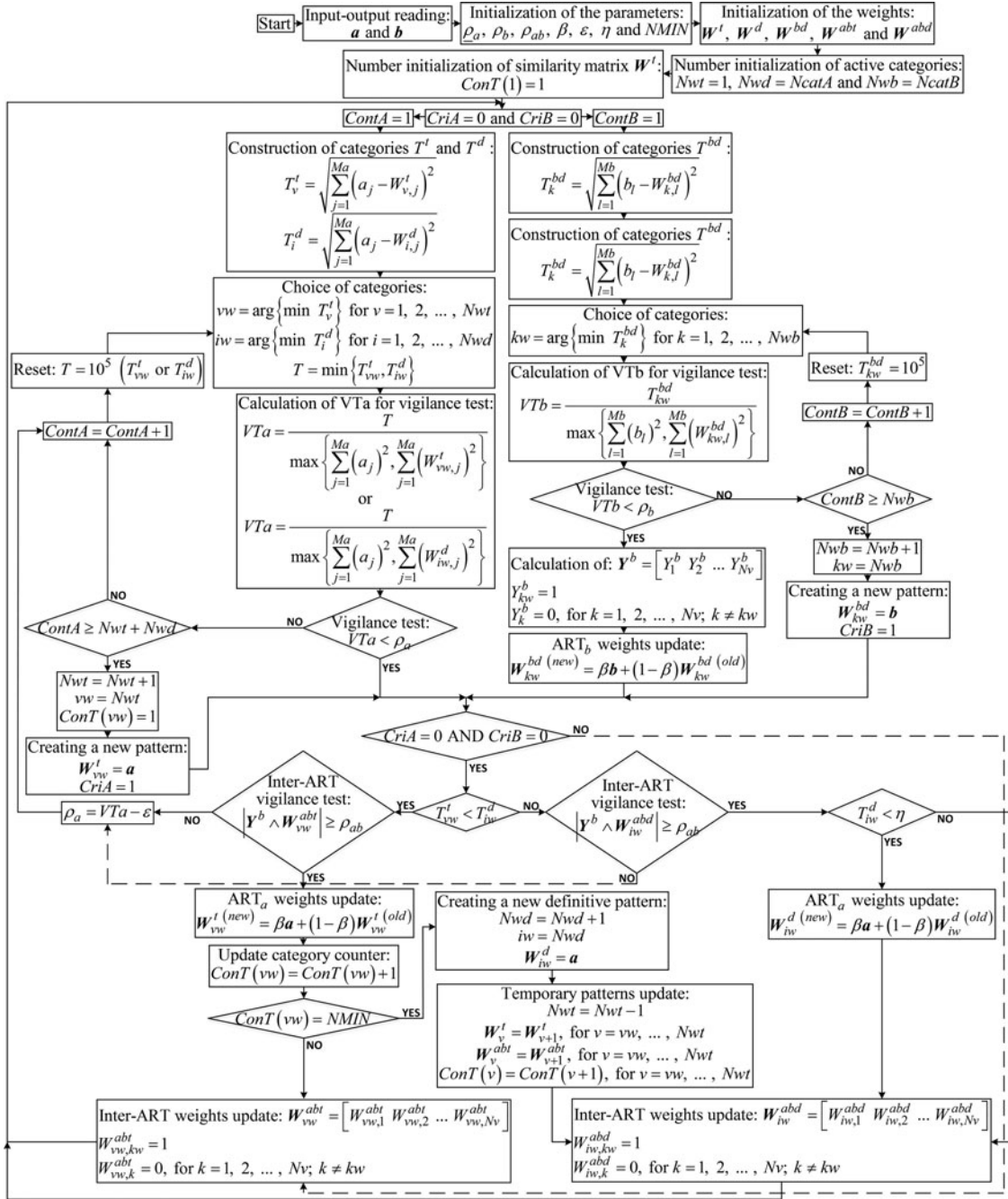


FIGURE 3. Flowchart of the MECT-ARTMAP neural network.

9.1. Model of the Simulated Feeder

Therefore, the proposed voltage abnormality diagnosis scheme was tested in a real 13.8-kV distribution system, obtained from [24]. This feeder (test system) was modeled using the software Alternative Transients Program (ATP) [25].

Simulations of the voltage disturbances were executed with one of the routines of the ATP containing the sources of the

disturbances approached in this study. Each simulation used a sample frequency of 15.36 kHz, corresponding to 256 samples per cycle.

The different signal acquisition devices generally use this sampling frequency. It is emphasized that the neural network accuracy rate will increase along with the number of samples employed in disturbances analysis, *i.e.*, better distinction.

Parameter	Decomposition level	
	First	Second
μ	0.005	0.07

TABLE 2. Parameter for voltage disturbance detection

10. RESULTS AND DISCUSSIONS

The methodology developed for voltage disturbance diagnosis in electrical distribution feeders is robust, efficient, and able to learn as time goes by.

The Daubechies mother wavelet [18] is used for detecting the disturbances with a fourth-order filter (*db4*). Table 2 presents the values of the limit parameters used by the operator to verify the operative state of the system. This module presents 100% accuracy in identifying abnormal situations with high computational performance.

Two cycles under disturbance and two cycles at pre-disturbance are selected once any abnormal operation on the distribution system is detected and after identifying the instant when the disturbance begins. Subsequently, they are analyzed in four resolution levels by MRA and aggregated by the energy concept. At this step, the mother wavelet is also the Daubechies with the fourth-order filter (*db4*). The input vector of the ME-ARTMAP module (off-line training) uses as reference the normal operation of the energy, referred to as the wavelet coefficients of the pre-disturbance cycles; this energy is subtracted from the energy of the detail and approximation coefficients of the cycles under disturbance.

At the classification step, there are 3024 voltage disturbance vectors of which 524 were selected for training the ME-ARTMAP module and 2500 for test. It is emphasized that this selection was done pseudo-randomly (with a predefined seed). Additionally, 432 disturbances from the harmonic class were included on the test pattern set. Thus, it was possible to visualize the capacity of the continuous training module in acquiring new knowledge, showing the improvement of the

Voltage disturbance	Pattern test	Accuracy (%)
Swell	346	83.51
Sag	338	54.73
Interruption	338	81.95
Harmonics	432	0
Swell with harmonics	359	93.31
Sag with harmonics	346	54.33
Oscillatory transient	341	99.70

TABLE 3. Accuracy rate without the continuous training module

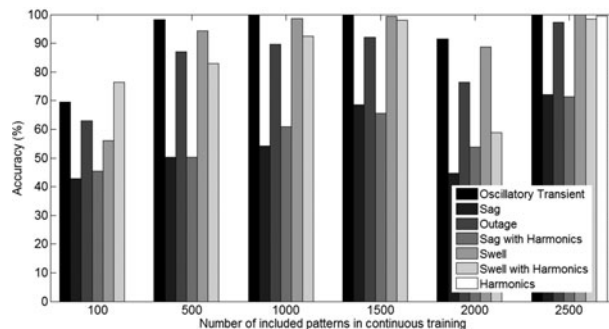


FIGURE 4. Evolution of the neural network with continuous training.

results as time passed. Table 3 shows the accuracy rate in the ME-ARTMAP module.

It is observed that by analyzing the accuracy percentage for each one of the disturbances, this percentage is zero for the voltage disturbance defined as harmonic. This occurrence is because of the lack of patterns representing the harmonic disturbance during the training of the neural network; *i.e.*, there is no harmonic disturbance on the off-line training of the neural network. Thus, the neural network is unable to learn such a disturbance, and when they are presented at the test step, the neural network classifies wrongly; therefore, the accuracy rate for this disturbance is zero.

Furthermore, the accuracy rate of the disturbances sag and sag with harmonic was very low. The errors in classifying these disturbances are because of the characteristic index, once the disturbances sag, outage, and sag with harmonic present the same behavior in amplitude. Therefore, the disturbances sag and sag with harmonic are classified as outage by the classification module.

Finally, at the off-line training step, the continuous training module is activated. Each one of the test pattern used at the ME-ARTMAP is presented separately, *i.e.*, one by one, for the MECT-ARTMAP. The MECT-ARTMAP provides a new diagnosis even as new patterns are presented to the network. Then, considering every test pattern, the network provides 2500 different diagnoses. Figure 4 presents the evolution of the accuracy rate after including each one of the test patterns on the continuous training. Table 4 shows the final result after including the 2500 patterns on the continuous training.

Comparing Tables 3 and 4, it is observed that there is an improvement in the classification step; *i.e.*, the neural network with continuous training is able to classify correctly disturbances that were wrongly classified previously. It is also observed that the accuracy of the disturbance harmonic is improved from 0 to 99.53. The increase of this accuracy rate is a consequence of the neural network incorporating new patterns

Voltage disturbance	Pattern test	Accuracy (%)
Swell	346	100
Sag	338	72.18
Interruption	338	97.33
Harmonics	432	99.53
Swell with harmonics	359	98.32
Sag with harmonics	346	71.38
Oscillatory transient	341	99.70
Total	250	91.20

TABLE 4. Accuracy rate with the continuous training module

into the data base, *i.e.*, disturbances that were previously unknown are now correctly identified at the test step. This case exemplifies what occurs if an unknown disturbance were presented to the ARTMAP-EMTC; *i.e.*, first, it cannot identify correctly, but after verifying the need to learn this unknown data, the neural network includes this pattern automatically to the memory and is able to correctly identify *a posteriori*.

The MECT-ARTMAP presented efficiency and robustness to the dynamism of the electrical power systems; *i.e.*, disturbances were detected and classified at different loading levels and locations (bus) of the distribution system. This improvement process is observed even as the neural network executes the diagnosis simultaneously with the continuous training. The parameters used at the training and test phases are training rate $\beta = 1$; vigilance parameters $\rho_a = 0.15$, $\rho_b = 0$, and $\rho_{ab} = 0.95$; incremental vigilance parameter $\varepsilon = 0.01$; novelty index $\eta = 2$; and similarity pattern $NMIN = 2$.

11. CONCLUSION

This study consists of a neural structure with continuous training applied to classify voltage disturbances in electrical distribution systems. This decision-making tool aids the substation automation process to restore normal operation in a faster, flexible, and robust manner. The voltage disturbance diagnosis module is projected to attend the needs of the distribution companies, considering the current economic situation of the electrical sector, and can be easily implemented with reduced costs, as it is only necessary to acquire equipment for signal acquisition and a data processing module.

By the combined use of signal processing techniques and methodologies based on artificial intelligence, the diagnosis system presents high generalization capacity, flexibility, and efficiency—important characteristics in aiding the decision making at substations. The detection process is able to identify every abnormal operational situation. Thus, once the presence of a voltage disturbance is identified, the voltage oscil-

lographies are analyzed by the MRA and the energy concept, generating characteristic indices that represent the detected disturbances. Therefore, these indices are presented to the MECT-ARTMAP neural network providing the operator the type of voltage disturbance. Furthermore, using a new different training concept, the neural module at each diagnosis improves or acquires new knowledge.

Therefore, the advantage of the MECT-ARTMAP neural network in relation to other conventional neural networks available on the literature is that it allows continuous improvement of the existent categories with the learning being continuously realized without the need to reinitialize the training. This important characteristic allows the application of the neural network in modern electrical energy systems, *i.e.*, smart grids, once it has the capacity to learn in real time.

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