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Short Circuit Classification using the Discrete Fractional Fourier Transform and Artificial Neural Network

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***Abstract*—*The basic principle of the protection philosophy is to select, coordinate, adjust and allocate the various equipment and protective devices in an electrical system to keep a specific relationship between them. An abnormality in the system can be isolated or removed without affecting other parts of the system. Another concern linked to protection systems is the efficiency of the distribution network at critical moments: many consumers can remain without electricity supply after the protection system has operated. Thus, the time spent by maintenance teams in locating the point of occurrence of the fault and preparing a diagnosis of the problem and corrective or even preventive measures should be as little as possible.This paper presents a methodology for detecting and classifying short-circuit faults in power distribution systems. An artificial neural network is applied to categorize short circuit types. The pre-processing of signals is carried out through the fractional Fourier transform, a variation of the Fourier transform, which allows the representation of signals in the domains between time and frequency. The developed system showed accuracy in all tests performed, detecting faults, classifying and identifying the phase affected by single-phase and two-phase faults.*

I. INTRODUCTION

The increase in demand for electric energy has led to a reformulation of the commercial and technical structures of the electric power system in recent years. Power quality has become an increasingly important object of study in the sector. It is directly related to market competitiveness and technical aspects of services offered by agents of generating, transmitting, and distributing electricity [3].

Especially in the last two decades, the Brazilian energy sector has changed, such as the diversification of the nature of loads, incorporation of direct current transmission systems, and the increase in the number of distributed generators connected to the system [12].

The impact of such changes in the energy sector motivated the National Electric Energy Agency (ANEEL in the Portuguese acronym) to publish the Procedures for the Distribution of Electric Energy in the National Electric System (PRODIST in the Portuguese acronym), a set of rules and guidelines that guide the actions of the agents in the electricity sector, facing the new scenario of the system [1]. In module 8, the PRODIST Processes procedures relating to the quality of electrical energy [2].

One of the faults related to various disturbances in the electrical power system is the short circuit. The characteristic of a short circuit is a closed path from very low impedance in an electrical circuit. Voltage increases, voltage interruptions, harmonic distortions, and current increases are disturbances related to short circuits in the Electric Power System.

Short-circuits can be classified according to their characteristics and are divided into Single-phase short-circuit, 2-phase short-circuit, 3-phase short-circuit, 2-phase ground short-circuit and 3-phase ground short-circuit.

The effects of each type of short circuit are felt differently by the electrical system; interruptions and voltage rises may occur due to permanent short circuits, phase voltage dips may be related to single-phase short circuits, among other disturbances.

The need to maintain energy quality presupposes that disturbances that degrade energy quality are studied and that new methods of analysis and classification of failures in the electrical system are proposed.

In [3], [15], the authors proposed a method based on artificial neural networks that classified disturbances in the electrical power system. The results obtained were satisfactory regarding the classification of voltage rises, impulsive transients, voltage sags, and harmonic distortions.

The use of artificial neural networks for fault classification was demonstrated in [7], where a system capable of determining the origin of faults in the windings of a power transformer was presented. The proposed system distinguished whether faults were due to mechanical or electrical defects in the windings.

A method to detect and classify ten short-circuit faults in distribution networks was proposed in [13] with the Fortescue approach and softmax regression to alleviate the adverse effects of transient data samples on fault classification.

A linear recursive model to detect faults using irradiance and temperature in the photovoltaic panel as input and power as output signals were proposed by [14]. The method used machine learning to classify each fault for short circuits, open circuits, partial shading, and degradation.

Given the advances in signal processing techniques, this article proposes a method based on the Discrete Fractional Fourier Transform (DFrFT) and artificial neural network to detect and classify short circuits.

The divisions of the article are sections and divided by: Section II presents the Fractional Fourier transform. Section III defines the types of short circuits. Section IV the methodology. Section V Results and Discourses. Section VI Conclusions.

II. FOURIER'S FRACTIONAL TRANSFORMATION

The Fractional Fourier Transform (FrFT) is the best-known example of a fractional transformation, whose applications are developed in several areas. Generally, it is a generalization of the Fourier transform that allows signals to be represented in intermediate domains, that is, domains that lie between time and frequency [8], [16]. One of the ways to represent the FrFT is through its integral form, as in equation (1):

$$F^{a}f(t)=\int_{-\infty}^{\infty}K_{a}(t_{a},t)f(t)dt \tag{1}$$

Where the term $K_a(t_a,t)$ is the core of FrFT that can be written through spectral expansion in terms of Hermite-Gaussian eigenvectors as in equation (2):

$$K_{a}(t_{a}.t)=\sum_{k=0}^{\infty}\psi_{k}(t_{a})e^{jka\pi/2}\psi_{k}(t) \tag{2}$$

The spectral expansion of the FrFT core in terms ofHermite-Gaussian eigenvectors is possible since they are a canonical family of eigenfunctions shared between the Fourier transform (F.T.) and the FrFT. In equation (2), the k-nth Hermite-Gaussian function is given by [10],[16]:

$$\psi_{k}(t)=\frac{2^{1/4}}{\sqrt{2^{k}k!}}H_{k}(\sqrt{2\pi}t)e^{\pi t^{2}}\forall\ k=0,1.2,\ldots \tag{3}$$

Several studies have been carried out in recent years to obtain a discrete version of FrFT and develop applications of the tool in the field of digital signal processing. The fractional discrete Fourier transform (DFrFT) can be obtained through the spectral expansion of the matrix F of length N of the Discrete Fourier transform (DFT), which can be written as:

$$F=EAE^{T} \tag{4}$$

Where DFT eigenvectors are defined in the matrix$E$ and the eigenvalues in the diagonal matrix A. Thus, it is possible to obtain the discrete version of the FrFT obtaining the i-th powers of the eigenvalues of the DFT, that is:

$$F = EA^{a}E^{T} \forall\, a \in \mathbb{R} \tag{5}$$

Obtaining the discrete version of FrFT through thisapproach depends on the method used in the spectral expansion of the DFT matrix F and on the determination of an adequate set of eigenvectors in this expansion since the F matrix has repeated eigenvectors.

One of the methods used to obtain the DFT eigenvectors is the implementation of generating matrices that, from an eigenvector v related to the eigenvalue t', determine the eigenvector v' associated with the eigenvalue t''. Methods based on matrices that switch with the DFT matrix are also used, that is, matrices that have standard sets of eigenvectors, and although these are in more recent studies, methods based on closed formulas are also used to obtain the DFrFT eigenvectors.

In addition to methods based on DFT autodecompositionto obtain a discrete version of FrFT, more straightforward methods are employed on continuous FrFT sampling.

The method used in this paper to calculate the DFrFT is based on the discretization of the integral form of FrFT through Shanon interpolation as proposed in [11], [16].

III. SHORT CIRCUIT

Several disturbances in the electrical system are related to short circuits, so it is necessary to implement efficient methods for classifying, detecting, and distinguishing events in the electrical power system. Statistical analyzes indicate single-phase short circuit as the most common fault in the electrical system (70%), followed by two-phase short circuit (15%), two-phase ground short circuit (10%), and three-phase short circuit (5%) [6], [15].

In this context, to carry out this study, the most common short-circuit of the electrical system were selected so that the characteristics of each one are used in the training of an ANN artificial neural network that classifies the types of short-circuits and distinguishes short-circuits. Circuit of other faults in the electrical power system.

Single-phase short circuit is a type of asymmetric short circuit that occurs when there is contact between the three phases of the system and earth. A single-phase short-circuit is called frank, or metallic when there is no reactance between an affected phase and a ground.

Generally, single-phase short circuits are associated with considerable drops in the phase voltage amplitude of thephase affected in the fault. Figures 1, 2, and 3 illustrate three examplesof single-phase short circuits in the system.

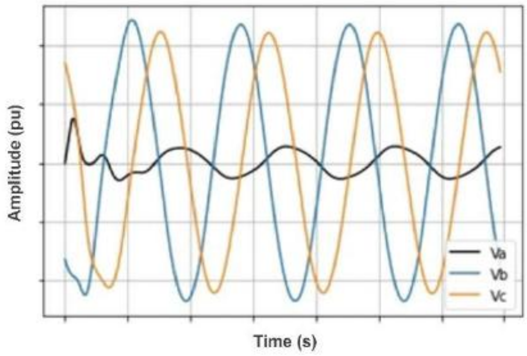

Fig 1. Single-phase short circuit in phase A

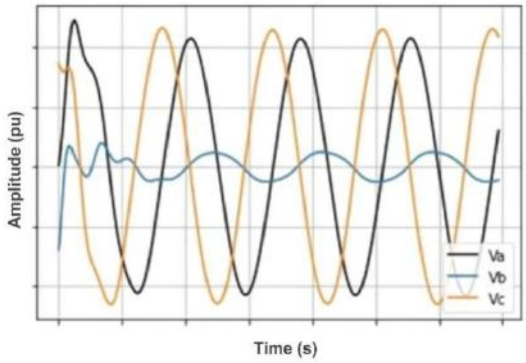

Fig 2. Single-phase short circuit in phase B.

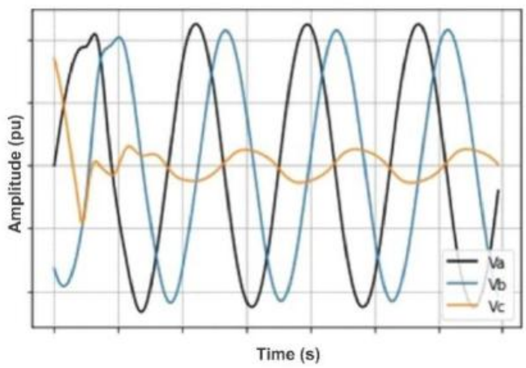

Fig 3. Single-phase short circuit in phase C.

A two-phase short circuit is a type of asymmetric fault that occurs between two phases of the system and may or may not be grounded. As with the single-phase short circuit, the contact between the two phases can occur through reactance, or metallic contact between the phases can occur.

Generally, the phases involved in a two-phase fault are also affected by voltage drops. Figure 4 illustrates Frank's two-phase short circuit between phases A and B of the system.

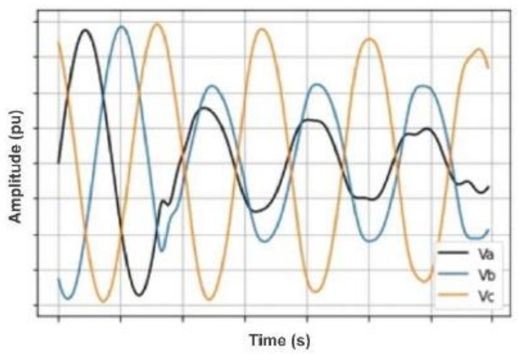

Fig 4. Two-phase short circuit in phases A and B.

A three-phase short-circuit is a symmetrical fault. That is, it does not cause unbalance in the system, as all phases are requested equally. As it is a balanced short circuit, there is no zero sequence. Even though the ground is involved, the current through the neutral is equal to zero. Figure 5 represents an example of a three-phase-to-ground short circuit.

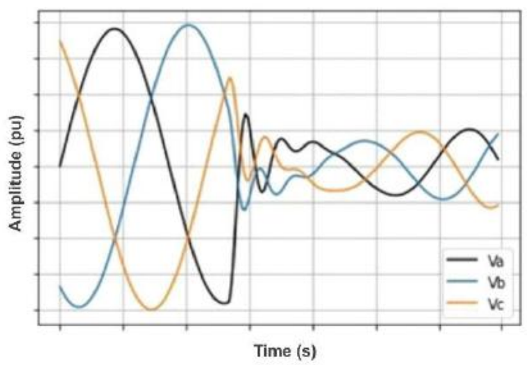

Fig 5. Three-phase-to-ground short circuit.

As the figures illustrate, each type of short circuit has specific characteristics and is related to several disturbances that degrade the quality of electrical energy. Therefore, it is necessary to implement analysis methodologies that allow a detailed study of this type of fault.

IV. METHODOLOGY

The field of digital signal processing has a close connection between theory and practical applications in new technologies. Finite length transforms initially defined in the real body, eventually give new signal synthesis and analysis tools.

This article presents an event classification method based on signal processing and computational intelligence in the electrical power system. The transformation used for the extraction of characteristics from the analyzed signals is the discrete fractional Fourier transform.

The algorithms used to classify events are multilayer perceptron artificial neural networks whose training is done through the backpropagation of the error.

The use of artificial neural networks in conjunction with DFrFT for pattern recognition was proposed [4]. The authors demonstrate that the error in pattern classification can be 5% lower using DFrFT than DFT and 14% smaller than results obtained without pre-processing the signals.

In this article, artificial neural networks were usedto classify input signals according to the type of short-circuit, identify the phase affected by two-phase and single-phase faults, and detect a short-circuit in the electrical network.

In all tests performed, 260 samples of each event were considered. Each of the samples considered contains the phase voltage in phases A, B, and C and the phase currents in phases A, B, and C.

Each artificial neural network (ANN) implemented was trained with 70% of the total samples considered (182 samples), and the test validation is performed with 30% of the total samples (78 samples).

A. ANN pre-processing and training

The signals used to carry out the work were obtained by simulating the IEEE 34 bus test network in the virtual environment Typhoon H.I.L. [5], [9], [17]. In the pre-processing of signals, see Figure 6, DFrFT is applied to signals whose fractional parameter a (which determines the order of the transform) varies from 0.5 < to < 0.8.

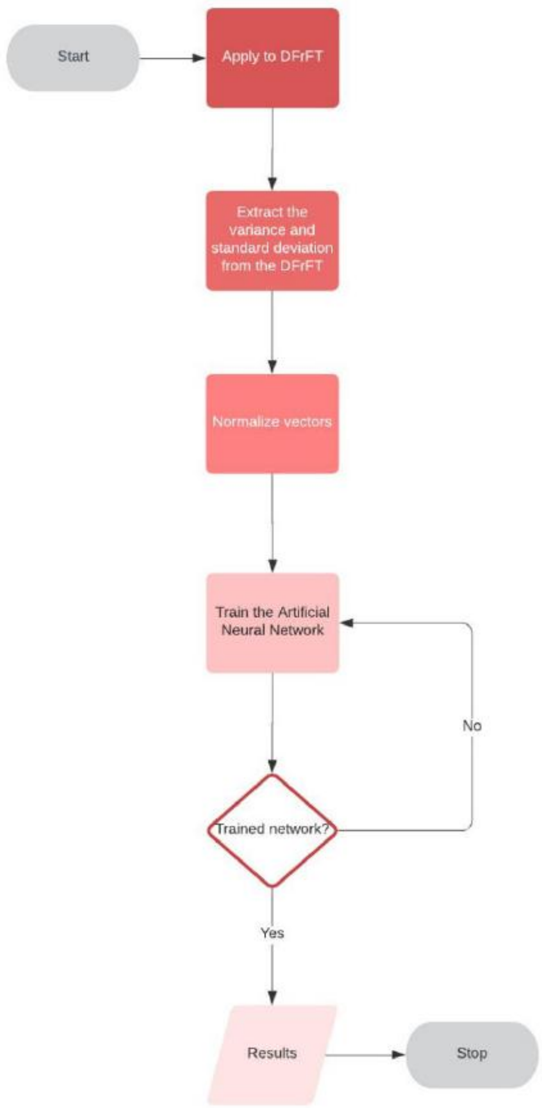

Fig 6. Basic flowchart of ANN pre-processing and training.

After applying the transform, the variance and standard deviation of each DFrFT vector were obtained according to equations (6) and (7).

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i, \mu)^2 \;\; \forall \;\; i = 1,2,\dots,N \qquad (6)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i, \mu)^2} \;\; \forall \, i = 1,2,\dots,N \qquad (7)$$

Finally, all resulting vectors are normalized between0 and 1 for the training of ANN to be carried out.

B. Artificial neural network for short circuit detection

The artificial neural network implemented for short circuit detection was trained using the Adam method, and the hyperbolic tangent activation function was used. The hidden layers have 20, 10, 9, and 8 neurons plus an input layer and an output layer, both with one neuron.In order to validate the model, tests were performed using DFT and DFrFT to pre-process signals with a = 0.5.

C. Artificial neural network for short circuit classification

The artificial neural network implemented for the short circuit classification was trained through the Adam method, and the activation function used was the Rectified Linear Unit – Relu. The network has four layers, two hidden layers, one input layer, and one output layer. The number of neurons per layer is 1, 25, 16, and 1. All tests were validated by comparing the results using DFT and DFrFT in pre-processing signals with a = 0.5.

D. Artificial neural network for identification of the affected phase in single-phase short circuit.

The artificial neural network implemented to identify the phase affected by single-phase faults was trained using the Adam method, and the activation function employed was the hyperbolic tangent. The network has five layers, three hidden layers, one input layer, and one output layer. The number of neurons per layer is 1, 20, 18, 15, and 1. All tests were validated by comparing the results using DFT and DFrFT in pre-processing signals with a = 0.8.

E. Artificial neural network for the identification of the affected phase in biphasic short circuit

The artificial neural network implemented to identify the phase affected by biphasic faults was trained using the Adam method, and the activation function employed was the hyperbolic tangent. The network has five layers, three hidden layers, one input layer, and one output layer. The number of neurons per layer is 1, 20, 18, 15, and 1. All tests were validated by comparing the results using DFT and DFrFT in pre-processing signals with a = 0.8.

V. RESULTS AND DISCUSSION

A. Short circuit detection

The method developed to detect short-circuits in the electrical network presented 100% accuracy for all test cases. The ANN trained with the variance and standard deviation of the DFrFT vectors showed faster convergence, in 194 iterations (Figure 7), against 200 iterations for the ANN trained with the variance and standard deviation of the DFT vectors (Figure 8). Table I shows the results obtained.

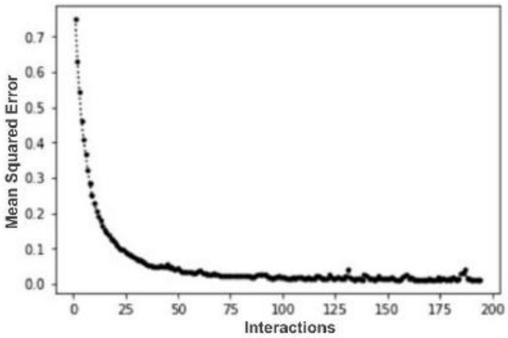

Fig 7. Decay the mean square error in relation to the number of iterations for the ANN trained with the DFrFT vectors.

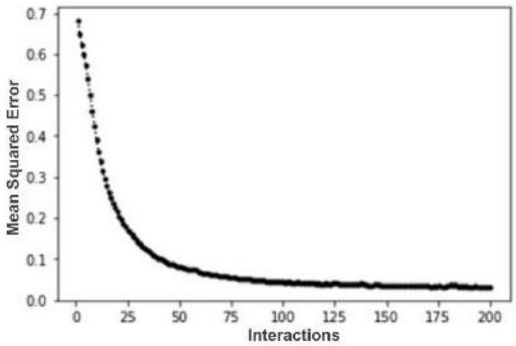

Fig 8. Decay the mean square error in relation to the number of iterations for the ANN trained with the DFT vectors.

Table I

Results Obtained for Short Circuit Detection

Transform used	DFT	DFrFT
Accuracy for short circuit detection	100%	100%
Number of iterations	200	194
Activation function	Hyperbolic Tangent	Hyperbolic Tangent
Initial learning rate	0,001	0,001

B. Short circuit classification

The results obtained for the classification of the short circuit demonstrate the advantage of using DFrFT over DFT. In addition to the faster convergence of the ANN, the accuracy obtained in the classification of events was greater.

Despite the greater precision and faster convergence, data pre-processing with DFrFT has a higher computational cost.This fact must be considered in real-time implementations. The results obtained can be seen in Figures 9 and 10.

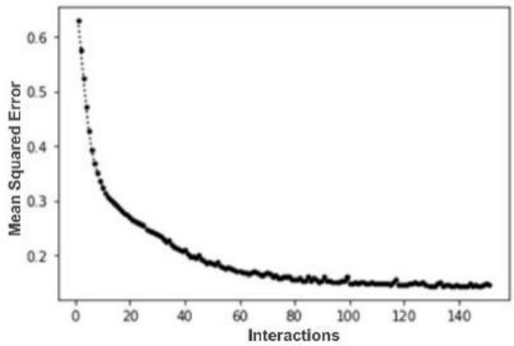

Fig 9. Decay the mean square error about the number of iterations for the ANN trained with the DFrFT vectors.

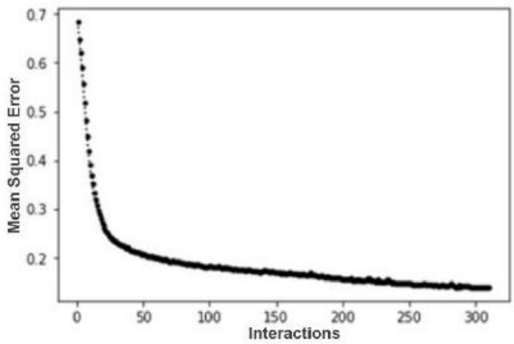

Fig 10. Decay the mean square error concerning the number of iterations for the ANN trained with the DFT vectors.

Table II

Results Obtained for Short Circuit Classification

Transform used	DFT	DFrFT
Accuracy for three-phase short circuit	99,18%	99,75%
Accuracy for two-phase short circuit	85,21%	94,97%
Accuracy for single-phase short circuit	96,74%	98,14%
Number of iterations	310	151
Activation function	Relu	Relu

Training method	Adam	Adam
Initial learning rate	0,001	0,001

C. Identification of the phase affected by the fault in single-phase short circuits

There was no evidence of the superiority of DFrFT over DFT, and vice versa, in the tests performed. Both ANN showed 100% accuracy in all cases considered, but ANN trained with DFrFT vectors showed a slightly faster convergence. The results can be seen in Figures 11 and 12 and Table III.

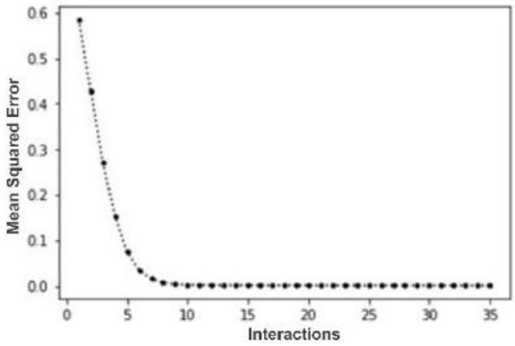

Fig 11. Decay the mean square error concerning the number of iterations for the ANN trained with the DFrFT vectors.

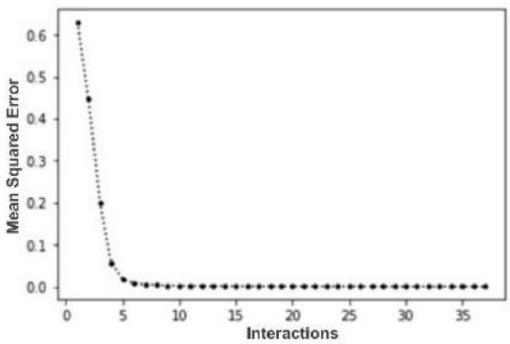

Fig 12. Decay the mean square error about the number of iterations for the ANN trained with the DFT vectors.

Table III

Results Obtained for The Identification of The Phase Affected by Single-Phase Faults

Transform used	DFT	DFrFT
Precision for phase A fault	100%	100%
Precision for phase B fault	100%	100%
Precision for phase C fault	100%	100%
Number of iterations	37	35

Activation function	Hyperbolic Tangent	Hyperbolic Tangent
Training method	Adam	Adam
Initial learning rate	0,01	0,01

D. Identification of the phase affected by the fault in two-phase short circuits

The results obtained are similar to the results in identifying the affected phase in single-phase faults. Both ANN has 100% accuracy; however, in this case, convergence was slightly higher in the ANN trained with DFT vectors. The results obtained can be seen in Figures 13 and 14 and Table IV.

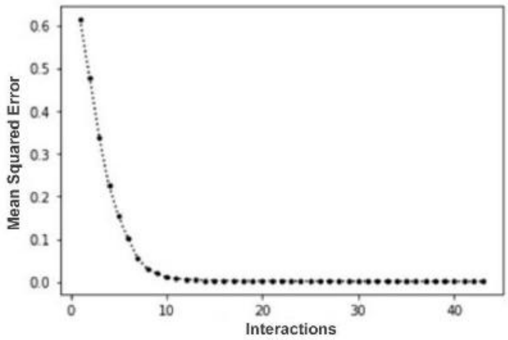

Fig. 13. Decay the mean square error with the number of iterations for the ANN trained with the DFrFT vectors.

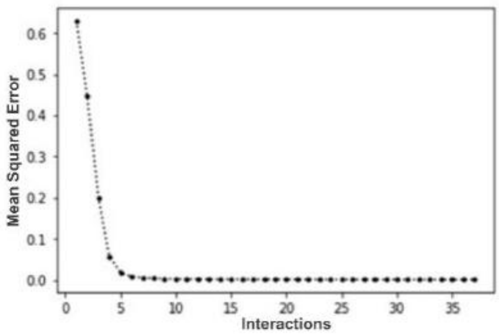

Fig.14. Decay the mean square error concerning the number of iterations for the ANN trained with the DFT vectors.

Table IV

Results Obtained for the Identification of the Phase Affected by Two-Phase Faults

Transform used	DFT	DFrFT
Precision for phase A fault	100%	100%
Precision for phase B fault	100%	100%

Precision for phase C fault	100%	100%
Number of iterations	37	43
Activation function	Hyperbolic Tangent	Hyperbolic Tangent
Training method	Adam	Adam
Initial learning rate	0,01	0,01

VI. CONCLUSION

The increase in distributed generators, the diversification of load types, and other changes have raised important questions regarding the power quality of the electrical system. Maintaining energy quality in the face of the new scenario requires new methodologies for managing, operating, and protecting the electrical power system. The method presented in this article showed promising results in the tests performed and highlights the increasingly important role of signal processing techniques and artificial neural networks. The results obtained show the potential for using DFrFT concerning DFT since DFrFT has a greater degree of freedom, which allows for more accurate results and faster ANN convergence.

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