ESPRIT-TLS and ANN Genetic Algorithm combination for an accurate discrimination of fault bearing in induction machines

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Abstract. Fault detection is a strategy that can be easily implemented. Indeed, electrical rotating machines have played and still play an important role in many applications where very often continuity of operation is crucial (aircraft, ships, electric vehicles, industries, etc.). In the case of electromechanical systems, several failures can occur and especially in inaccessible locations (bearing faults, rotor bar breakage, misalignment, eccentricity, cracks, or gear breakage).To ensure acceptable levels of reliability and safety, effective diagnostic methods (at the earliest stage of fault occurrence), fault monitoring, and fault handling are mandatory to avoid any production downtime or loss and to reduce additional repair costs. The detection of these faults by MCSA (Motor Current Signature Analysis) and Principal Component Analysis (PCA) has been widely explored and applied. These techniques are mainly based on the analysis of the stator current by advanced signal processing algorithms to extract useful information for the detection and characterization of defects and their accurate classification. The remarkable limitations of these approaches have prompted researchers to improve their accuracy and to enhance their complexity. In this work, we propose by study the application of ANN-GA (Artificial Neural Networks - Genetic Algorithm) combined with ESPRIT method variants for efficient faults recognizing in real-time. Computer simulations in MATLAB demonstrated that ESPRIT TLS (Estimation of Signal Parameters via Rotational Invariant Techniques Total Least Square) variant allows satisfactory precision in discriminating bearing fault even with a noisy signal. Moreover, this algorithm is suitable for application in dataset preparation and in ANN training for the development of a classification model. According to study finding, Genetic Algorithm optimize ANN architecture for identifying each fault type with very good accuracy in time or frequency domains.

1 Introduction

No one is unaware that today, rotating machines are present in almost every sector of our daily life. We find them in the aeronautics, naval, energy production consumed in our homes and industries, in the industries, in the mines and in these last decades in the intelligent vehicles. However, it should be kept in mind that these machines are more than 85% electromechanical components. Thus, it happens sometimes during their use, due to internal and external factors, that they are affected by fatigue. These fatigues, when not intercepted in time, can lead to the damage of the machine over long periods of time. This could lead to material and human damages. The aim is to develop a system that can detect these failures as soon as they appear. Several methods have indeed proved their worth, including artificial neural networks (ANN). The only problem with this one is the parameterization of the final model which can sometimes be heavy. To improve this task, we have chosen to support it with genetic algorithms (GA). Indeed, further research has shown how this combination could optimize the process of parameterization of the final model by exploiting the computing power of computers. Moreover, instead of exploiting vibration, ultrasound, or thermal methods for the machine's signal acquisition, in this study, we will use the MCSA (Machine current Signature Analysis) method. Thus in this study, After a brief presentation of the previous research works, secondly we will talk about the MCSA method and the ESPRIT (Estimation of Signal Parameters via Rotational Invariant Techniques) algorithm, then thirdly we will talk about artificial neural networks and their association with the genetic algorithms and before ending with the conclusion and the perspectives, we will present in the fourth point the results obtained with the ANN-GA association on the data prepared with the ESPRIT_TLS.

2 Related work

In the diagnosis of electromechanical faults in electrical induction machines, there is not only the combination of MCSA with high-resolution signal processing (HRM) methods and machine learning algorithms as is the case in this study. Indeed, in the past, combinations such as MCSA, PCA, and other signal processing methods have been used to perform the same work. These methods are among others, the FFT [1] (Fast Fourier Transform), the DWT (Discrete Wavelet Transform) and PCA [2].

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However, although these algorithms have been able to address the work in their way, it must be mentioned that each of them has limitations. Based on this observation, researchers have gradually migrated to more appropriate solutions, hence the choice of this association which, in addition to being free of the nature of the system studied, offers an intelligent and adaptable diagnosis as the machine operates.

3 MCSA and ESPRIT method

3.1 MCSA approach

Motor current signature analysis (MCSA) is a rotating machine condition monitoring technique used to diagnose problems in induction motors [6,7]. Previous results of the researchers showed that it was possible to detect the impact of a fault when it occurs in electromechanical machines from the stator current of the latter. Thus, it was sufficient to know the characteristics of the fault to model its signal. From this, the expression can be formulated as follows [8] :

$$x[n] = \sum_{k=-L}^{L} a_k \, cos(2\pi f_k(w(n)) \times n/F_k + \phi_k) + b[n] \quad (1)$$

Where x[n] corresponds to a single sample of the stator current, b[n] is a sample of Gaussian noise. The parameter L is the number of side frequencies introduced by malfunctions. The quantities fk(w(n)), ak, ϕk corresponds to frequency, amplitude and phase respectively. ω(n) is a parameter to be estimated at each instant of order n. It depends on the fault studied. The only problem with this signal is that it is not sufficient on its own to correctly diagnose the states of the machine (for example, when we want to decide on the operating state of the machine at a given time). This is why it is important to associate it with the ESPRIT method.

3.2 ESPRIT method and its variants

ESPRIT is a method of estimating signal parameters using the rotational invariance technique. It is an algorithm for the determination and detection of harmonics with a very high accuracy of frequency and amplitude estimation. This is independent of the window size used. It is an appropriate approach to get reliable spectral estimation results without synchronization effects [8]. It is based on shift invariance. In this case, the eigenvectors U of the signal autocorrelation matrix define two subspaces (signal and noise) using two selection matrices $\gamma 1$ and $\gamma 2$.

$$S_1 = \gamma_1 U, \;\; S_2 = \gamma_2 U \quad (2)$$

The rotational invariance between the two subspaces leads to the following equation:

$$S_1 = \phi S_2 \quad (3)$$

where

$$\phi = \begin{bmatrix} e^{j2\pi f_1} & 0 & \cdots & 0 \\ 0 & e^{j2\pi f_2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & e^{j2\pi f_N} \end{bmatrix} \quad (4)$$

The matrix ϕ contains all the information on the N frequency components. The estimated matrices S1 and S2 may contain errors [8]. The determination of this matrix allows to obtain the estimates of the frequency defined by the following formula:

$$f_k = Arg(\phi_{k,k})/2\pi, \qquad k = 1,2,\dots,N \quad (5)$$

The application of all these methods makes it possible to carry out a comparison between their performances below. They are used in the detection of faults that may occur in an electric induction machine. In this work, we use 6 variants which, like their roots, are used to estimate the frequencies and amplitudes contained in the stator current signal of the machine. Except for the TLS variant which takes as argument a third parameter which is the window length, these variants take two essential parameters, the signal vector and the number of harmonics or the mode of estimation of the number of harmonics which is based on order selection models (MOS). These variants are: ESPRIT_TLS, ESPRIT_ITCMP, ESPRIT_SVDSSA, ESPRIT_IRLBA, ESPRIT_SVD, ESPRIT_ECON. The procedure for estimating frequencies and amplitudes by these variants is given in Figure 1.

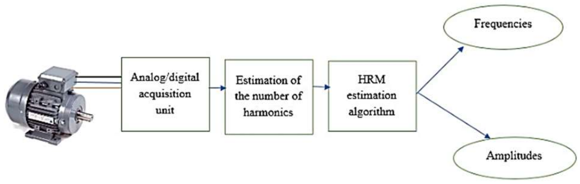

Fig. 1. Fault detection procedure with an HRM.

4 Artificial Neural Networks and Genetic Algorithms

4.1 Artificial neural networks (ANN):

Artificial neural networks based on the functioning of the human brain are developed in the form of parallel distributed network models [9]. These networks are composed of input layers, hidden layers and output layers. At each layer, there is a number of variable neurons that are conditioned by a weight, a bias and an activation function, and it should be noted that the number of neurons at the level of the hidden layers, play an important role on the final nature of the model thus formed. Today, there are several types of networks, depending on the need. The type that interests us are the multi-layer perceptions (MLP). The figure Fig 2 below shows an example of MLP.

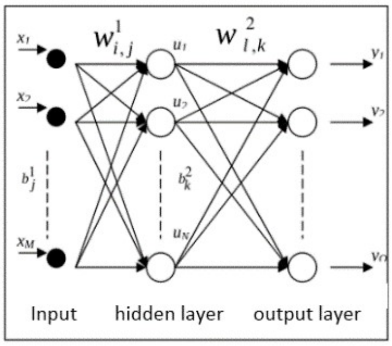

Fig. 2. Example of a Multi-Layer Perceptron.

The principle is that they take data in input and by successive passage to the levels of layers, build an image or a trace of the analyzed data which will condition the output.

4.2 Genetic Algorithms (GA) :

The goal of using the genetic algorithm in our study is to find the fastest possible and achieve an optimal architecture giving good accuracy in the classification of the bearing fault. But as any genetic algorithm, there are steps to respect in order to achieve its employability [10]. These steps are: the coding of the chromosomes which consists in finding the nature of the genes which will form the individuals of the process; the generation of the population which gives him the means to make the first choice of a set of individuals of departure and the evolution which consists in the creation of new individuals by the operations of mutation and crossing.

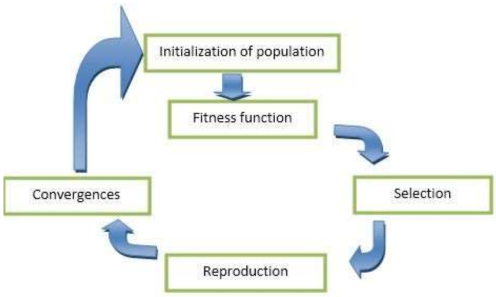

Fig. 3. Principle of the Genetic Algorithm.

4.3 ANN and AG Association

The algorithm starts with ten randomly generated individuals for a given number of hidden layers. Each individual is evaluated. For any individual in the population, if the accuracy is greater than or equal to a given max, the max is updated and saved. At the same time, each individual and its accuracy is saved. At the end of the evaluation of these ten individuals, we extract from the backup the 5 best ones on which we first mutate and then crossbreed by returning a candidate population to the 2nd generation. This process is repeated until the tenth generation and the number of hid-den layers is changed, then we start again from the beginning. After evaluation on the interval of the number of hidden layers, we come out with 4 architectures which according to the algorithm, are the bests. Figure 4 shows the diagram of such an association

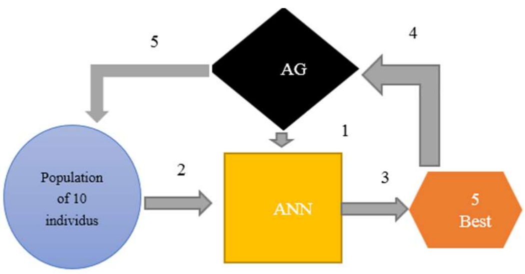

Fig. 4 Association of the ANN and the GA.

5 Results and discussions

In this section, we present the results obtained by applying the above-mentioned algorithms on the stator current signal from the machine and modeled above. But before the results, we present the simulation parameters in table 1 below:

Table 1. Simulation parameters.

Parameters	Value
f_r	29.01 Hz
f_0	50 Hz
n_b	12
$f_{i,o}$	139.248 Hz
F_s	1000 Hz
k	1
SNR	[0-102] dB
$Amplitude\ of\ the\ stator\ current\ a_0$	10A
$Processor$	*intel* Pentium(R) CPU B950 @ 2.1GHz× 2

In this study, we have only worked on the bearing defect since the principle remains the same for the other types of faults. The formula giving the expressure of the bearing fault is:

$$f_{bng} = |f_0 \pm k f_{i,o}| \tag{6}$$

Where $k = 1, \dots, N$

And

$$f_{i,o} = \begin{cases} 0.4 f_r \\ 0.6 f_r \end{cases} \tag{7}$$

With $f_{i,o}$ is the inner and outer frequency.

5.1 Simulation Results of ESPRIT variants

For this simulation, we have worked only with the frequencies of the bearing fault ([f0=50, f1=89.248, f2=189.248] Hz) with the following amplitudes: [a0= 10, a1= 0.2, a2= 0.07] A. Here are the results obtained:

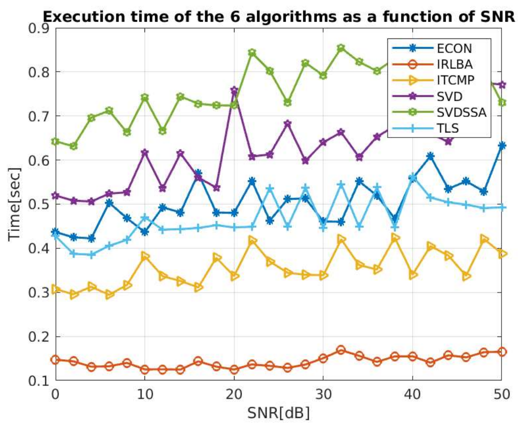

Fig. 5. Execution time of the 6 algorithms.

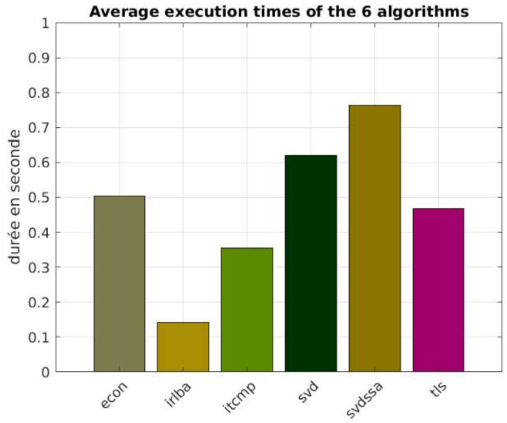

Fig. 6. Average execution time of the 6 algorithms.

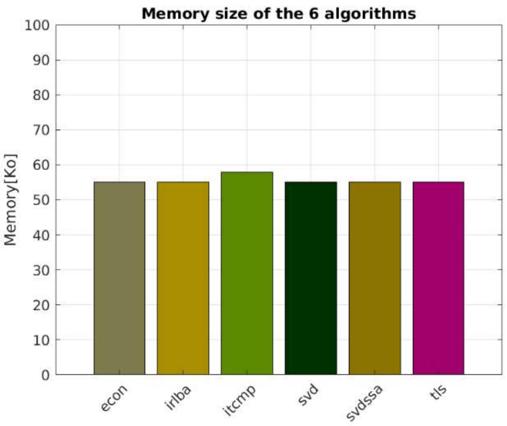

Fig. 7. Memorysize (right) of the 6 algorithms.

Moreover, to see the convergence, we present as an example the results on the estimation of amplitudes for the 6 algorithms for SNR values between 30 and 50 dB.

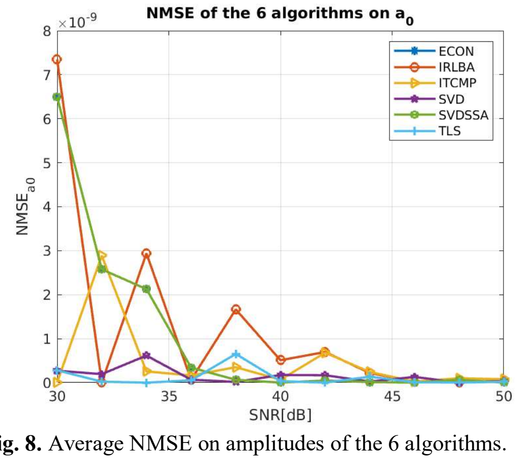

Fig. 8. Average NMSE on amplitudes of the 6 algorithms.

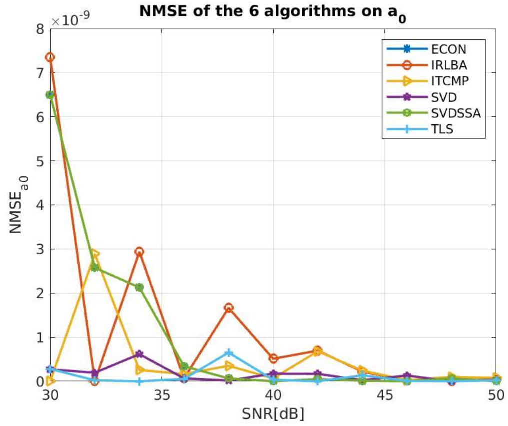

Fig. 9. NMSE on a0 (right) for the 6 algorithms.

Thus, based on the results of the execution times and memory size of these 6 algorithms as shown in Fig. 5, 6 and 7 and their convergence on the amplitudes in Fig. 8 and 9, we could see that the ESPRIT_TLS variant is the one that would estimate the parameters the best although, a bit more expensive in terms of time behind ESPRIT_IRLBA and ESPRIT_ITCMP. This was mentioned in the abstract of this work.

5.2 Results of the ANN-GA association

Once we found the variant that best estimates the signal amplitude and frequency parameters, all that remained was to build up the classified data to be divided into two categories, the healthy and the faulty. In addition, since the operating conditions of the machine mean that from one moment to the next the noise can vary, we modeled this as a series of SNR step variations that took their value in the interval [1,4] dB. The results obtained in the time and frequency domains with the ANN-GA association are respectively given in table.2 and table.3 below. We used a number of layers varying between 1 and 4, the number of neurons in each layer varying between 1 and 10 and activation functions logsig, tansig, hardlin for the hidden layers and softmax, tansig for the output layer. The obtained architectures are tested on the data formed by the other SNR steps to measure the generalization of the different architectures in case of abrupt change of the signal to noise ratio.

- **In temporal domain.**

For the 4 learning steps (1,2,3 and 4), the respective numbers of neurons in the two hidden layers are: (5,6), (1,3), (1,110), and (2,7).

Table 1. Results of Best Architectures according to the trainning data steps.

	Train step [dB]	Accuracy [%]	Others steps	Accuracy [%]	Time [sec]	Memory [Ko]
ANN	1	72.5	2	88.5	0.801	148
			3	84.6	0.797	148
			4	86.5	1.833	188
	2	88.46	1	72.54	3.645	214
			3	84.61	1.742	148
			4	86.53	1.611	148
	3	94.23	1	66.66	4.835	214
			2	57.69	0.361	148
			4	78.84	5.768	148
	4	82.69	1	73.52	5.577	214
			2	73.07	0.335	148
			3	82.69	0.346	148

Finally, in the temporal domain, the best model retained is an architecture with two hidden layers, the first of which has a single neuron and the second 3 neurons. The activation functions are respectively tansig and tansig. As for the output layer with two neurons, the activation function retained by the genetic algorithm is softmax. The figure Figure 11 presents this last architecture.

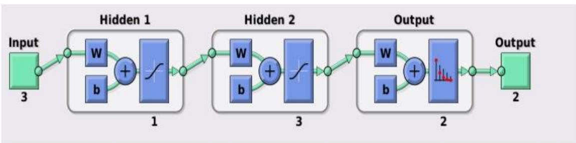

Fig. 10. Best architecture in time domain.

Here are also these confusion matrixes on the 1dB training step data and on the other steps to measure its generalist.

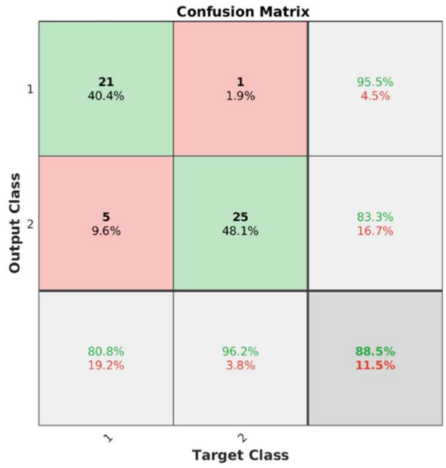

Fig. 12. Test on a data with step of 2dB

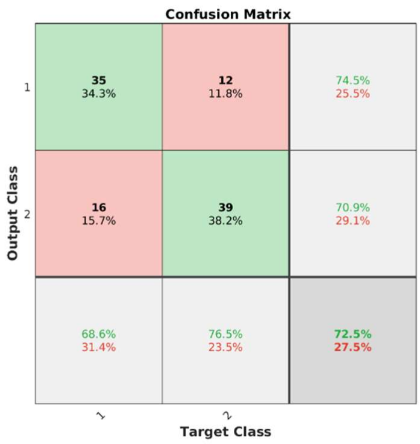

Fig. 11. Training on a data with step of 1 dB.

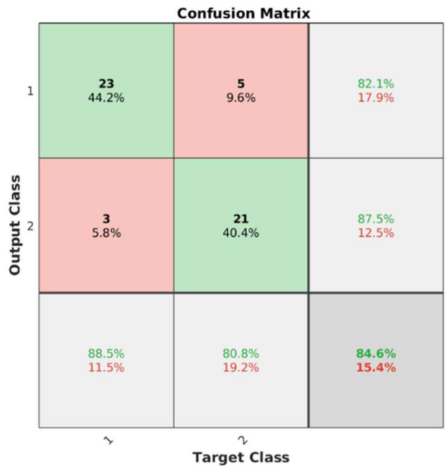

Fig. 13. Test on a data with step of 3 dB.

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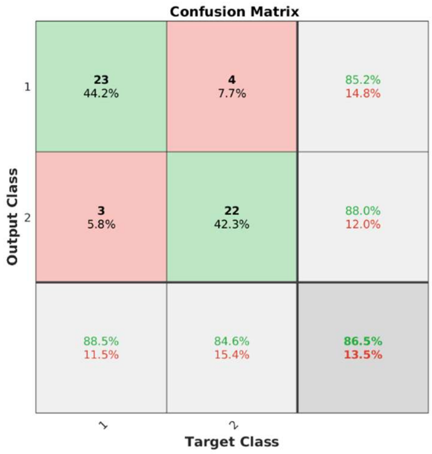

Fig. 14. Test on a data with step of 4 dB.

- **In frequency domain**

For the 4 learning steps (1,2,3 and 4), the respective numbers of neurons in the two hidden layers are: (4), (7), (9), and (7

Tableau 2. Results of Best Architectures according to the trainning data steps.

	Train step [dB]	Accuracy [%]	Others steps	Accuracy [%]	Time [sec]	Memory [Ko]
ANN	1	99	2	100	0.4125	115
			3	100	0.3195	115
			4	100	0.3135	115
	2	100	1	99.01	0.5504	132
			3	100	0.2957	115
			4	100	0.3150	115
	3	100	1	98.03	0.5097	132
			2	98.07	0.3239	115
			4	100	0.2254	115
	4	100	1	98.03	0.5686	132
			2	98.07	0.3525	115
			3	98.07	0.3889	115

Finally, in the frequency domain, the best model retained is an architecture with one hidden layer with seven neurons. The activation function is tansig. As for the output layer with two neurons, the activation function retained by the genetic algorithm is softmax. The figure Figure 12 presents this last architecture.

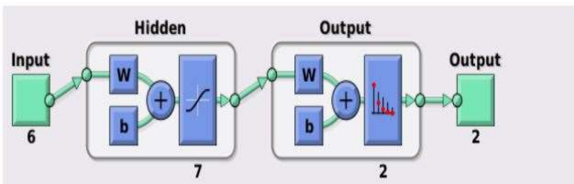

Fig. 15. Best architecture in frequency domain.

Here are also these confusion matrixes on the 1dB training step data and on the other steps to measure its generalist.

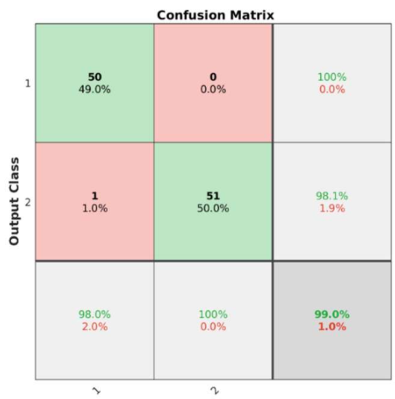

Fig. 16. Training on a data with step of 1 dB.

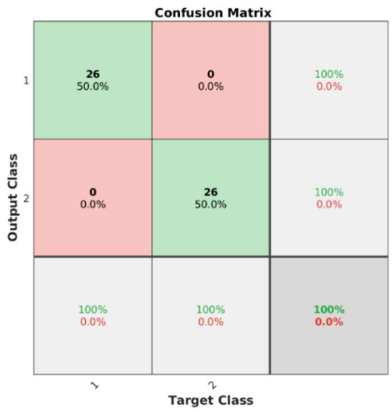

Fig. 17. Test on a data with step of 2dB

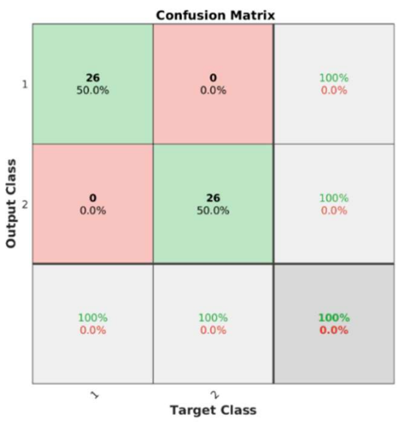

Fig. 18. Test on a data with step of 3 dB.

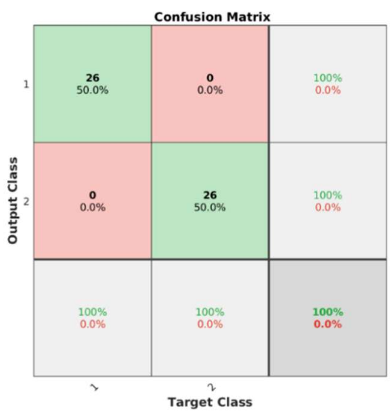

Fig. 19. Test on a data with step of 4 dB.

5.3 Discussions

compared to the time domain (Table 2) in terms of classification precision, elapsed time, and memory occupied to train the neural network. This can be justified by the reason for the wealth of information characterizing a defect in the spectral domain, especially when the SNR step used to form the dataset is very small (architecture with a learning step of 1 dB).

In addition, we observed by comparing Figure 7 and Table 3 that the approach we proposed which combines an ANN network driven by frequency signals obtained by applying the ESPRIT-TLS algorithm is strongly favored for detection early in real-time of a bearing fault by comparison with the application of the ESPRIT-TLS algorithm alone.

6 Conclusion

In this work, we have aimed at the objective of seeking, in the time or frequency domains, an ANN architecture or model allowing monitoring in real-time of each bearing defect. Based on two signal datasets classified as healthy or faulty, we built, trained the ANN obtained by using genetic algorithm (which optimizes the process of setting up the different possible architectures of ANNs), and then examined its performance. The simulation results demonstrate that by using GA we can develop an ANN architecture fulfilling a precise satisfactory classification offering early detection in real-time. Given their wealth of information, the stator current signals forming the used dataset (which one is obtained by ESPRIT-TLS) in the frequency domain are better suited and favored for the training and design of such neural networks. As perspectives, we recommend extending this study by applying the CNN (convolutional neural network), RNN (recurrent neural network), and Machine learning methods and others optimization algorithms like cuckoo algorithm, firefly algorithm in the fault classification as well as determining the indicators of their expected robustness by using more than one fault harmonics. In addition, we propose an experimental implementation of these algorithms on electronic board prototypes like DSP Card or FPGA associated with a test bench with all types of bearing fault to validate the simulation results obtained.

References

1. Saad Chakkor, Mostafa Baghouri, Abderrahmane Hajraoui, High Accuracy ESPRITTLS Technique for Wind Turbine Fault
2. Bart de Ketelaere, Mia Hubert, and ERIC Schmitt, Overview of PCA-Based Statistical Process-
3. Monitoring Methods for Time-Dependent, High-Dimensional Data, 12 January 2018.
4. B. Aubert "Détection des courts-circuits inter-spires dans les Générateurs Synchrones à Aimants Permanents : Méthodes basées modèles et filtre de Kalman étend-Application à un canal de génération électrique en aéronautique", Thèse de doctorat, Toulouse, 2014.
5. J. Chatelain " Machines électriques ", Edition Georgi, Lausanne ,1983
6. S. A. S. Al Kazzaz and G. K. Singh, "Experimental investigations on induction machine condition monitoring and fault diagnosis using digital signal processing

techniques," Electric Power Systems Research, vol. 65, pp. 197-221, 2003.

7. W. T. Thomson and R. J. Gilmore: Motor Current Signature Analysis to Detect Faults in Induction Motor Drives – Fundamentals, Data Interpretation, and Industrial Case Histories, Proceeding of the Thirty-Second Turbomachinery Symposium, Houston, Texas, Sept. 2003
8. A. Gheitasi, Motors Fault Recognition Using Distributed Current Signature Analysis, PhD Thesis, Auckland University of Technology, School of Engineering, 2013.
9. Saad Chakkor, E-diagnostic de processus physiques à base des méthodes de haute résolution Application : machines éoliennes thèse doctorale, 22 juillet 2015.
10. S.S. Mohamed; E.F. El-Saadany; T.K. Abdel-Galil; M.M.A. Salama, ANN-based technique for fault location estimation using TLS-ESPRIT, https://doi.org/10.110/MWSCAS.2003.1562484.
11. MuhammetUnal, Mustafa Onat, Mustafa Demetgul, Haluk Kucuk, Fault diagnosis of rolling bearings using a genetic algorithm optimized neural network, https://doi.org/10.101/j.measurement.2014.08.041.