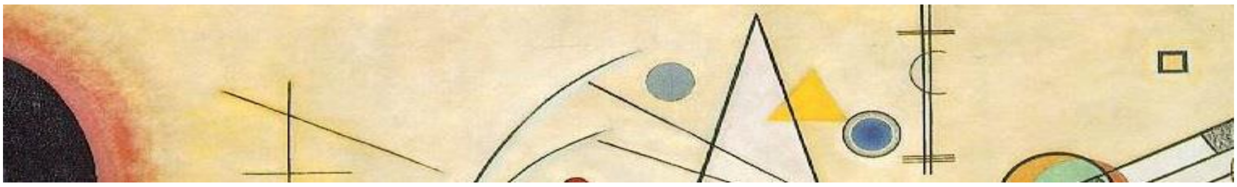

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Artigo

HARMONIC CLASSIFIER FOR EFFICIENCY INDUCTION MOTORS USING ANN

CLASSIFICADOR HARMÔNICO PARA MOTORES DE INDUÇÃO DE EFICIÊNCIA USANDO RNA

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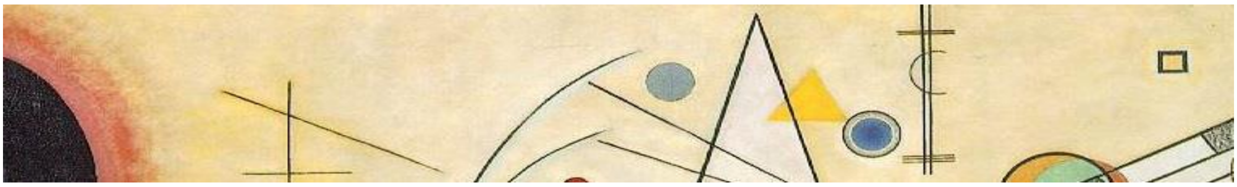

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ABSTRACT: Modern electrical systems have a significant presence of electronic loads, which in turn produce negative impacts on distribution systems and loads, this has motivated their study to be increasingly prioritized, aiming to reduce their impacts from corrective actions. Harmonics are classified as positive, negative, and zero sequence, and their impacts on loads can vary according to the harmonic present. In the case of electric motors, negative sequence harmonics result in the greatest impacts. This work presents a classifier of existing harmonics in the input waveform of electric motors classes IE2, IE3 and IE4 using artificial neural networks (ANN), for that purpose, negative (2nd), positive (7th) and zero sequence harmonics (3rd) were applied separately and combined in the electric motors, the data was exported for a classification algorithm to identify existing harmonics. The results show how the algorithm presents good approximations of the present harmonics, mainly with those of positive and negative sequence.

KEYWORDS: Harmonic Analysis, Energy Efficiency, Electric Motors, ANN, LSPMM, Predictive Maintenance, Machine Learning.

RESUMO: Os sistemas elétricos modernos possuem uma presença significativa de cargas eletrônicas, que por sua vez produzem impactos negativos nos sistemas de distribuição e cargas, isso tem motivado seu estudo a ser cada vez mais priorizado, visando reduzir seus impactos a partir de ações corretivas. Os harmônicos são classificados em sequências positiva, negativa e zero, e seus impactos sobre as cargas podem variar de acordo com o harmônico presente. No caso dos motores elétricos, harmônicos de sequência negativa resultam nos maiores impactos. Este trabalho apresenta um classificador de harmônicos existentes na forma de onda de entrada de motores elétricos das classes IE2, IE3 e IE4 utilizando redes neurais artificiais (RNA), para tanto, harmônicos negativos (2º), positivos (7º) e zero (3º) foram aplicados separadamente e combinados nos motores elétricos, os dados foram exportados para um algoritmo de classificação para identificar harmônicos existentes. Os resultados mostram como o algoritmo apresenta boas aproximações dos harmônicos presentes, principalmente com os de sequência positiva e negativa.

PALAVRAS-CHAVE: Análise Harmônica, Eficiência Energética, Motores Elétricos, RNA, LSPMM, Manutenção Preditiva, Aprendizado de Máquina.

1. Introduction

Electric motors represent today the main global load, their technological evolution has allowed their efficiencies to be higher than those seen 20 years ago, and their use extends to the industrial, commercial, residential, and recently, the automotive sector with the introduction of electrical vehicles. The new applications require greater degrees of monitoring, mainly to avoid unintended stops and accidents in the land and maritime transport sectors. These needs have also existed in the industry; however, their importance is gaining more interest given the new potential markets.

In electrical systems, motors can be subjected to different power quality disturbances that can result in a reduction of their service life [1]–[3]. One of the most present disturbances in modern electrical systems is harmonics, produced mainly by non-linear loads existing in all electronic devices in the aforementioned sectors, Continuous operation of motors on a polluted harmonic system results in higher temperatures in stator and rotor windings and core due to additional harmonic losses, torque reduction, noise and mechanical vibrations—some of the main effects found in the literature [4]–[10]. The close interaction between current harmonics, saturation, and mechanical problems, such as bearing failure and static eccentricity, can result in premature failure and, consequently, reduced service life, as presented in [11]–[15], however, these effects vary according to the order of the existing harmonic, as well as the percentage present, so the correct identification can allow evaluating its impacts and causes as well as proposing possible corrective solutions.

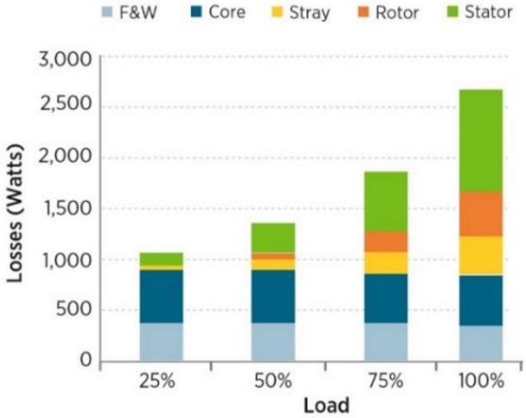
The present work proposes a classifier and predictor of the harmonic currents present in an electric motor using artificial neural networks, and the input data of electrical motor classes IE2, IE3 & IE4 in the presence of harmonic voltages of 2^{nd}, 3^{rd}, and 7^{th} order harmonics. The methodology and results will be presented in Sections IV and V, while the next section will present a theoretical foundation related to the topic.

2. Induction Motors

2.1 Induction Motors

Induction electric motors continue to be the main global load, their construction and operational characteristics are the main advantages over other technologies. Two types of losses that occur in the electric motor, are those which are fixed, occurring whenever the motor is energized, and remaining constant for a given voltage and speed, and those which are variable and increase with motor load [16]. Figure 1 presents their variation based on power output load percentage.

Figure 1 – Losses versus motor output load for a standard efficiency motor [17].



Source: U.S. Department of Energy, Energy Efficiency & Renewable Energy, "Premium Efficiency Motor Selection and Application Guide – A Handbook for Industry," Energy.gov. https://www.energy.gov/eere/amo/downloads/premium-efficiency-motor-selection-and-application-guide-handbook-industry.
(Accessed Aug. 15, 2019).

However, the presence of disturbances in the network results in variations in said distribution, mainly in the Joule losses in the stator and rotor, as well as in the core. Harmonics are classified as positive, negative and zero sequence, with the negative sequence being the most detrimental, followed by positive sequence harmonics, and finally zero sequence harmonics that do not result in impacts due to the isolated star or delta connection in the electric motor input. Table 1 presents this classification.

Table 1 – harmonic order sequence.

Harmonic Sequence		
Positive Sequence	Negative Sequence	Zero Sequence
Harmonic order	Harmonic Order	Harmonic Order
1	2	3
4	5	6
7	8	9
10	11	12
13	14	15

Source: The authors.

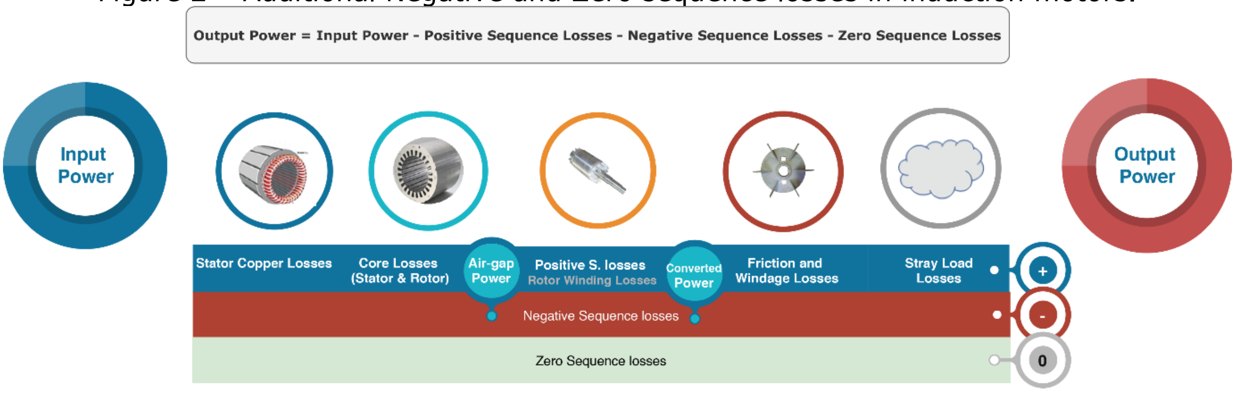
Harmonic currents are those that circulate at a frequency different from the fundamental. Negative sequence harmonics produce a contrary magnetic field that results in a torque opposite to the resulting one, as well as increases in current, decrease in speeds and decrease in power factor [6], [7], [18], [18]–[27].

In relation to the positive sequence harmonics, their magnetic fields result in a positive torque, which however also results in an increase in currents, and decreases in power factor and speed.

Zero-sequence harmonics do not have considerable impacts on electric motors, so for rotating machines they were neglected in this study. Figure 2 presents the main losses in electric motors.

However, it is important to highlight only fundamental frequency current can provide real power [116], so the presence of these harmonics results in losses, which can reduce the useful life of the motor when added to other mechanical or operating problems.

Figure 2 – Additional Negative and Zero sequence losses in induction motors.



Source: The authors.

3. Artificial Neural Networks (ANN)

a) Artificial Neural Networks (ANN)

An Artificial Neural Network, ANN, can be defined, in general, as a machine designed to model the way the biological brain performs a specific task.

It is composed of a set of layers, which are made up of units known as artificial neurons, interconnected through synapses, which are represented mathematically by numerical weights. The structure of a neural network is usually composed of three basic types of layers.

The input layer, which is responsible for receiving information from the external environment and passing it on to the intermediate layers, which shape their synaptic weights through a learning algorithm so that it can comply with the modeling requirements for each application. The output layer, on the other hand, has the function of adapting the output values looking for a good visualization and interpretation by the user [24]–[26].

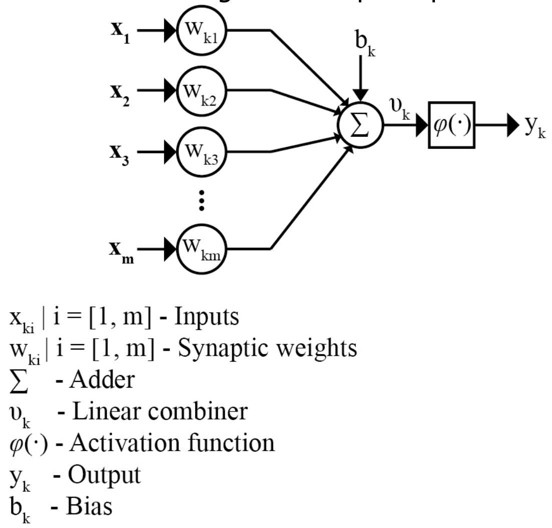
The numerous ANN architectures are the result of changes in this basic structure, or even in constituent functions. Among the most used network architectures are the Multilayer Perceptron, MLP's.

b) Perceptron Neuron

Developed between 1950 and 1960, by Frank Rosenblatt, inspired by the work of Warren McCuloch and Walter Pittts, the perceptron is considered the simplest format that a neural network, used for classifying linearly separable patterns, can assume. Its operation consists of receiving, weighting and summing the input data, followed by the application of a non-linear function.

Each perceptron, k, receives the input values, x_i, and weights them through a set of synapses, characterized by numerical weights, w_{ki}, inherent to each one. The weighting of each value is applied to an adder, characterizing the operation of a linear combiner. Then, a nonlinear function, known as an abrupt limiter, $\varphi(\cdot)$, is applied to this result, limiting the neuron's output to binary values, usually [0, 1] or [1, -1]. This structure can be seen in Figure 3. [24]–[26].

Figure 3 – Block diagram of a perceptron neuron.



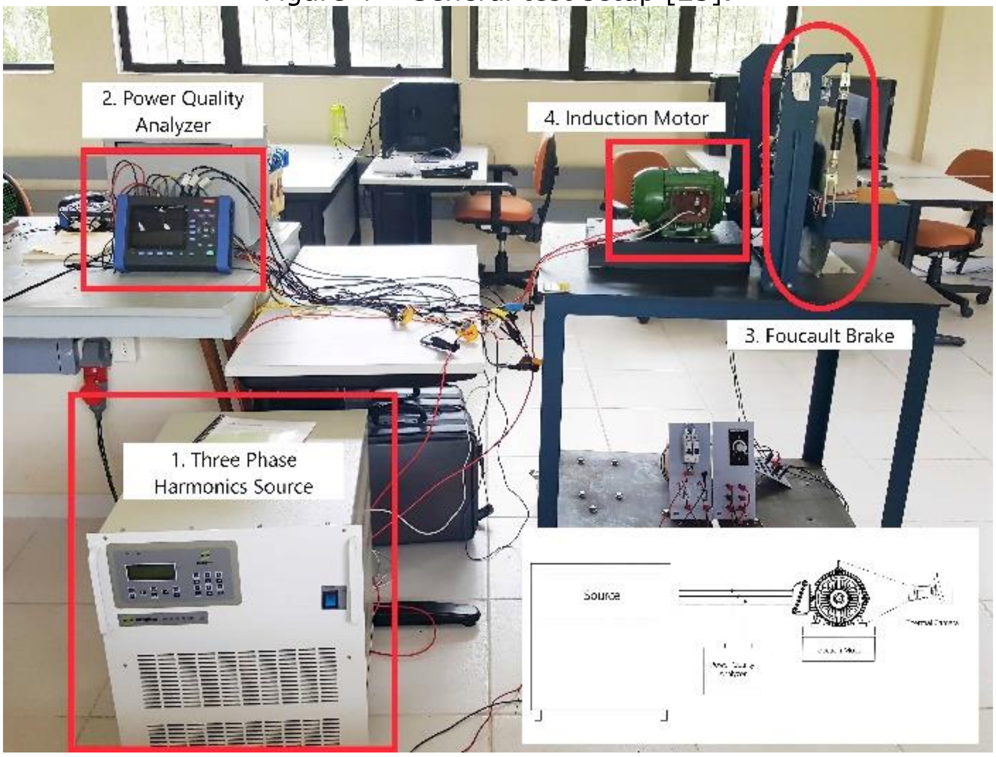
Source: The authors.

4. Methodology

In order to generate the data useful to identify the existing harmonic in SCIM´s in the presence of harmonic voltage distortion conditions, experimental measurements were performed on a bench composed of a delta connected SCIM and an electromagnetic brake as electrical load. Tests were performed in the Amazon Energy Efficiency Excellence Center (CEAMAZON) in the Federal University of Pará (UFPA). Figure 4. shows the general test setup.

At first, the induction motors were subjected to a perfect three-phase sine voltage of 220 V for 1 h and 10 min so that they reached their thermal equilibrium. In a second moment the value of each voltage harmonic (2nd, 3rd, and 7th) increased by 2% every 10 min until it reached 25%.

Figure 4 – General test setup [23].



Source: The authors.

The voltage harmonics was generated using a three phase AC source (1), capable of generating a pure sine wave as well as harmonics (up to the 50th order) with different distortion magnitudes. For the study, the magnitudes of each harmonic voltage analyzed were increased every 10 min until reaching 25%. To measure the induction motor input parameters, class “A” HIOKI^{TM} power quality analyzer (2) model PW3198-90 was used, which recorded the input parameters during all the experiments at 1 s intervals.

The electric load used in this experiment consists of an electromagnetic brake or Foucault brake (3), which includes two load cells that are connected to the ends of the brake with which it is possible to measure the adjustable opposite force produced by eddy currents. When multiplied by the distance to the axis, it is possible to find the torque demanded by the load. For the test, a torque of 3.8 Nm was applied to the Foucault brake, which represents

92–95% of the nominal torque of motors (4). The nominal data of each motor are presented in Table 2.

Table 2 – Induction Motor Parameters.

IM Class	IE2	IE3	IE4
Technology	SCIM	SCIM	LSPMM
Power	1 Hp	1 Hp	1 Hp
Voltage	220/380 V	220/380 V	220/380 V
Speed (rpm)	1730	1725	1800
Torque (Nm)	4.12	4.13	3.96
Current (A)	2.98/1.73	2.91/1.68	3.08/1.78
Efficiency (%)	82.6	82.6	87.4
Power Factor	0.80	0.82	0.73

Source: J. Muñoz Tabora, M. E. de Lima Tostes, E. Ortiz de Matos, T. Mota Soares, and U. H. Bezerra, "Voltage Harmonic Impacts on Electric Motors: A Comparison between IE2, IE3 and IE4 Induction Motor Classes," Energies, vol. 13, no. 13, Art. no. 13, Jan. 2020, doi: 10.3390/en13133333.

The methodology used is detailed in Figure 3. Initially, the measurement campaigns were carried out with the individual harmonics and in a combined way for each of the motors, the data generated was processed as a basis for the computational analysis with ANN. The collected data were stored in .CSV format, in separate files according to each harmonic distortion class applied to the motors.

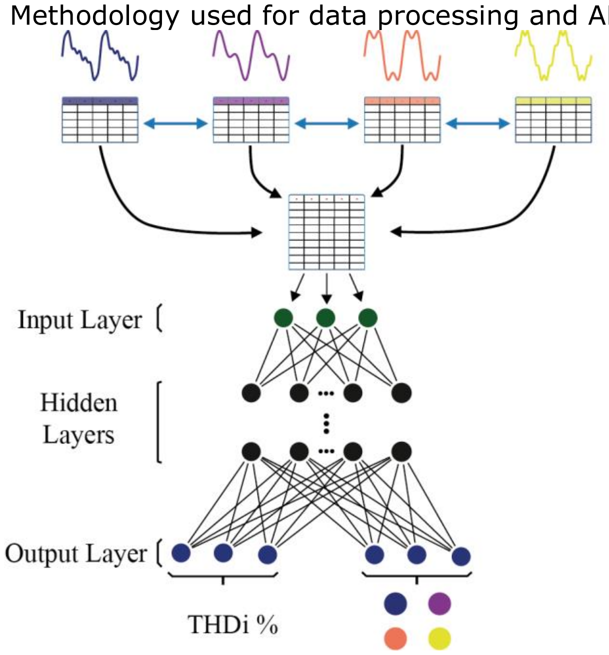
Primarily, an exploratory analysis of the data must be carried out, looking for patterns that may be interesting for the final objective of the model or for new studies. For this, the packages Numpy, Pandas and Matplotlib were used, based on the Python programming language, which is widely used for data analysis and data science.

After this step, the data sets go through a pre-processing, in which they are molded, seeking to facilitate the ANN learning process. For this, each subset of samples is joined in a single matrix, "M", in which each row refers to each sample and the columns represent each electrical quantity measured during the tests. To avoid network bias during the learning routines, the samples are mixed together, and the data undergo a feature scaling process, using the sklearn package, this transformation facilitate the application of the gradient descent algorithm.

The learning model used was the supervised one, in which the ANN receives input values and the expected output for these respective values. Therefore, the matrix "M" was divided into three new matrices, Inputs, "IN", Class Outputs, "CLASS_OUT" and Regression outputs, "REG_OUT". Furthermore, each new matrix must be split between training and validation data.

The network architecture used was the multilayer perceptron, which has 5 intermediate layers, each with 20 neurons, in addition to a LeakyReLu activation function with a default ɑ of 0.3 and a Dropout rate of 20%, that is, each hidden layer passes by an annulment of 20% of neurons, randomly, during each epoch. Figure 5. illustrates the entire methodology used for data pre-processing and network training.

Figure 5 – Methodology used for data processing and ANN training.



Source: The authors.

Due to the objectives for the model, the ANN has two output layers, one responsible for the regression process, which returns the total harmonic distortion value, THDi%, and the other, responsible for the classification among the applied harmonics.

To evaluate the model, the metrics mean squared error, MSE, with a general formula (1), and Accuracy, ACC, with a formula expressed by (2) were used.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (1)$$

$$ACC = \frac{n^{\circ}\ of\ correct\ predictions}{total\ number\ of\ predictions} \qquad (2)$$

In which:

n = number of dataset samples.
y_i = Real outputs.
$\hat{y}_i$ = Outputs returned by the model.

5. Results

After the network training routines, it was possible to use the resulting model to classify the 4 different types of harmonics applied during the tests, in addition to predicting the rate of injected harmonic distortion. The outputs returned by the model have two formats. The regression layer returns the predicted value itself, while the classification layer returns 4 values, referring to probabilities for each class, that is, the model does not return the class itself, but a set of probabilities for each one, as can be seen in Figure 6, which shows part of the model predictions for samples with 3rd harmonic.

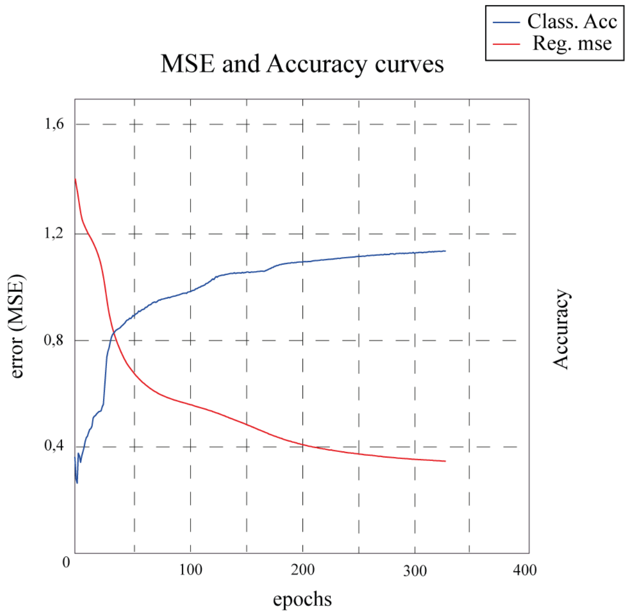
Figure 6 – Output returned by the model for classification of harmonic disturbance.

	All	2nd	3rd	7th
0	0.132551	4.704299e-10	0.867364	8.582426e-05
1	0.002206	6.105147e-14	0.997794	1.003221e-08
2	0.001515	2.871370e-05	0.997646	8.105679e-04
3	0.000344	1.877645e-16	0.999656	8.357349e-11
4	0.005101	5.029115e-03	0.947269	4.260064e-02
5	0.005603	1.077889e-05	0.992067	2.319412e-03
6	0.002963	3.676535e-13	0.997037	5.543053e-08
7	0.001221	6.760245e-15	0.998779	1.982004e-10

Source: The authors.

Using the chosen metrics, the model was validated, having a classification accuracy of 97.44% and an error rate (mse) of 0.0351, as can be seen in Figure 7.

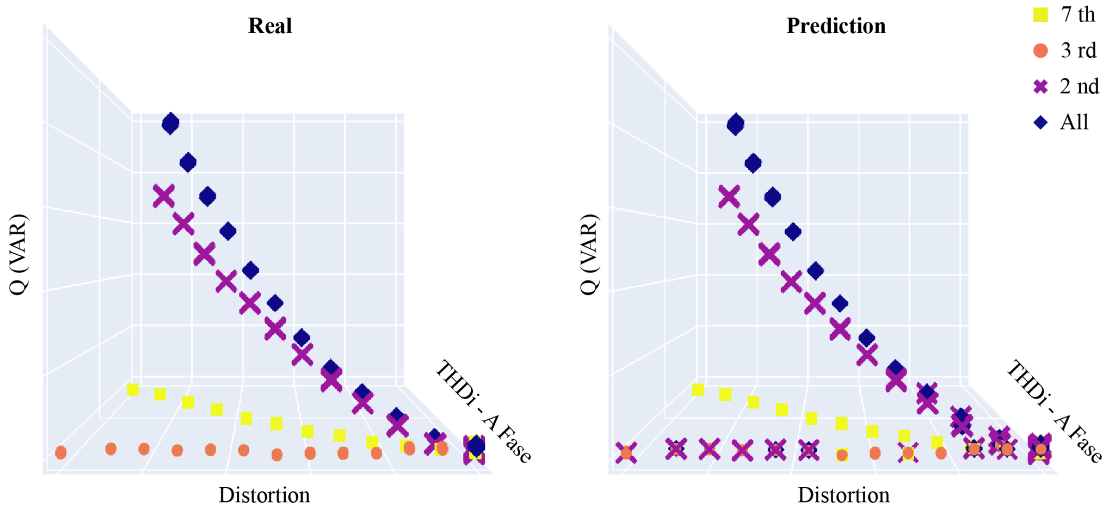
Figure 7 – Classification accuracy and regression mse curves during the training process.



Source: The authors.

An interesting result to observe is that the final model has a greater difficulty in differentiating samples with 3^{rd} and All harmonics, since the difference between the probabilities returned is very low for these cases. This difficulty can also be seen in Figure 8.

Figure 8 – Comparison between actual validation data and the prediction returned by the model.



Source: The authors.

6. Conclusions

Based on the results obtained, it is possible to affirm that the model created satisfy its purpose, performing both classification and regression with a low error rate. However, during the execution of the methodology used to create this network, it was found that the training routine may present instabilities, since, in some cases, it reached classification accuracy values of 70%, far below the values found in other tests. Furthermore, for harmonic classification, the model seems to confuse samples that contain 3rd harmonic and samples that contain all used harmonics.

Therefore, it is necessary to improve training routines, seeking to reduce this instability, ensuring that the network works correctly in cases of new training to adapt the model.

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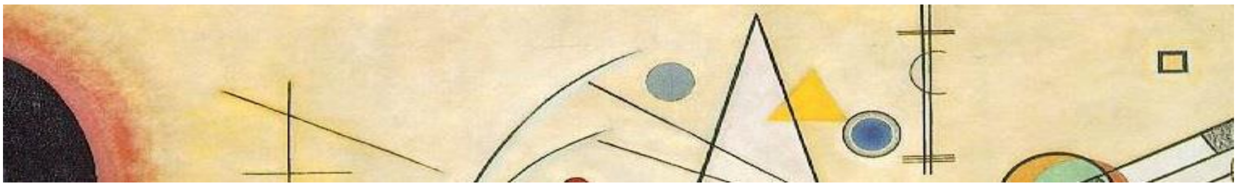

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List of Abbreviations and Acronyms

LSPMM: Line Start Permanent Magnet Motor

SCIM: Squirrel Cage Induction Motor

ANN: Artificial Neural Network