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USE OF ARTIFICIAL NEURAL NETWORKS IN THE DETECTION AND DIAGNOSIS OF FAILURES IN THREE-PHASE INDUCTION ENGINES

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Abstract. *Owing the current search for computerization, especially supported by the use of artificial intelligence, the industrial maintenance field shows itself to be a fertile environment and with great openness for the use of tools such as artificial neural networks. The application of these resources to equipment as common in the industrial environment as the three-phase induction motors allows an increase in the efficiency of several maintenance KPIs. By monitoring only a few electrical parameters of the motors, neural networks are quite capable of identifying patterns, thus detecting and diagnosing equipment failures. Algorithms capable of simulating the behavior of a three-phase induction motor have been implemented in the Matlab® software, generating the electromagnetic conjugate data, rotor axis speed, stator current and rotor current through a perceptron neural network with 20 artificial neurons in its hidden layers. From the confusion matrices generated for the training, testing and data validation cases, it shows that it can sometimes be difficult for the network in training to differentiate the normal functioning of the engine from its behavior when there are stator or rotor failures, however, 100 % of mechanical or contamination failures were classified correctly. The percentages of correct classifications during the training phase are matched during the validation and test phases. It was demonstrated that at the epoch number 768, the best performance of the ANN was obtained, with an error rate of only 3.1% in the classification of failures. The 96.1% correctness performance during the validation phase was satisfactory compared to the values obtained by other authors.*

Keywords: *three-phase induction motor, maintenance, artificial neural networks.*

1. INTRODUCTION

An indispensable part of the industrial process, maintenance activities in industries directly affect not only the final value of a product, but also the profit margin on its production cost. In addition, efficient maintenance and monitoring processes and systems can significantly increase the useful life of all equipment in a manufacturing plant. The average cost for managerial and operational activities related to maintenance can represent, in the final value of a product, a portion of 15% for more common industries such as food, reaching up to 40% for heavier industries, such as steel, paper and cellulose, mining, among others (Baccarini, 2005).

In this sense, induction motors are critical components of various industrial processes and are often integrated with other equipment sold on the market. Equipment powered by these engines often play essential roles for the success of a business and for the safety of other equipment and people (Benbouzid, 2000). There are numerous known techniques and several commercially available tools for monitoring induction motors and ensuring a high level of reliability. Despite this, several companies continue to be surprised by unexpected system failures and reduced engine life.

It is also important to emphasize that failures in induction motors can be identified and effectively classified as to vibrations of magnetic origin and vibrations of mechanical origin, both being perceptible from the analysis of electrical variables (Baccarini, 2005). The main sources of magnetic vibrations would be: Offset of the magnetic center – eccentricity, defects in rotor bars, imbalance of the supply network and insulation problems. We also have the most frequent sources of mechanical vibrations that is: unbalance, misalignment, bent shaft, mechanical clearance and bearing problems.

Unplanned corrective maintenance, in particular, is always unwanted. As stated by Kardec and Nascif (2009, p. 9), it should be taken as a motto that “[...] Maintenance exists so that there is no maintenance [...]”. The authors also describe an increase in the use of predictive maintenance techniques, which aim to monitor systems through the use of sensors and other tools, acting only when there are changes in condition or performance parameters, thus reducing not only the number of non-planned stops, as well as preventive or scheduled maintenance.

The use of a predictive maintenance system sometimes requires a high investment cost, according to Kardec and Nascif (2009). Furthermore, systems that function independently, without the need for operators, could reduce the risk of human failure. As a result of this scenario, a movement emerges that is based on the latest developments in electronics and computing and on the recent intensification of the use of both by the so-called "Industry 4.0", looking for ways to integrate the already consolidated various types of electronic sensors with more modern computerization techniques, such as the creation and use of artificial intelligence systems in the analysis and monitoring of industrial equipment and processes.

Fault diagnosis is very important in manufacturing system. To show that importance its possible to analyze works developed recently with respect to neural networks in faults identifications.

Zhang *et al.* (2020) developed a method for bearings fault diagnosis based on a modified convolutional neural network (CNN). This method extracted the features and converted into two-dimensional images eliminating the need for a expert to collect signal. The results of bearing faults based on an intelligent algorithm CNN show that the proposed method is effective and can meet the timeliness requirements of fault diagnosis and there is ways to improve adaptability in future works.

The work of Wu *et al.* (2020) showed an adaptive deep transfer learning method for bearing faults diagnosis that firstly generated auxiliary datasets using a long-short term memory recurrent neural network model based on instance-transfer learning. The second step was to reduce the differences in probability distributions between an auxiliary dataset and target domain dataset joint distribution adaptation with a feature-transfer learning method. The grey wolf optimization algorithm is used after the first and second steps to adaptively learn key parameters of joint distribution adaptation of the bearing faults diagnosis. The results showed the effectiveness and robustness of the deep learning method when the labeled fault data are scarce.

A new method proposed by Liang *et al.* (2020) for Intelligent fault diagnosis of rotating machinery with good results in the stability of testing accuracy and with better effectiveness and testing accuracy of the proposed approach than other intelligent failure detection approaches in the literatures even in different environment conditions. To generate an image of time-frequency is used a Wavelet Transform (WT) and the training image samples is obtained with a Generative Adversarial Nets (GANs). Finally, an CNN model was used to accomplish the fault detection of rotating machinery to achieve results.

Within this aspect, some technologies are more suitable for application and use for defect recognition in three-phase induction motors. Silva, Spatti and Flauzino (2016) discuss the high abilities that artificial neural networks have in mapping non-linear systems and learning the behaviors involved in this system from the information obtained, with measurements, samples or patterns. Such ability allows the recognition of image patterns, texts, numerical patterns and, in this case, fault patterns. In view of this its defined the objectives of this work, it was proposed the development of a system that allows detecting, diagnosing and classifying failures in three-phase induction motors, using only its electrical properties.

Abdulhamid *et al.* (2019) studied an ANN algorithm with confusion matrix analysis for the detection of e-banking phishing websites, that is cloning websites. The proposed ANN algorithm produced a good percentage accuracy and reduced errors rate during detection. This shows that, the ANN algorithm with confusion matrix analysis can produce a competitive results. This also shows the versability of ANN’s that can be used in multiple types of applications.

2. LITERATURE REVISION

This chapter presents important concepts and definitions from the literature for the development of this work.

2.1 Three-phase induction motors

Electric motors are electrical machines capable of transforming electrical energy into mechanical energy, and are widely used in industry, sometimes being indispensable parts of the industrial process. In this article, we analyze a three-phase induction motor (TIM), commonly used due to its relatively low cost, robustness and high reliability. Figure 1 shows a three-phase induction motor in section, identifying its components.

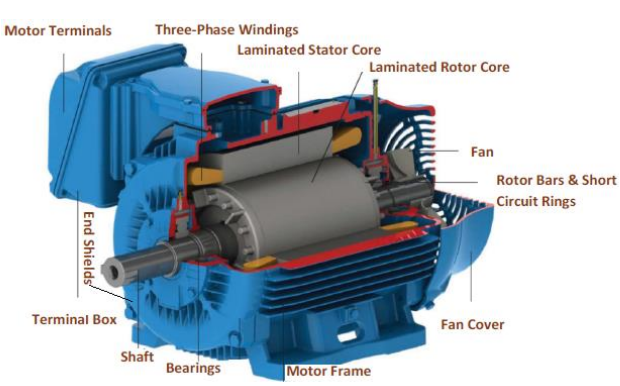

Figure 1. Sectional view with identification of the main parts of an MIT. Font: Adapted from WEG (2017)

The stator, the fixed part responsible for the rotational movement of the motor, is basically composed of the three-phase winding, formed by three coils displaced by an angle of 120º, accommodated between the grooves of a laminated ferromagnetic material, whose blades are isolated from each other, in order to mitigate any effects caused by eddy currents, as pointed out by Oliveira (2018) in his work.

For the moving part of the motor, the rotor, there are two types, the coiled type or the squirrel cage type. The first type has a set of three-phase windings similar to the stator, with the terminations of each of its phases connected to slip rings on the rotor shaft. In addition, for the windings to be short-circuited, brushes rest on the slip rings (Chapman, 2013). These motors are used in specific applications, as their maintenance cost is higher thanks to the wear of the slip rings and brushes.

2.2 Working Principles

Since it is a three-phase current that flows through a three-phase winding, with the current phases having the same intensity and a 120° phase difference between them, then a rotating magnetic field of constant intensity is produced, as described by Chapman (2013), causing the induced conjugate rotor armature continually tries to align itself with the stator's magnetic field, producing the rotary motion of a three-phase induction motor. This can be seen as a simplified definition of the rotating magnetic field theory. The rotation speed of this magnetic field, called synchronous speed, is expressed by the equation:

$$n_{sinc} = \frac{120\,f}{P} \tag{1}$$

where n_{ninc} , f , and P are the synchronous speed in rpm, line voltage frequency in Hz, and number of poles, respectively.

The behavior of an induction motor, as evidenced by Chapman (2013), is dependent on the current and voltage in the rotor, as the voltage induced in the rotor bars varies according to the rotor speed in relation to the magnetic fields. Therefore, it would be more practical to treat the relative motion of the rotor and magnetic fields using relative velocity. Slip (s), which deals with relative speed expressed as a percentage, is defined by the equation:

$$s = \frac{n_{sinc} - n_m}{n_{sinc}} (\times\, 100\%) \tag{2}$$

where n_m is the mechanical speed of the motor shaft.

The circuit of an induction motor can be simplified into an equivalent circuit per phase, referred to the stator part, which allows a better understanding and facilitates calculations related to induction motors. It is also important to emphasize the existence of a relationship between the machine rotor resistance and slip, and there may be variations in the equivalent circuit due to different impedance arrangements in the stator or rotor (CHAPMAN, 2013). Thus, a three-phase induction motor has three arrangements as shown in Figure 2.

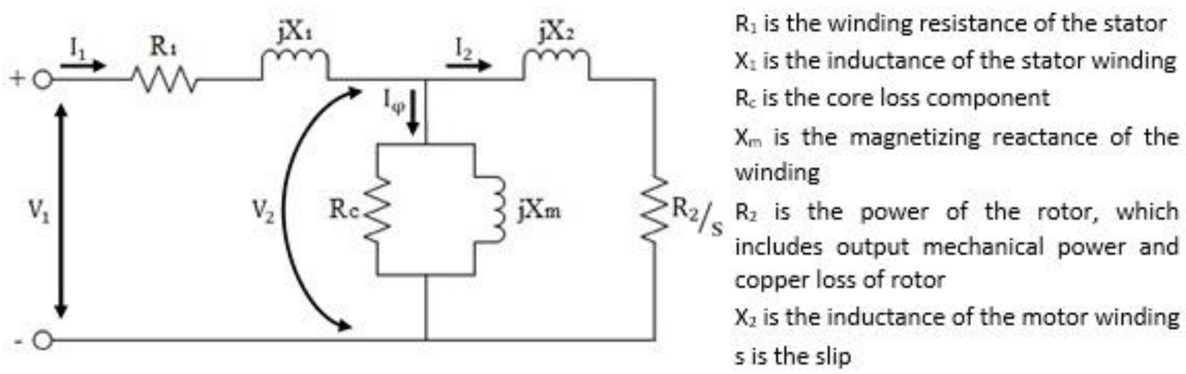

Figure 2. Equivalent circuit per phase of an induction motor. Font: Adapted from Oliveira (2018)

The values of the parameters of R_1, R_2, X_1, X_2 and X_m shall be determined according to the instructions for performing the no-load test, locked rotor test and measurement of stator winding resistances, as defined in a Brazilian standard named ABNT NBR 17094-3: 2018, for test methods in three-phase induction motors.

2.3 Mathematical modeling

Although it is possible to express mathematically the operation of an induction motor in a simplified way, it is necessary to take into account that in the real case there are power losses, whether electrical or mechanical. It is possible to see in Figure 3 the power flow diagram of an induction motor.

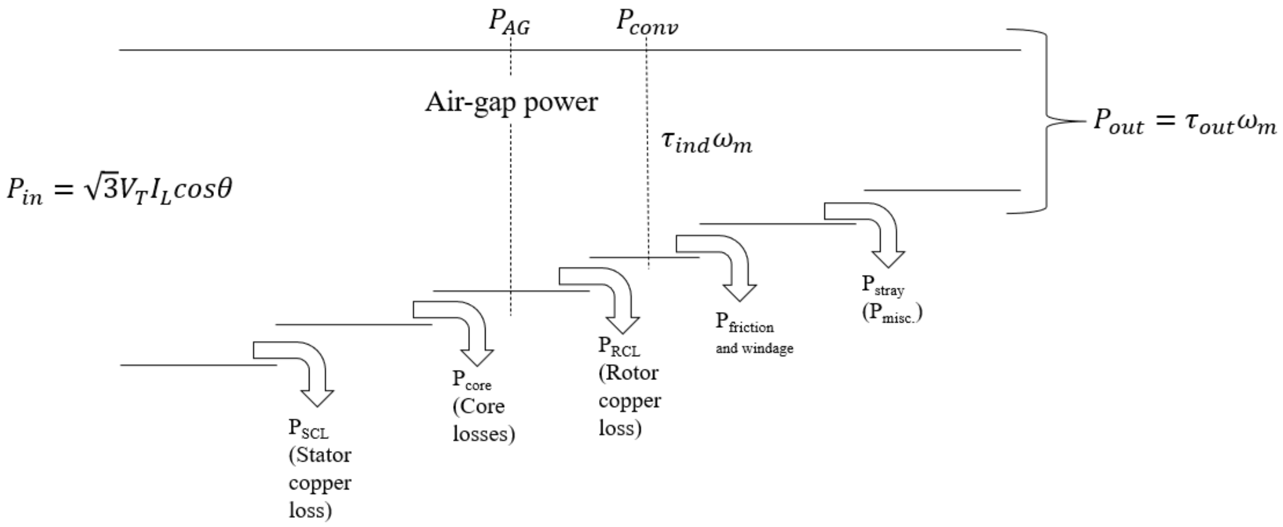

Figure 3. Power flow diagram of an induction motor

Let's see that in the diagram, between the input and output powers, there are five power losses, the two most relevant being the air gap and converted powers, expressed by the equations:

$$P_{AG} = 3I_2^2\frac{R_2}{s} \tag{3}$$

$$P_{conv} = 3I_2^2R_2\left(\frac{1-s}{s}\right) \tag{4}$$

where P_{AG}, P_{conv}, I_2 and R_2 are the air gap power, rotor current and rotor resistance, respectively.

As evidenced by Chapman (2013), the air gap and converted powers are highlighted due to the relationship between the electrical power supplied to the machine rotor through the stator P_{AG} and the total converted mechanical power P_{conv}, both applied to the motor rotor. These powers are also used to express the torque induced in a machine, through the equations:

$$\tau_{ind} = \frac{P_{EF}}{\omega_{sinc}} \tag{5}$$

$$\tau_{ind} = \frac{P_{conv}}{\omega_m} \tag{6}$$

where τ_{ind}, ω_{sinc} and ω_m are the induced torque, synchronous angular speed or grid frequency and angular speed of shaft, respectively.

Analyzing the equivalent circuit and the equations described, it is possible to see the existence of a relationship between stator and rotor resistances, speed, power and torque.

Changes in values in stator resistance R_1 would also imply changes in stator current I_1, rotor current I_2, air gap and converted powers, as well as create variations in the mechanical speed curve × induced conjugate, but in a different way from the resistance R_2 of the rotor.

2.4 Failure identification in induction motors

Three-phase induction motors can present several failures, whether of mechanical or electrical origin. Nandi, Toliyat and Li (2005) state in their publication that several types of failures, such as failures in windings, stator, rotor, eccentricity, etc., although they are mechanical failures, imply changes in the behavior of electrical quantities of the motor. According to statistical studies carried out by the Institute of Electrical and Electronics Engineers (IEEE) and the Electric Energy Research Institute (EPRI), when it comes to failures in induction motor components, 41% of failures are in bearings, 33% without stator , 9% on the rotor and 17% for other types of faults.

Bearings are quite common components, especially in rotating machines like induction motors. Despite its simple construction, failures of this type can cause changes in electrical parameters of both the stator and the rotor (JAMIER, 2010). In addition, bearings have the highest percentage of failures compared to induction motors, with some of the most common causes being: misalignment, vibration, excessive load, damage due to transport, poor or excessive lubrication, manufacturing defects and defects in other components.

As the second most frequent failure in induction motors, with 33% of cases, failures in machine stators, or stator failures, have, according to Jamier (2010), as main causes: electrical discharges, slack in winding connections, constructive errors, short circuit, overheating, contamination by objects, oils, dust, etc., degradation of insulation and defects in other machine components. Kliman *et al.* (1996) defines in their work that it is possible to identify stator failures by monitoring variations in its impedance and inductance. Variations greater than 10% in stator resistance and inductance may indicate a stator failure, according to Jamier (2010).

While stator failures can limit or interrupt machine operation in minutes or even seconds, according to Bellini *et al.* (2008) rotor failures allow the engine to continue running for a longer period. Toliyat and Kliman (2004) describe that about 9% of failures in induction motors occur in the rotor, which is a low percentage due to the robustness of this component.

In wound rotor motors, the most common causes of failures are similar to those of the stator, as they are also made up of copper windings. In squirrel cage type rotors, the breakage of cage rings and bars are the most common causes, being the latter responsible for about 35% of rotor failures, as cited by Silva (2008). Filippetti *et. al* (2000) also describe that it is possible to identify the presence of broken bars in a rotor from variations of 10% to 30% of the resistances ΔR and R_r, since these imply direct variations in the current amplitude.

2.5 Artificial neural networks

Artificial neural networks are the result of applying computational methods, inspired by the way the nervous system of living beings works, to solve non-linear problems. These systems are composed of several artificial neurons, or processing units, interconnected by artificial synapses, which are represented by vectors or matrices of synaptic weights (Silva *et. al*, 2016). Some of the abilities of an artificial neural network (ANN) includes: adaptation by experience, learning ability, generalization ability, data organization, fault tolerance, distributed storage and prototyping facility.

Analyzing the abilities shown above, it becomes clear the fact that, despite being a computational model, ANNs have abilities very similar to those of humans, and are in fact computational models inspired by the nervous system of living beings, especially human beings.

Neural networks are composed of a network of artificial neurons, which try to emulate the functioning of biological neurons. These are the main responsible for data processing in our nervous system, and can be divided into three main parts: dendrites, cell body and axon (Silva *et. al*, 2016).

The artificial neuron model used in most ANN architectures encompasses the main characteristics of a biological neural network, with high connectivity and parallelism. This model of an artificial neuron is shown in Figure 4.

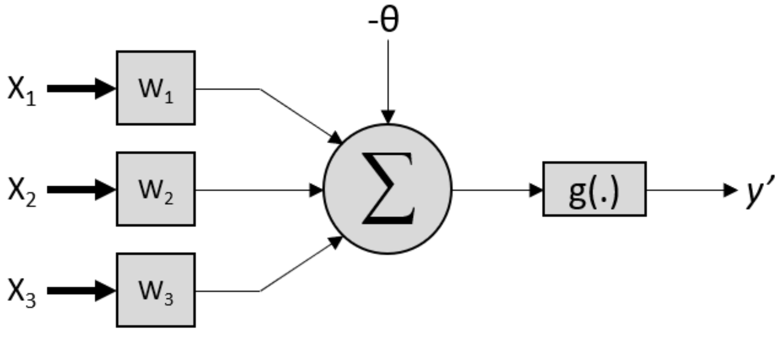

Figure 4. Artificial Neuron

The signals coming from the external environment, represented by $(x_1, x_2, \ldots, x_n)$, are analogous to the impulses picked up by the dendrites in a biological neuron. The weights of the input signals, represented by synaptic weights $(w_1, w_2, \ldots, w_n)$, are analogous to neurotransmitter substances existing in the biological system. After weighting, the sum of inputs (Σ) is compared to an artificial neuron activation threshold (θ), thus being analogous to the cell body of a biological neuron. Finally, the signal (u) is conditioned by an activation function (g), in order to leave the output levels (y) correct (Silva *et. al*, 2016).

Artificial neural network architectures can be divided into three parts:

• Input layer, responsible for receiving information (data), signals, characteristics or measurements from the external environment;

• Hidden layers, responsible for processing input signals;

• Output layer, responsible for presenting the results of the network.

The different ways in which neurons are arranged, the interconnections in the hidden layers and the constitution of layers, are the architectures of neural networks that can be divided into: single layer feedforward networks, multiple layer feedforward networks, recurrent networks and reticulated networks. A multilayer feedforward network was used in this work.

Networks with multilayer feedforward architecture have several layers of hidden neurons. They are applied in problem solving such as function approximation, pattern classification, system identification, optimization, robotics, process control, among others. An example is shown in Figure 5.

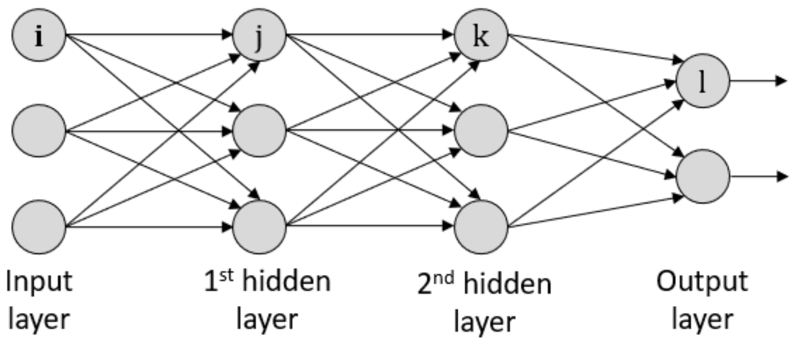

Figure 5. Multiple layer network

The data to be used in the ANN are inserted by the input layer, which has size n equal to the number of input signals. In the study proposed in this work, the data of the conjugate τ_{ind}, speed ω_m, stator current i_1 and rotor current i_2 were used, hence $n = 4$. Both the number of neurons in the first layer n_1 and the number of neurons in the layer n_2 are variable numbers, being defined by the user. The number m of neurons in the output layer corresponds to the number of output values of the application. In the case of this work, $m = 4$, since there are four possible outputs from the ANN analysis: normal behavior, stator failure, rotor failure and contamination failure.

Artificial neural networks especially stand out for their ability to learn about the behavior of a system from samples and then extrapolate generalized solutions. For this to occur, however, the ANN needs to go through a training process, which consists of the application of ordered steps, necessary to tune the synaptic weights and thresholds of the neurons in the network. This set of steps is called the learning algorithm, which allows the neural network to extract the discriminant characteristics of the system to be mapped and, subsequently, provide solutions.

In this work, the training method used is supervised model, where a database with input signals and their corresponding outputs is presented, allowing the model to adapt the free parameters of the network through pure inductive inference.

3. TESTING PROCEDURES

Using the methodology of experimental academic research, a bibliographical study was initially carried out on types of failures in three-phase induction motors and how to detect them, and on the use of artificial neural networks in the identification of patterns. After that, we defined the use of a multi-layer perceptron network, capable of analyzing the parameters of the three-phase induction motor.

In sequence, algorithms capable of simulating the behavior of a three-phase induction motor were implemented in the Matlab® software, generating data for induced torque, rotor shaft speed, stator current and rotor current, using equations 1, 2, 3, 4, 5 and 6, previously presented in this work. Numerous situations were simulated with values of resistances R_1 and R_2 and reactance's X_1, X_2 and X_m with variations between 30% and 300%, forming a database with 33 thousand samples of τ_m, ω_m, i_1 and i_2 for training the neural network artificial.

An example of the influence of the rotor resistance is available in Figure 6.

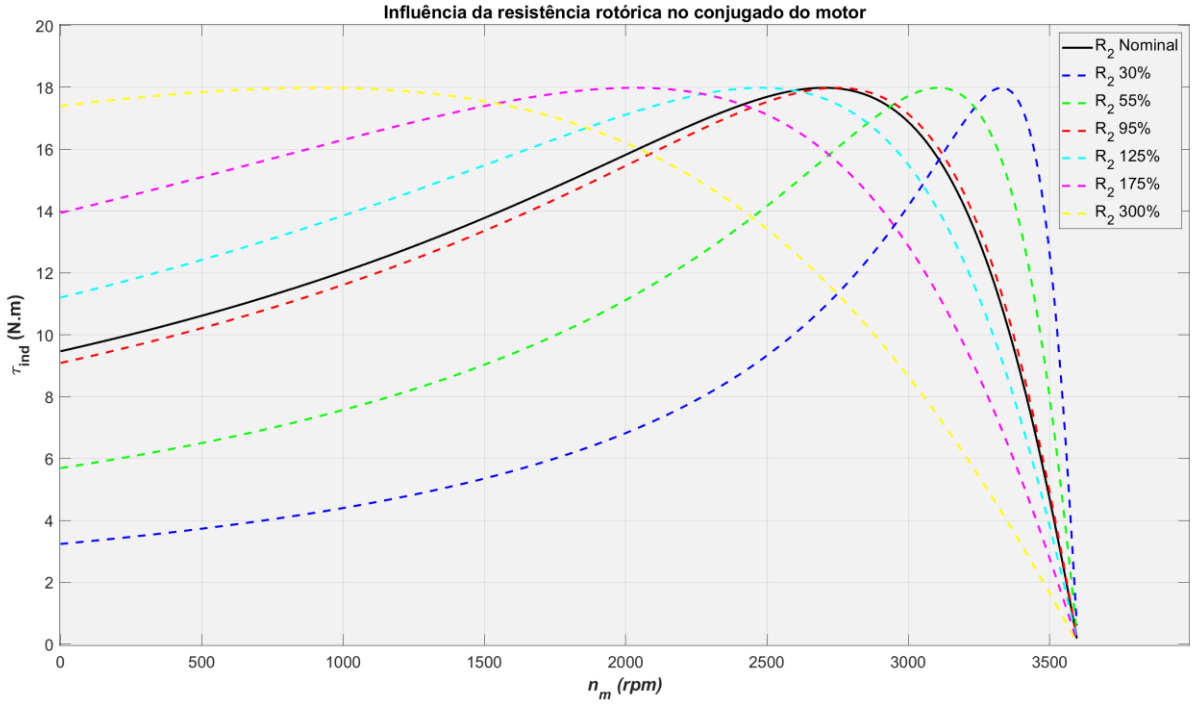

Figure 6. Example of the influence of rotor resistance on motor induced torque

Finally, using the database generated from the simulations, the training of the neural network was performed, using a sample of 60% of the data for training, 20% for validation and 20% for the test. The perceptron neural network used had 20 artificial neurons in its hidden layer, as can be seen in the ANN diagram in Figure 7.

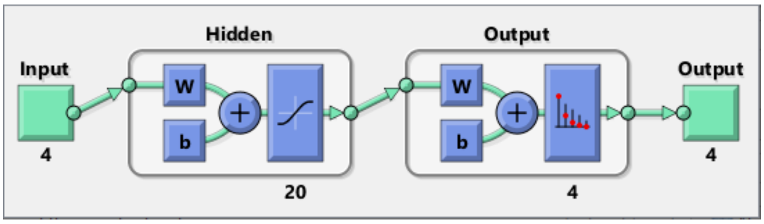

Figure 7. Diagram of the artificial neural network used

4. RESULTS AND DISCUSSION

For all results, data from a WEG brand three-phase induction motor were used and these data are shown in Table 1.

Table 1. Main features of the simulated three-phase induction motor

Manufacturer	WEG
Out Power	2,2 (3,0) kW (cv)
Voltage (Δ/Y)	220 / 380 V
Current (Δ/Y)	8,39 / 4,86 A
Frequency	60 Hz
Mechanical Speed	3450 rpm – 2 poles
Efficiency	81,9%
Power Factor	0,84
Service Factor	1,15

Font: WEG (2017)

At the end of the research work, implementation of algorithms, simulations of the equivalent circuit and obtaining data for training the neural network, the results achieved were satisfactory. The operating states of the simulated engine, whose manufacturer's specifications can be found in table 1, were defined as 4, as follows: 1 – normal operation, 2 – stator failure, 3 – rotor failure, 4 – mechanical failure/contamination. These numbers correspond to the confusion matrix generated after training the neural network, as can be seen in Figure 8.

After the training and validation phases, the developed neural network was tested, in order to define its degree of efficiency in detecting and diagnosing simulated failures. Any changes in the values of R_1 and X_1 greater than 10% of their nominal value determine a stator fault. Changes greater than 10% of the nominal values of R_2 and X_2classify a rotor fault. On the other hand, deviations from R_1, X_1, R_2, X_2 and X_m greater than 10% of their nominal values determine mechanical or contamination failures.

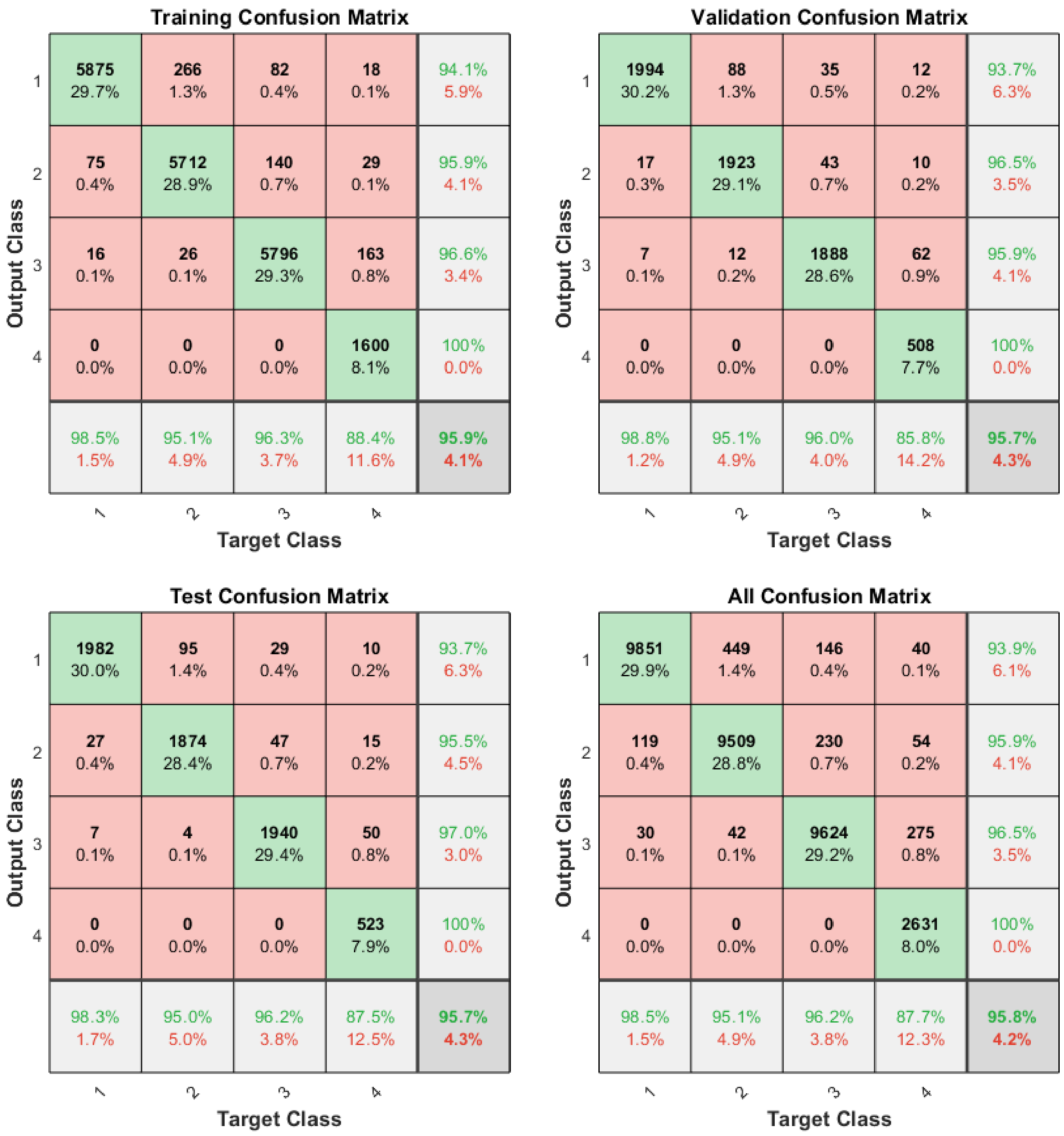

Figure 8. Confusion matrices of the artificial neural network

In Figure 8 we can see all generated matrices. The first matrix, related to training, shows that sometimes it can be difficult for the network in training to differentiate the normal functioning of the motor from its behavior when there are stator or rotor failures, however, 100% of mechanical or contamination failures were correctly classified. The hit percentages during the training phase are matched during the validation and testing phases, as can also be seen in Figure 9.

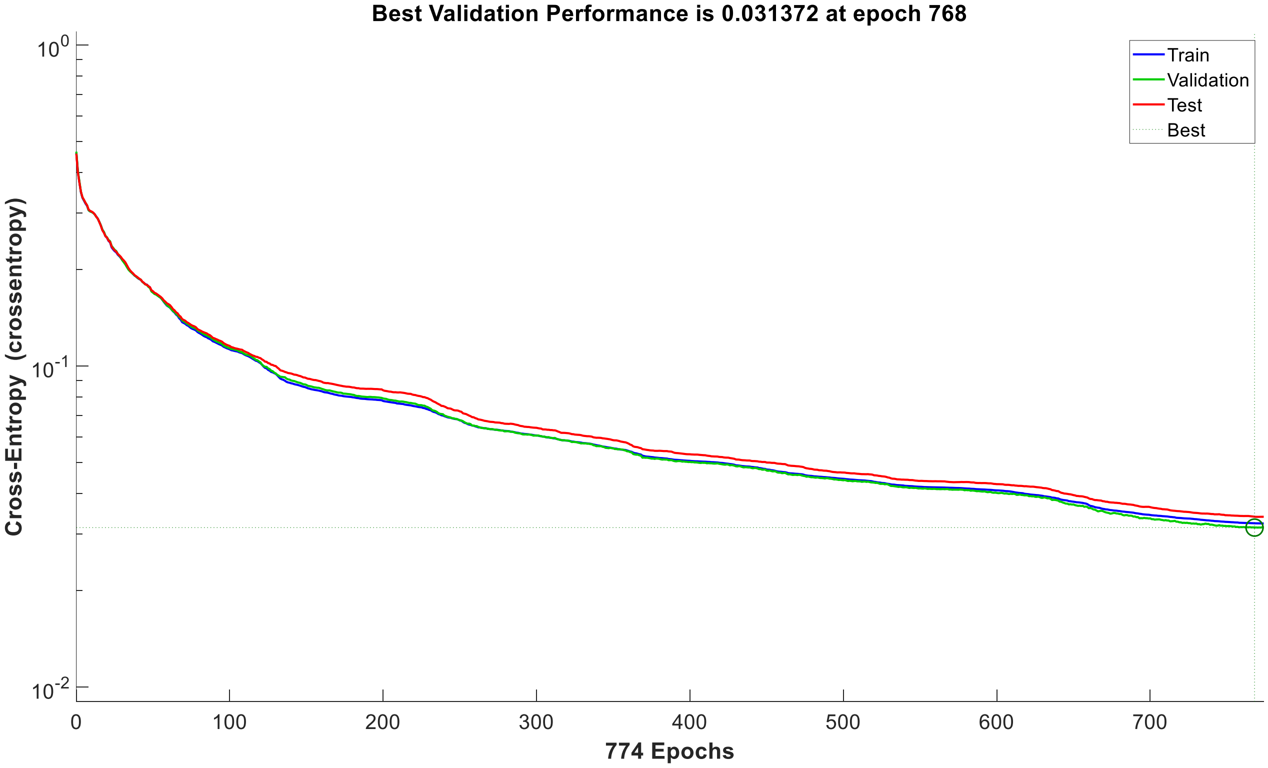

Figure 9. Validation performance

During the validation phase, 774 times were used, that is, the sampled data were evaluated, weighted and classified 774 times. The graph shown in Figure 9 demonstrates that at the time of number 768, the best ANN performance was obtained, with an error rate of only 3.1% in the classification of failures. The 96.1% correctness performance during the validation phase was satisfactory when compared to the values obtained by other authors, such as Jamier (2010), whose best performance was 95.8% correctness during the validation.

Ending the experiment with an average hit rate of 95.8% in the classification of failures, this value is very close to those found by Baccarini (2005), of 94%, and by Jamier (2010), of 98.6%, it becomes evident that both the chosen neural network, of the perceptron type, and the training method used were efficient when applied to the situation proposed in this work.

The results also shows that the technique of neural networks is used with reasonable similarities like in the research of Abdulhamid *et al.* (2019) that used the same methodology and found 97,4% of best performance in a problem of detecting of pishing websites.

5. CONCLUSION

It is therefore concluded that for the case analyzed in this study as it follows.

- The experiment was successful in demonstrating the efficiency of neural networks in monitoring three-phase induction motors, detecting and diagnosing failures that may occur with an average hit rate of 95, 8%.
- In addition, it is an accessible alternative for use in industries, being relatively easy to implement and helping to expand the use of predictive techniques applied to industrial maintenance activities.
- The development of such a simple system and with a high degree of efficiency not only makes it possible, but also popularizes the access and use of predictive techniques.
- Despite an already satisfactory number, the ANN could be even more accurate in the detection and diagnosis of failures, if the database used was more robust, there were more parameters to be monitored and there was the possibility of training network with real data, collected from different MITs, in different work regimes.
- It is therefore suggested that, in future work, other inputs that can help in the identification of faults be implemented, such as mechanical vibration data generated by accelerometers coupled to engines, as well as online monitoring of a real engine, thus validating the applicability of this type of tools in industrial environment.

6. REFERENCES

Abdulhamid, S. *et al.* (2019). A Soft Computing Approach to Detecting E-Banking Phishing Websites Using Artificial Neural Network. Journal on Computer Science. https://doi.org/6. 10.26634/jcom.6.3.15696.

Associação Brasileira De Normas Técnicas., 2018. NBR 17094-3: "Motores de indução trifásicos - Métodos de ensaio". Rio de Janeiro.

Baccarini, L. M. R., 2005. "Detecção e Diagnóstico de Falhas em Motores de Indução". 179 f. Tese (Doutorado em Engenharia Elétrica) – Programa de Pós-Graduação em Engenharia Elétrica, Universidade Federal de Minas Gerais, Belo Horizonte.

Bellini, A. *et al*., 2008. "Advances in Diagnostic Techniques for Induction Machines". IEEE Transactions on Industrial Electronics, v. 55, 12. ed. p. 4109-4126.

Benbouzid, M. E. H., 2000. "A Review of Induction Motors Signature Analysis as a Medium for Faults Detection". IEEE Transactions on Industrial Electronics. v. 47, n. 5, p. 984-993.

Chapman, S. J., 2013. "Fundamentos de Máquinas Elétricas". 5 ed. Porto Alegre: AMGH., 684 p.

Filippetti, F.; Franceschini, G.; Tassoni, C., 2000. "Recent developments of induction motor driver fault diagnosis using AI techniques". IEEE Transactions on Industrial Electronics, v. 47, 5. ed. p. 994-1004.

Jamier, A., 2010. "Reconhecimento de Padrão de Falhas em Motores Trifásicos Utilizando Redes Neurais". 88 f. (Dissertação de Mestrado em Engenharia Elétrica) - Universidade Federal do Rio Grande do Norte, Natal.

Kardec, A.; Nascif, J., 2009. "Manutenção - Função Estratégica". 3 ed. Rio de Janeiro: Qualitymark, 361 p.

Kliman, G. B. *et al.*, 1996. "A new approach to on-line fault detection in ac motors". In: IEEE INDUSTRY APPLICATIONS CONFERENCE, 31., San Diego, p. 687-693.

Liang, P. *et al.*, 2020. "Intelligent fault diagnosis of rotating machinery via wavelet transform, generative adversarial nets and convolutional neural network". Measurement, Volume 159, ISSN 0263-2241, https://doi.org/10.1016/j.measurement.2020.107768.

Nandi, S.; Toliyat, H.; Li, X., 2005. "Condition monitoring and fault diagnosis of electrical motors – a review". IEEE Transactions on Energy Conversion, v. 20, 4. ed. p. 719-729.

Oliveira, C. A., 2018. "Plataforma para ensaios de motores de indução trifásicos e simulação de cargas mecânicas: acionamento, operação e monitoramento com auxílio de fonte programável". 95p. (Dissertação de Mestrado em Engenharia Elétrica) – Universidade Federal de Uberlândia, Uberlândia.

Silva, I. N.; Spatti, D. H.; Flauzino, R. A., 2016. "Redes Neurais Artificiais para Engenharia e Ciências Aplicadas". São Paulo: Artliber, 431 p.

Toliyat, H. A.; Kliman, G. B., 2004. "Handbook of Electric Motors", 2. ed. New York: CRC Press, 850 p.

Wu, Z. *et al.*, 2020. "An adaptive deep transfer learning method for bearing fault diagnosis". Measurement, Volume 151, ISSN 0263-2241, https://doi.org/10.1016/j.measurement.2019.107227.

Zhang, J. *et al.*, 2020. "A new bearing fault diagnosis method based on modified convolutional neural networks". Chinese Journal of Aeronautics, Volume 33, Issue 2, Pages 439-447, ISSN 1000-9361, https://doi.org/10.1016/j.cja.2019.07.011.

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