Analysis of the Power Quality using Intelligent Techniques

VICTOR GARRIDO ARÉVALO*, JORGE LUIS DIAZ R, ALDO PARDO GARCIA*****
Department of Electrical, Electronic, Telecommunication and System Engineering.*,**
Department of Mechanics, Mechatronics and Industrial Engineering.***
Universidad de Pamplona, Pamplona, Norte de Santander.
Ciudadela Universitaria, Km. 1 via Bucaramanga, Pamplona.
COLOMBIA
vimaga86@gmail.com* , jdiazcu@gmail.com**, apardo13@hotmail.com***

Abstract: **-** In this work, the mathematical modelling and simulation of some of the phenomena that affect the power quality is presented, Discrete Wavelet Transform is applied to obtain characteristic patterns of each signal. With these patterns several intelligent classifiers (neural networks and support vector machine) are trained and determine which of these they have better results in terms of predicting the class to which belongs each of said patterns. Knowing the energy distributions of the coefficients of detail, a general power quality index is formulated and compared with the existing ones.

Key-Words: Power Quality, Harmonics, Sag, Swell, Flicker, Wavelet, Neural Networks, Support Vector Machine.

1 Introduction

There are phenomena that affect the Power Quality, and they are very harmful to electronic equipment, even for all devices that operate on the basis of electricity. Identification of these phenomena is essential to improve the Power Quality. In this paper the mathematical model for some of the phenomena that affect the power quality (LDLT, THDI, sag, flicker, swell) , in which they will get a processing by wavelet transform to obtain characteristics patterns in order to these processes be the input to different intelligent classifiers and to determine which kind they belong to.

In the studies presented in [1], [2], [3], [4], [5], [6], [7], [8], [9], [10] it is shown the use of intelligent classifiers have been common subject of study in quality applications energy, especially neural networks, likewise have they been limited to study these phenomena throughout measurement set rates, and they are being individual to each of the phenomena without any relationship between them.

In this work we do comparison different intelligent classifiers in order to determine which it has better response in the identification of phenomena they affect the Power Quality, in fact a general index with which to give a measure of distortion is proposed signal to any phenomenon that affects this and they compare which of these phenomena has higher or lower severity.

2 Power Quality

The study of the Power Quality is the first and most important step to identify and to solve problems of the power system. They can damage the equipment performance and reduce its reliability, reducing productivity and profitability, and may be damage the personnel's security [11].

2.1 Harmonic

Harmonics are sinusoidal voltages or currents whose frequency is an integer multiple value in which the system is designed for (fundamental frequency, typically 50 or 60 Hz) [12]. A harmonic signal can be represented by equation 1.

$$y(t) = Y_0 + \sum_{n=1}^{\infty} \sqrt{2} Y_n \sin(n\omega - \varphi_n) \quad (1)$$

Where:
Y_0: The amplitude of the DC component, which is usually zero in a stable state.
Y_n: The rms value of the component of n rank.
φ_n: It is the gap of the harmonic component.

2.2 Sag and Swell

Sags and swells are similar phenomena; the first corresponds to a decrease in signal amplitude between 0.1 and 0.9 in pu, while the second goes to an increase between 1.1 and 1.8 in pu.

2.3 Flicker
The Flicker is the "subjective impression of light fluctuation". Being a subjective effect implies that depends on a physiological phenomenon as it is relative to each observer and how it is affected by this phenomenon [13]. The flicker can be represented in equation 2.

$$v(t) = A\left[1 + M \cdot u_{\Omega} \cos\left(\omega_0 t\right)\right] \qquad (2)$$

Where:
A: The peak value of the voltage before fluctuation appearing.
M: It is the amplitude of the modulating signal.
ω_0: It is the frequency of the voltage.
$u_{\Omega}(t)$: It represents the frequency signal which modulates the voltage and whose amplitude is M, which varies between 0 and 1. Usually it is a square wave.

3. Artificial Intelligent Classifiers
The classifiers used in this work now are going to described.

3.1 Neural Networks
Artificial neural networks are parallel structures based on biological neurons. A neural network is composed of a multitude of simple elements, neurons, interconnected in a way more or less dense and which all together performance can lead to a complex non-linear processing. Networks are able to adjust their behavior from experimental data and based on any Figs of merit which are very useful in problems where its knowledge is incomplete or varies over time [14].

In this study the following neural networks will be used as:

Multilayer Perceptron - Net 1
Radial basis function - Net 2
Cascade Forward Back propagation – Net 3

3.2 Support Vector Machine
Support Vector Machines (SVM) are a set of learning algorithms based on statistical learning theory. This technique was initially a linear classifier double kind for separable data and finding a linear model that separates the elements of both kinds, then this technique was adapted to classification problems with non-separable data and even for solving regression problems [14], [15].

For the present work, will be used double class settings (SVM1), *Minimum Output Coding* (code_MOC) (SVM2), *Error Correcting Output Coding* (code_ECOC), (SVM3and Classification *One vs. All*. (SVM4).

4. Simulations
The development of simulations of obtaining signals of each of the phenomena to be analyzed, in Fig. 1, 2, 3 and 4 are shown as an example of each of the signals used in this study.

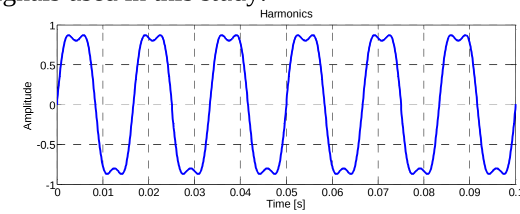

Fig. 1: Signals with Harmonics

To simulate the harmonics, use the IEC 61000-3-6 for the delineation of each component will be considered. An example of signal containing harmonics is shown in Fig. 1.

The simulated swell and sags phenomena, which set are the generation code , the duration of these at a random, more therefore variation ranges magnitude are set unit according to the above mentioned. In this way is presented in Fig. 2 and Fig. 3 sags and swells signals respectively.

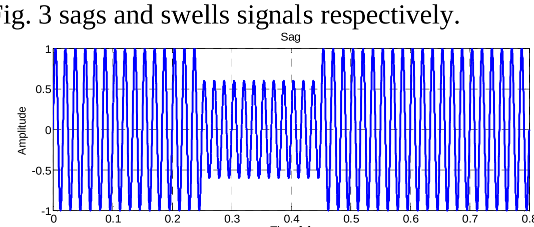

Fig. 2: Signals with Sags

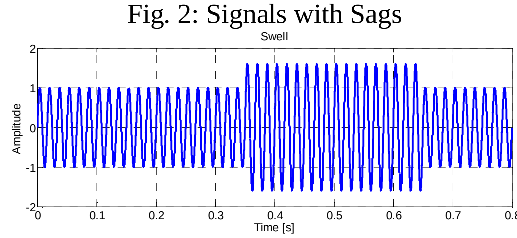

Fig. 3: Signals with Swell.

Flicker signals simulations are performed considering these signals described in Equation 2, as follows:

A = 1 p.u.
ω_0 = 60 Hz.
$u_{\Omega}(t)$: Used two modulating signals, a sine and a square wave are used.
M: Variable value between 0 and 1.0

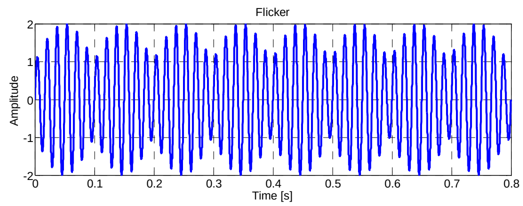

Fig. 4: Signals with Flicker

Furthermore, the Wavelet Transform is applied to each of the signals in order to obtain the detailed coefficients. Using the described technique in [15], which it is shown in equation 3:

$$dp(j)\% = \left[\frac{en_{dis(j)} - en_{ref(j)}}{en_{ref(7)}} \right] \cdot 100 \qquad (3)$$

Energy distribution of each of the decomposition levels and the signal are obtained, thus they can achieve characteristics for each of the kinds of signal patterns.

So in Fig. 5 can be seen the patterns of distribution of energy for harmonic signals, the signal are easily identified by having two peaks: one positive coefficient of detail 5 and a negative peak in the coefficient 7.

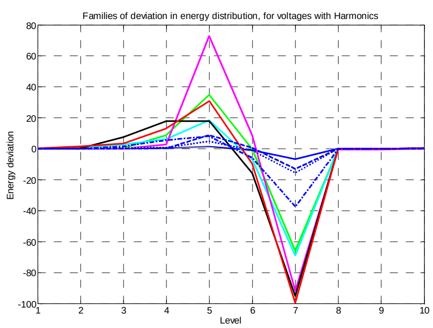

Fig. 5: Characteristic patterns – Harmonics

In Fig. 6 the patterns of energy distribution for signals with swell are shown, it can be seen that this signal has only one positive peak in the coefficient of detail 7, and can be presented in some samples showing this peak at level 6.

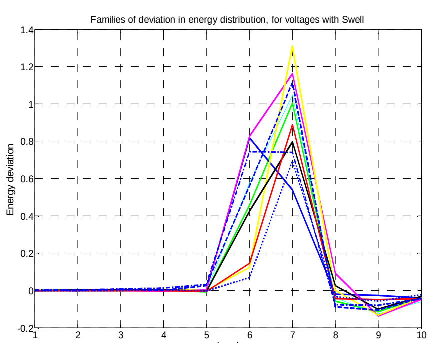

Fig. 6: Characteristic patterns – Swells

For the case of sags, characteristic patterns are shown in Fig. 7, for these it is seen that the peak in the coefficient of detail 7, in this case, is negative and is related to the source signal, instead of in swell, which is an elevation of the voltage level peak is positive and the sag which is a decrease of the voltage level peak is negative.

In Fig. 8 it can be seen the characteristic patterns of signal flicker, these patterns are the most complex than the previous since getting two positive peaks in the detail coefficients 6 and 8 and a negative peak pointer out in the coefficient 7.

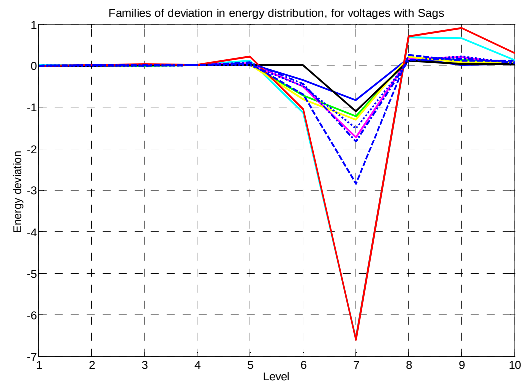

Fig. 7: Characteristic patterns - Sags

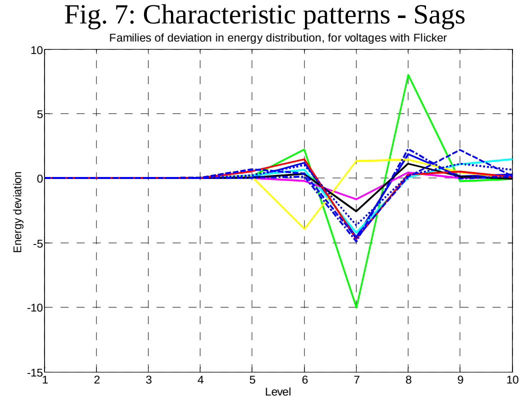

Fig. 8: Characteristic patterns – Flicker

5. Results

The patterns obtained by means of the equation 3 are the input data to the selected classifiers, therefore for the training of these 500 samples are used per class, for validation 200 and for the test 1000 samples are used per class.

5.1 Neural Networks

Multilayer Perceptron: For this case the neural network will have three layers, It has 10, 4 and 1 neuron in each layer.

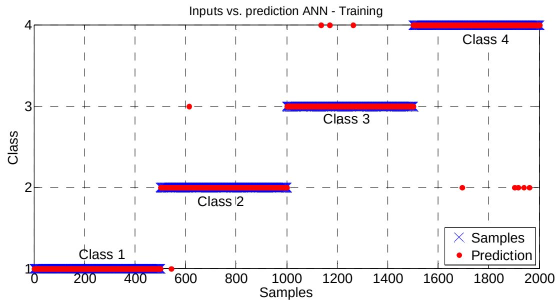

Fig. 9: Results MLP - Training

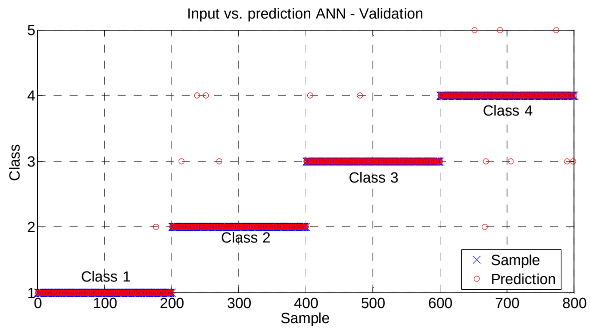

Fig. 10: Results MLP – Validation

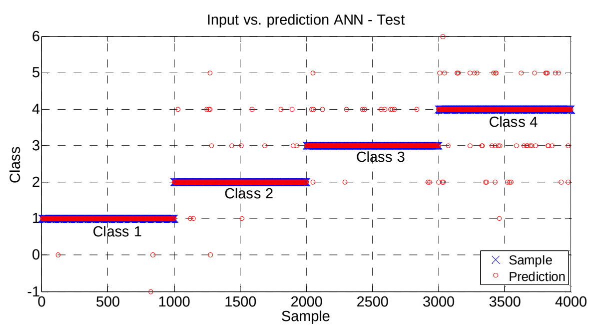

Fig. 11: Results MLP – Test.

5.2 SUPPORT VECTOR MACHINE

In Fig. 12 comparing the expected elements and predicted for training case are shown, also in Fig. 13 and Fig. 14 is presented the results for simulations of validation and test data are shown.

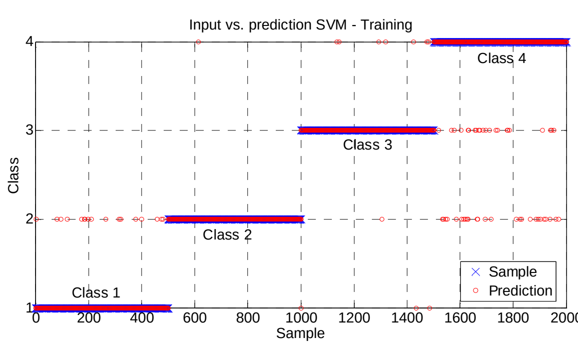

Fig. 12: SVM Results 1 - Training

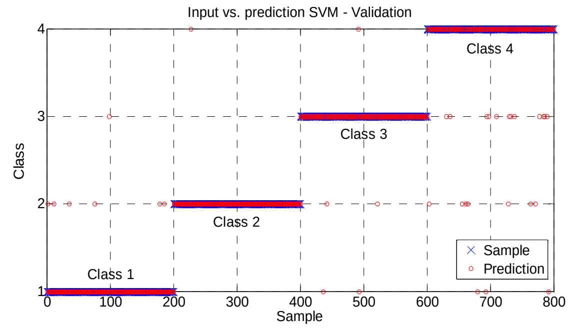

Fig. 13: SVM Results 1 – Validation

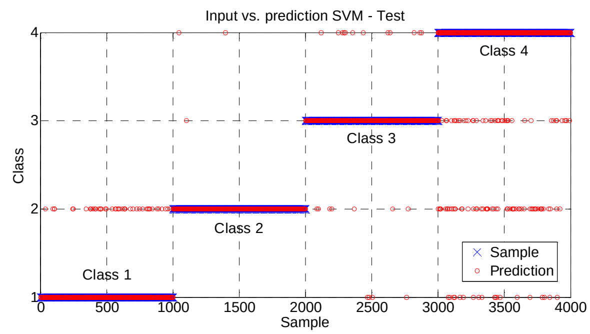

Fig. 14: SVM Results 1 – Test

5.3 Comparison of Errors

In Table 1 it can be appreciated that the network 1, in this case the multilayer perceptron, it is the simplest, the best results are presented in classes identification. Being the opposite case the radial network base, which has error 100% in the validation and testing, as it was previously earlier possibly due to overtraining. Moreover, in the case of SVM, the configuration that best results is presented using the Minimum Output Coding algorithm to decode the output and turn it into the required classes.

Table 2 the total errors of classifiers are shown , following Table 1, they were shown which are predictable that the neural network perceptron multilayer is even the one with the best results at the global level, even above any SVM of those were used to this work.

Table 1: Percentage of errors per class

Classifier	Harmonic	Swell	Sag	Flicker
1Newff Net	0.9	1.9	1.1	3.3
2Newrb Net	98.7	50.9	62.7	66.2
3Newcf Net	1.8	1.8	0.8	2.0
SVM 1	4.5	3.5	5.2	5.8
SVM 1 one vs. all	4.7	0.5	4.6	14.3
SVM 3 ECOC	5.7	0.4	2.5	14.4
SVM 4 MOC	3.8	0.5	2.3	11.1

Table 2: Percentage of Total Errors

Classifier	Training	Validation	Test	Total
1Newff Net	0.50	1.87	2.20	1.52
2Newrb Net	0.15	100	84.0	61.39
3Newcf Net	0.80	2.00	1.97	1.59
SVM 1	4.72	4.72	4.72	4.72
SVM 1 one vs. all	5.60	6.25	6.22	6.02
SVM 3 ECOC	4.95	6.00	5.50	5.48
SVM 4 MOC	4.00	4.37	4.80	4.39

6. **Quality Power (PQ) Index**

As it is mentioned in [16], [17], there are numerous indexes for each of the different phenomena affect the power quality, they are not related to each other , as for example , to keep in mind a signal present harmonics, it will be calculated the THD and another sign to show a swell and this will be determined using the variation of the amplitude or duration, there is no way , with only those values, to classify if it is the first or second signal the one presents the bigger affected. This whole process should have a number measures how close or far the signal is studied in reference to the pure sinusoidal signal, for which the index will score 0.0, and this becomes the reference, so the biggest, it is the general proposed index, it will be evidence that the signal in question is far from sinusoidal.

Thus by equation 4 defines the PQ index.

$$Index = \frac{\sum_{i=1}^{n} \left| E_{coefi} \right|}{n} \quad (4)$$

Where:

E_{coef_i} : Is the energy of the detail coefficient i.

Thus, the following results for 10 test signals are obtained. According to Fig. 15, we can deduce that the signal is 6, the lowest index, so it will be closer to the pure sinusoidal and instead of the signal 4 which presents a greater distortion. As it is shown in Fig. 16.

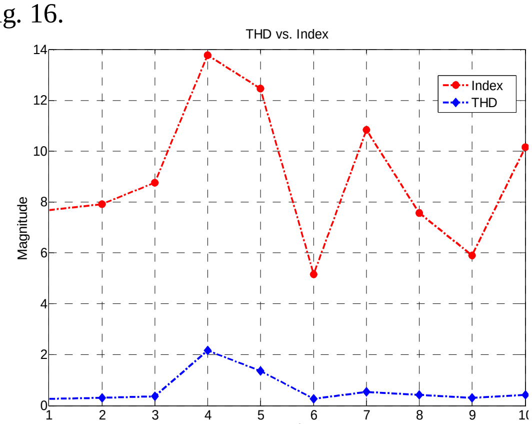

Fig. 15: Harmonic Parameters vs Index

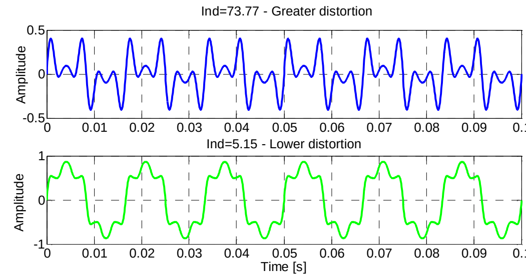

Fig. 16: Higher and lower harmonic distortion.

In Fig. 17 we see that the signal 1 is the lowest distortion index, while the signal 7 corresponds to the higher distortion, the difference between these signals can be seen in greater detail in Fig. 18, in this , it can be seen that while signal 1 neither amplitude variation nor shorter duration, if it has lower index, this is because this signal does not show changes, but a change smooth, opposite occurs in the signal 7, where you can see that there is an abrupt jump at the appearance of swell. These sudden changes cause an increase in the energy of the coefficients, and therefore also an increase in the general index.

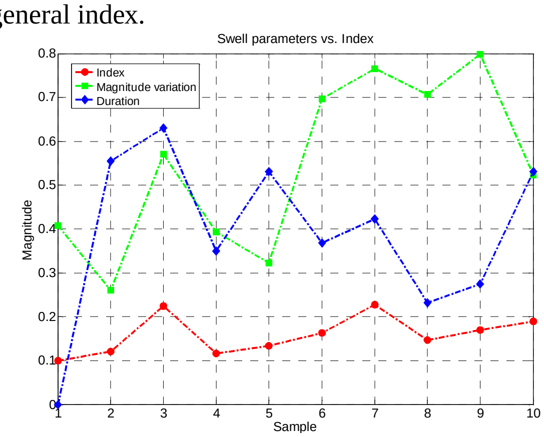

Fig. 17: Parameters vs Swell. Index

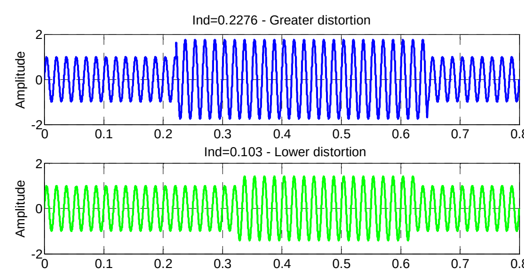

Fig. 18: greater than and less than– Swell

Likewise in Fig 19 is shown the relationship between the measurement parameters and the proposed sags general index is approximated to a linear relationship. We also can see the signal 5 has the greater degree of distortion, while the signal 9 has a lower index. In Fig. 20 can be seen in greater detail the greater and lower signals of distortion.

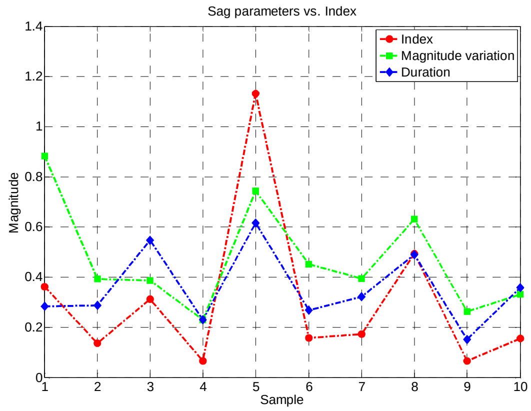

Fig. 19: Parameters Sag vs. Index

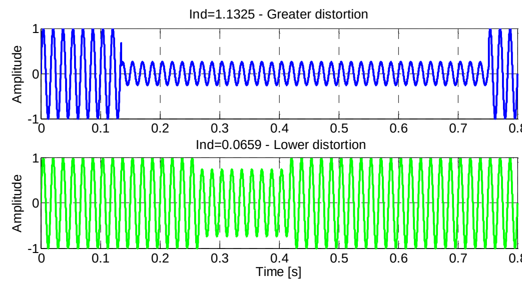

Fig. 20:– Greater and lower signals - Sag

In Fig. 21 the comparison between the index 100 signals sags and 100 signals swell are shown, they can be seen, the data are in the range 0.2 to 0.4, even with a small deviation, reaching the maximum index to a value close to 2.0.

Comparison between indexes of harmonics and flicker are shown in Fig. 22, these values are given in the sags and swell greater range, since the first harmonics and flickers have values between 0 and 18, the harmonics have higher display distortion, which is compared with the other three signals to other signals., they are more distant from the pure sinusoidal signal and on the contrary, the swell present s the lowest index general way.

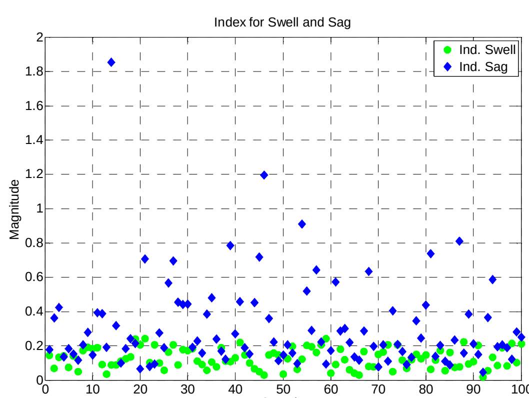

Fig. 21: Comparison Index - Swell and Sag

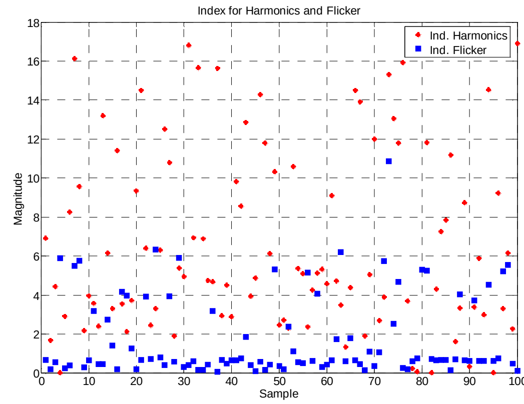

Fig. 22. Comparison Index - Swell and Sag

6. Conclusions

In this work the first 10 detail coefficients of wavelet transform since these allow obtaining different for each of the signal patterns are used. Also, the energy distribution of each of the coefficients can further differentiate patterns since otherwise they will have the same shape, with a peak in the coefficient of detail 7, in which the largest amount is presented energy.

In the group of neural networks, the best classifier was the multilayer perceptron, the simplest of the network analyzed in three steps, training, and validation and testing. For the case of Support Vectors Machine, the best performing configuration was presented Minimum Output Coding.

Mainly, the research conducted in the work it was identified the best classifier is undoubtedly the multilayer perceptron and having a percentage of total error of 1.52 %, followed closely by Cascade Forward Back propagation with an error of 1.59 %. Likewise, and as the main distinguishing feature of this work, a general Power Quality index for comparing all phenomena that disturb the signal , where the ideal value is zero , which is corresponding to the sine wave is established , this index in proportion to classical indexes of each of the disturbances being greater for the phenomena harmonics and flicker being greater magnitude, since these signals with respect to the greater distortion pure sine wave , on the contrary are the sags and swell those with lower index.

References:

[1] Venkatesh, C. et al. "Wavelet based modular neural network for power quality disturbance classification". *XXXII National Systems Conference*, NSC, Uttarakhand, India. 2008.

[2] Elango. M. K., et al. "Application of Neural Networks for Power Quality Disturbance Classification Using Hilbert Huang Transform". *European Journal of Scientific Research* [On line], Vol.47, No.3, 2010, pp. 442-454.
[3] Wijayakulasooriya, J. V. et al. "Electric power quality disturbance classification using self-adapting artificial neural networks", IEE Proceedings of Generation, Transmission and Distribution, Vol.149, No.1. 2002. pp. 98-101.
[4] Machado, R. N. M., Bezerra, U. H., Tostes, M. E. L., Freire S. C. F. and Meneses L. A. "Application of Wavelet Transform and Artificial Neural Network to Extract Power Quality Information from Voltage Oscillographic Signals in Electric Power Systems". *Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology*, Ed. InTech. 2012.
[5] Vega, V., et al. "Detección e identificación de eventos de la calidad de la Energía eléctrica utilizando la transformada Wavelet discreta y redes neuronales". *Revista UIS Ingenierías.* [On line]. 2006.
[6] Ajith, A. and Baikunth, N. Artificial neural networks for intelligent real time power quality monitoring system. [On line]. 56 (6). 2004.
[7] Resende, J. W. "Identification of power quality disturbances using the MATLAB® Wavelet Transform Toolbox". *International Conference on Power Systems Transients* (IPST). Rio de Janeiro, Brasil. Junio 24-28. 2001.
[8] Tovar, D. A. "Wavelet transform and support vector machines for the arrhythmia identification". *Revista de Investigación Universidad del Quindio*. 19 (10). Colombia. 2009.
[9] García, E. "Valoración de la Calidad de la Energía Eléctrica Respecto a Huecos de Tensión: Índices y Niveles de Calidad". Tesis Doctoral. Universidad Politécnica de Valencia. España. 2008
[10] Santafé G., P. "LSSVM aplicada en la estimación de la resistencia de rotor en motor de inducción Jaula de Ardilla". Tesis de Maestría. Universidad de Pamplona, Colombia. 2012.
[11] Saucedo, D. y Texis, J. "Factores que afectan la calidad de la energía y su solución". Tesis de Maestría. Escuela Superior de Ingeniería Mecánica y Eléctrica. México. 2008.
[12] Collombet, C., et al. Cuaderno Técnico No. 152: Los armónicos en las redes perturbadas y su tratamiento, Schneider Electric, enero, 2001.
[13] ECAMEC. Medición de Parámetros de Calidad de Energía bajo el estándar IEC61000-4-30. Primera parte. Medición de Flicker en redes eléctricas, ECAMEC Tecnología, abril, 2009.
[14] Pajares, G. Aprendizaje Automático. Ediciones de la U. Colombia. 2011.
[15] Jiménez, L. "Al Interior de una máquina de soporte vectorial". *Revista de Ciencias*, Universidad del Valle, Cali, Octubre, 2010.
[16] Navarrete Mejía, M. y Andrade Mora, S. Análisis y Tratamiento de la Señal Electrocardiográfica Para la Detección de Parámetros de Normalidad Bajo la Plataforma Labview "Adpan-Ecg" Universidad Pontifica Bolivariana – Colciencias. Bucaramanga. 2006.
[17] Suárez, J. A. Análisis de la distorsión armónica y los efectos de atenuación y diversidad en áreas residenciales. *IEEE Latin America Tansactions*. Vol. 3 No. 5. 2005.