International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-2, July 2019

Levenberg-Marquardt based MLP for Detection and Classification of Power Quality Disturbances

Serge Raoul Dzondé Naoussi, Jean Paul Ngon

Abstract: *In recent years, power quality (PQ) has become an important issue for utilities and users. In order to improve PQ, a method for detecting and classifying power quality disturbances (PQDs) is proposed. Hence in addition to identifying the disturbance signals, the proposed method is able to determine its type when occurring. This approach is based on Multilayer perceptron and Levenberg-Marquardt training rule. It is inspired by the desire to take advantage of the parallelism inherent to neural networks in view of hardware implementation using reconfigurable chips. The inputs of these networks are the samples obtained on the power grid in various conditions. The proposed method is tested for sags and swells. To classify the disturbances, the neural architectures have been generalized and configured according to the number and type of disturbances to be treated. To validate and test the proposal, a grid model was built with a three-phase fault generator under Matlab / Simulink R2017a. After comparing the results with those obtained by certain methods in the literature, the proposal proves to be an efficient and reliable tool for monitoring PQ. In fact it has the smallest mean square error and a highperformance with precision of 96%.*

Index terms: *electrical disturbances; Multilayer perceptron; Levenberg Marquardt algorithm, detection and classification*

I. INTRODUCTION

The proliferation of sensitive electronic equipment, besides the deregulation of the electric power industry, is making the quality of delivered power an increasingly important issue [1], [2]. Even in the domestic and public field there are several electrical disturbances which negatively diminish performance and lifetime of electrical equipments. Among these disturbances we find the voltage sag [3, 4], swell, transient oscillations and harmonics. In the interests of preventing malfunction and even destruction of electrical equipments, it is necessary to implement systems for compensating these disturbances. This can only be possible if we know their origins and if we are able to classify them accurately. Many disturbance classification techniques have already been implemented [4-8].

Revised Manuscript Received on 30 July 2019.
***** Correspondence Author
Serge Raoul Dzonde Naoussi*, Laboratory of Technology and Applied Sciences, University of Douala, Douala, Cameroon.
Jean Paul Ngon, Laboratoty of Electronics, Power Engineering, Automation and Telecommunication, University of Douala, Douala, Cameroon.

Although these efforts,there is still need of further research. Indeed there are several problems associated with modernpower systems, such as a massive proliferation of non-linear loads that generate harmonic contentand a distributed generation that produces intermittent and variable power [9].

These require both the development of new solutions to reduce their negative impact, such as active power filters, and the integration of energy storage, among others [10]. PQ monitoring systems should provide information on voltage and current waveforms for subsequent processing and analysis of measured signals [11]. For the latter, the proposal of efficient and reliable methodologies in terms of computing resources and performance, respectively, for detecting and classifying PQDs is desirable. Among the recent works, some methodologies for the identification of PQD emerge. Those based on signal processing techniques such as the Fourier transform (FT), the short-term Fourier transform (STFT) and the wavelet transform (WT) can be mentioned. FT is characterized by its ease of implementation, but lacks time-frequency localization capabilities and is not suitable for non-stationary disturbances [12]. STFT itself contains time and frequency information and can analyze non-stationary signals by sliding windows [13]. Nevertheless, this method is limited by the size of the sliding window used. Although the WT is capable of improving the time-frequency resolution for disturbance analysis [14], the analysis results may be affected by the noise present in the signal. Other methods for classification of disturbances use the Decision Tree (DT) and Artificial Neural Networks (ANN) [15]. DT is a decision support tool in the form of a tree graph used to derive classifications by describing relationships between different characteristics. This is how it has also been tested with encouraging results to recognize PQDs. However, this method generates cumulative errors in classifying all disturbances over the iterations. To overcome this, classifiers based on neural techniques have been widely used via a quick learning process without cumulative errors. In these algorithms, the training dataset,training algorithm, topology or structure (size, complexity, and elements), and designer expertise areissues that have a direct impact on their performance. Therefore, special attention and, sometimes,great effort, have to be applied in order to obtain a good enough performance.

Although neural classifiers require a great amount of dataset, they can be suitable for this task for they are faster and more accurate than many other methods. In this way a research opportunity can be highlighted, e.g.,development andapplication of low-complexity methodologies, and proposal of simplerclassification schemes.

In this paper, a neural approach for PQDs detection and classification, based multilayer perceptron (MLP) topology is investigated. It consists of a single hidden layer with an optimal number of neurons. The learning rule is based on the Levenberg-Marquardt algorithm.This approach intends to show the effectiveness and usefulness of the methodology for voltage sags and swells detection and classification even when they appear simultaneously. The theoretical background related on PQ monitoring, and MLPare primarily presentedin Section 2. Section3explains the proposed methodology based on Levenberg Marquardt learning algorithm (LM-MLP) for detection and classificationof PQDs. Finally, simulation results are presented in Section 4 and the ensuing discussion justifies the use of this method.

II. THEORETICAL BACKGROUND

In this section, theoretical aspects are presented respectively on the PQ monitoring and MLP neural networks driven by a Levenberg-Marquardt algorithm.

A. PQ Monitoring

PQ indices that meet the required standards can be used to illustrate the negative impact of electrical disturbances [16]. These disturbances correspond to significant variations in amplitude or RMS values of the currents or voltages relative to the nominal value during a time interval. The IEEE 1159 standard [17] and the European standard EN 50160 [18] categorize the aforementioned disturbances as indicated in Table I. On the other hand, the estimation of harmonics in a regulatory framework is carried out in accordance with the requirements of IEC 61000-4-7 [19]. The discrete Fourier transform of the current or voltage signals affected on the waveform is referred to within a rectangular window of length equal to 10 or 12 cycles for 50 Hz systems.

Table I: Power Quality disturbances

PQ disturbance	Duration	Values
Sag	> 0.5 cycles	0.1 to 0.9 p.u.
Swell	> 0.5 cycles	1.1 to 1.8 p.u.
Outage	> 0.5 cycles	< 0.1 p.u.
Flicker	-	0.9 to 1.1 p.u.
Harmonic	-	THD > 5%
Interharmonic	-	

B. The Multilayer Perceptron and Levenberg Marquardt training rule

The use of MLPs for solving some complex problems is not new today. It has been successfully applied several times through supervised learning with a very popular algorithm known as the error-forwarding algorithm. This algorithm is based on the error correction learning rule. Figure 1 shows a typical three-layer perceptron architecture. In order to avoid local minima and to have a stable network, we must pay attention to the choice of initial conditions for weights. Note that the number of neurons in the hidden layer is a significant problem. If it is too high, the learning error of the neural network is low, but there is a risk of over-learning. This means that we must choose an optimal number of neurons in the hidden layer to obtain a restricted architecture.

The Levenberg-marquardt training rule is based on the Newton algorithm given as follows:

$$W_{k+1} = W_k - H_k^{-1} g_k \qquad (1)$$

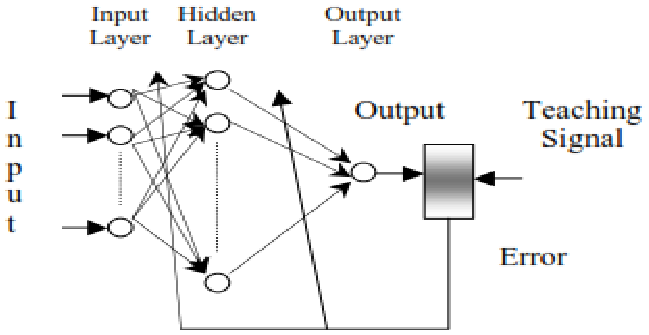


Fig. 1. A typical 3-layer Perceptron architecture

where W is the weights matrix, H is the Hessian matrix and g is the gradient. By choosing this method for weights updating, the calculation of the Hessian matrix requires a second derivative of the error function, which is complicated. Instead of calculating the matrix H,we introduce a new matrix called the Jacobian matrix J. Thus the Hessian matrix is replaced by the Jacobian matrix by the following relation known as Gauss-Newton:

$$H = J^T J \qquad (2)$$

The gradient g is calculated from the following relation:

$$g = J.e \qquad (3)$$

So the learning algorithm is given by the relation:

$$W_{k+1} = W_k - j^T j_k^{-1} j_k e_k \qquad (4)$$

However, the Gauss-Newton method is also faced with a difficulty like the Newton algorithm. For example, the convergence problem for a complex optimization of the error space. Mathematically, this problem is often due to the difficulty of inverting the matrix $J^T J$. Thus modifications have been made to the Gauss-Newton algorithm to overcome the previous problem from which we arrived at the Levenberg-Marquadt algorithm. To allow inversion of the matrix $J^T J$, an approximation is then performed as follows

$$H \approx J^T J + \mu I \qquad (5)$$

where μ is a combination coefficient always positive. I is the identity matrix. Thus the learning rule forweights modification becomes:

$$W_{k+1} = W_k - j^T j_k^{-1} + I^{-1} j_k e_k \qquad (6)$$

III. PROPOSED METHODOLOGY

A. The power grid model

Detection and classification of power disturbances, based on neural networks, is carried out by considering the scheme of fig. 2. The combination of several PQDs can be performed by adding the desired disturbances at a specific time. Their propagation on the network will cause a disruption in the three-phase load. The RMS voltage values across the load will be used as dataset input for the neural networks to detect the presence of distortion. The characteristics of the electrical system used to simulate sags and swells are summarized in Table II.In case of a fault between phase A and the ground, under the parameters of table III, we obtain the results

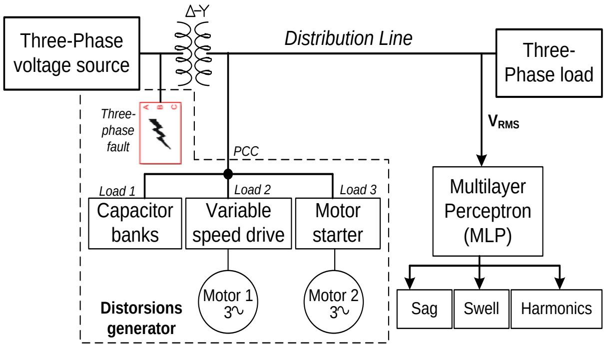


Fig.2. Electric circuit to generate PQ disturbances

Table II: power grid parameters

Parameter	Value
Three-phase voltage source	15kV, 30MVA
Transformer :	15kV/400V
Load voltage nominal value	400V
Active power	0,05KW
Reactive power	0,02 KVAR

Table III: Parameters during generation of a single-phase fault

Fault between:

☑ Phase A ☐ Phase B ☐ Phase C ☑ Ground

Switching times (s):	[0.1 0.168] ☐ External
Fault resistance Ron (Ohm):	0.5
Ground resistance Rg (Ohm):	1
Snubber resistance Rs (Ohm):	1e6
Snubber capacitance Cs (F):	inf

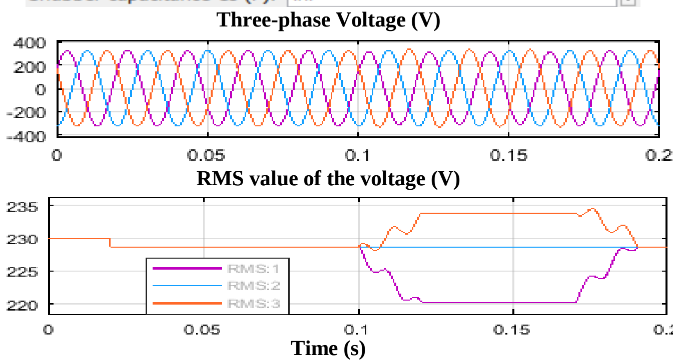


Fig. 3. Short-circuit between phase A and the ground from 0.1 to 0.168s

presented on fig. 3.In case of generation of a short circuit between phases A and B the results is presented in fig. 4.

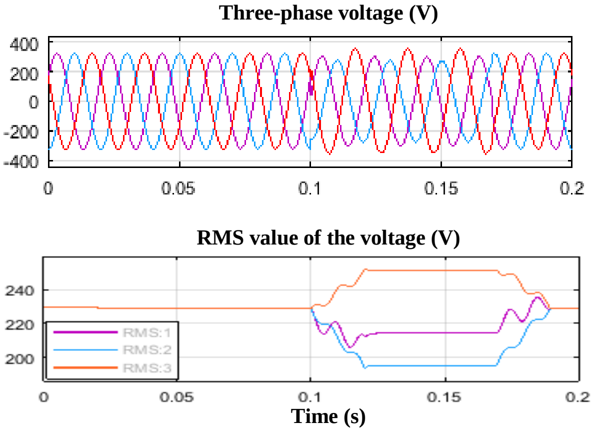


Fig. 4. Short-circuit between phases A and B from 0.1 to 0.168s

While starting a squirrel motor from 0.1 to 0.15s with the parameters presented in table IV, the results of fig.5 are then obtained. Considering sag generation between 0.1s and 0.3s presented

Table IV: Parameters of the connected squirrel motor

Nominal power, voltage (line-line), and frequency [Pn(VA),Vn(Vrms),fn(Hz)]:	[75000 400 50]
Stator resistance and inductance[Rs(ohm) Lls(H)]:	[1.405 0.005839]
Rotor resistance and inductance [Rr'(ohm) Llr'(H)]:	[1.395 0.005839]
Mutual inductance Lm (H):	0.1722
Pole pairs p ():	4

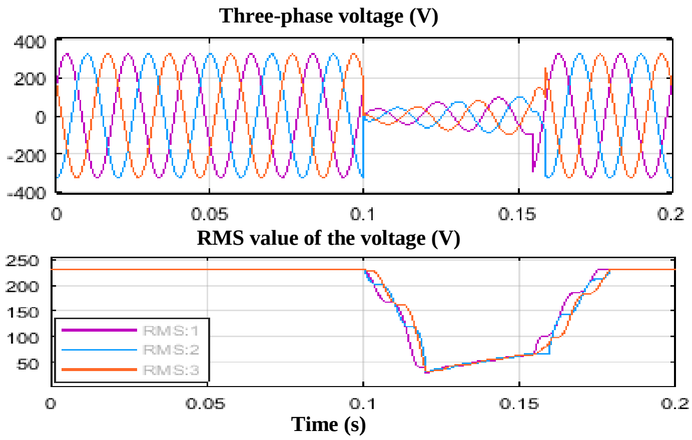
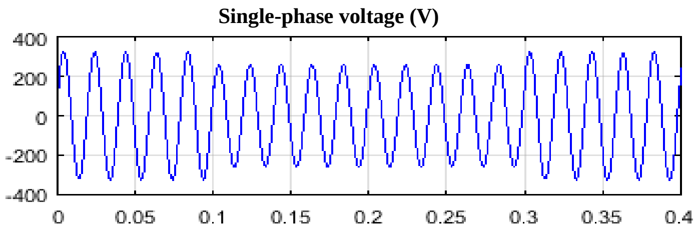


Fig.5. Starting of a squirrel cage asynchronous motor from 0.1 to 0.15s



RMS Single-phase voltage (V)

Retrieval Number: A2227058119/19©BEIESP
DOI: 10.35940/ijrte.A2227.078219
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

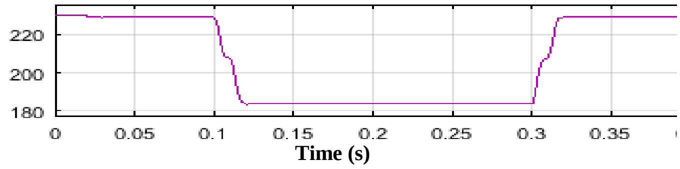


Fig.6. Sag simulation from 0.1 to 0.3s: a) voltage waveform, b) voltage RMS value in sag condition

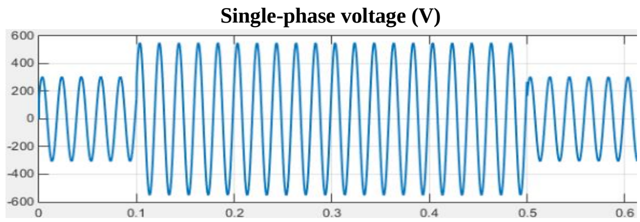


Fig.7. Swell simulation between 0.1 and 0.3s

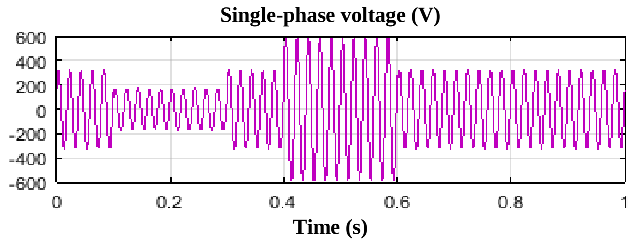


Fig.8. Sag from 0.1 to 0.3s combined with swell simulation between 0.4 and 0.6s

in fig. 6, the voltage waveform and acase of RMS voltage value during this condition are shown. This reveals that the sag issetat 0.47p.u of the nominal value of 230V. In fig. 7, a short swell also generated with a magnitude of 1.8 p.u. of the nominal value, is shown. Later on, both distortions appearing together are presentedin fig 8.

B. Methodology of detection of electrical disturbances

Figure 9 presents the architecture of the neural network. A process input for the learning data, two hidden layers of which the first has 20 neurons and the second a neuron for the output. Block 'W' contains the different weights of said layer; while block 'b' contains network biases. All elements are added and transferred to the sigmoidal tangent activation function. The obtained values are retrieved from the block a{1} and transferred to thesecond layer. The data arriving at layer 2 passes through the weights block LW {2,1}. By addition with the biases of layer 2 (block b {2}), the data will travel through the linear activation function of the output layer before being available at the process output.

In this paper, the learning process of the MLP involves generating the learning data, determining the size of the network, choosing the algorithm and analyzing its performance. The deployment of the neural network is done under Matlab/Simulink R2017a installed on a computer with a Windows 8.1 professional 64-bit, a 4GB RAM and INTEL core processor i5 2.53GHz. The learning dataset was generated from an electrical distribution model. 500 samples of voltage sags and swells are thus acquired, respectively. The neuron output is set at one if one or more disturbances exist and to zero when there is no disturbance. 60% of the input samples are used for learning, i.e. 300 samples. Determining the size of the proper network is very important in order to reduce the learning time and for better resolution of the given problem. However, there is no mathematical relationship to determine the number of layers and the number of neurons per hidden layer. Thus, we carried out several simulations to choose its optimal structure. For

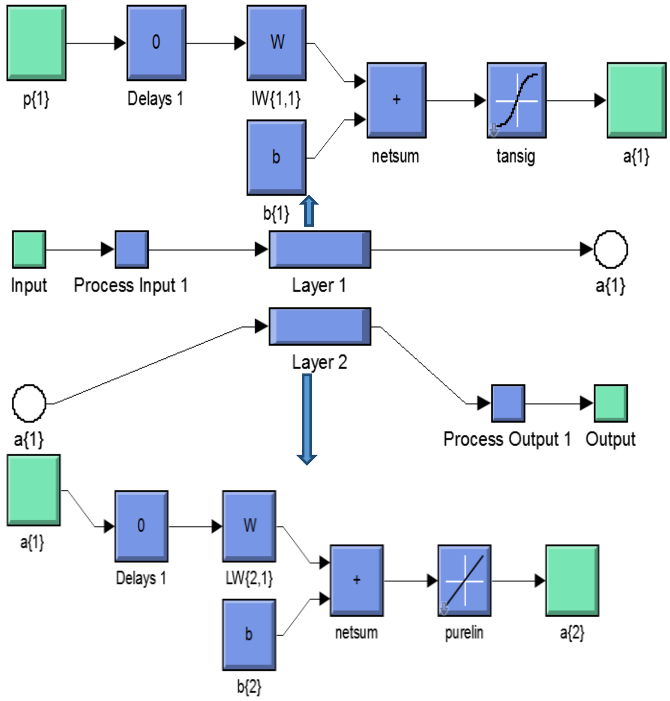


Fig. 9. Neural network deployed under Simulink

validation and testing of the neural network we used 20% of the samples. The learning performance of the ANN is based on the observation of the mean square error between the observed and desired outputs, in order to measure its ability to detect and classify combined disturbances (voltage sags and swell). The learning process ends when the value of the error is low enough. The results were obtained for a neural network with three layers and 20 neurons in the hidden layer. At first, it will be a question of observing the performances of the neural network in the detection of simple faults, the voltage sag and then the swell. Thereafter we will observe its ability to detect and classify combined disturbances. In figure 10, is presented the architecture of the neural network, with one neuron in the input layer, 20 neurons in the hidden layer with the sigmoidal tangent as activation function, an output neuron with a linear activation function. The learning algorithm is that of Levenberg-Marquardt and the criterion of performance is the mean squared error (MSE).The performance evaluation is presented in fig. 11, where the learning process, the validation process and the test process are indicated. The horizontal dotted line represents the best approximation for the learning process. As soon as the validation curve touches this line, the learning ends at the fifth iteration with a MSE of 9.5319×10^{-12}. This reflects a rapid learning of the neural network and a better approximation of the desired outputs. Similarly, in the case of the detection of swells, we kept the same neural network architecture. The learning process stopped after 5 iterations with an average squared error of 9.2672×10^{-13}. This means that the chosen Levenberg-Marquardt algorithm allows quick learning for the neural network and also ensures a better convergence.

IV. RESULTS AND DISCUSSION

In this study, in order to test the PQ events, a balanced distribution system, presented in fig 12 is considered. The original system consists of 15KV/50Hz power source, a 15KV/400V, 1MVA transformer and a three-phase RLC load of 400V/50Hz with 50W of active power and 20VAR of inductive reactive power

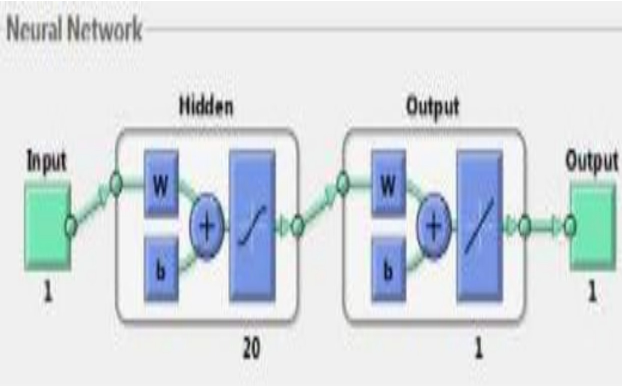


Fig. 10. Network Architecture for Voltage sag Detection

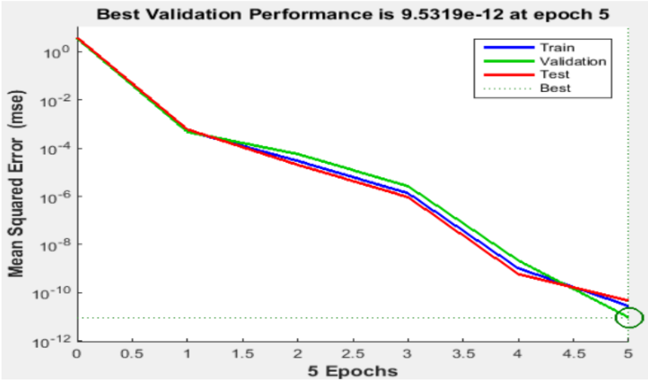


Fig. 11 Network performance for voltage dip detection

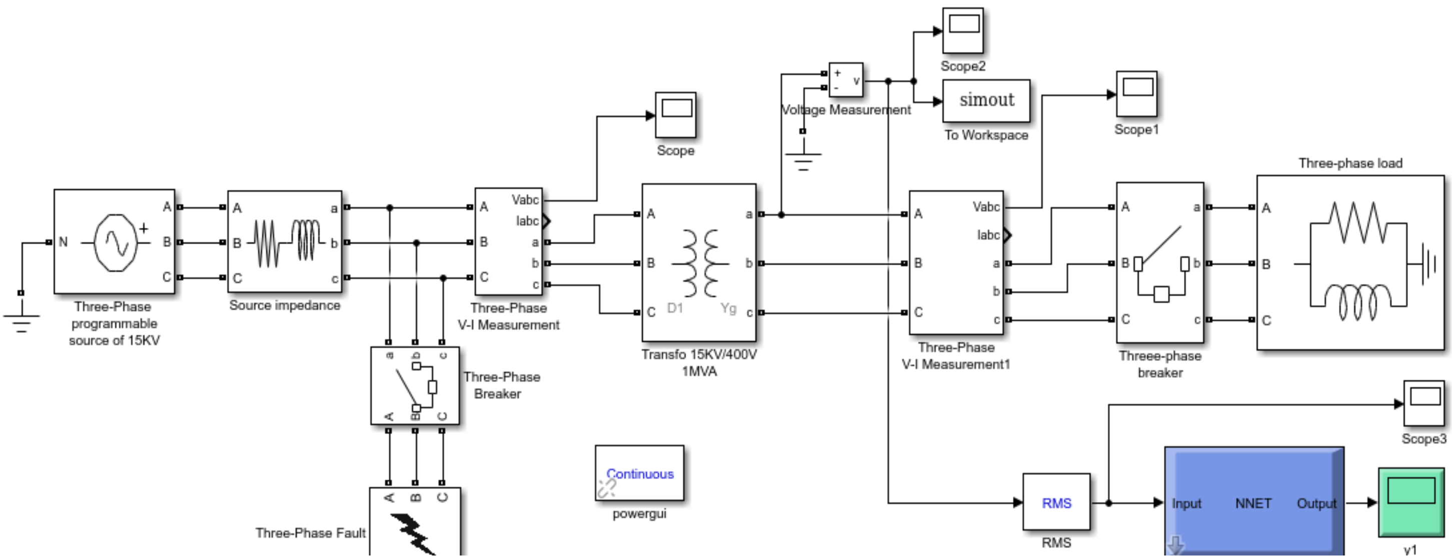
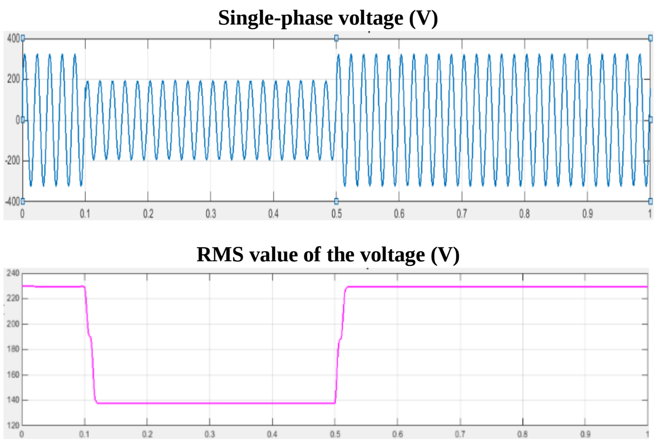
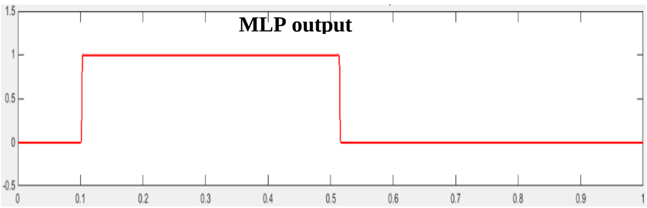


Fig. 12 Network performance for voltage dip detection

A. *Detection of sags and swells*

The first electrical disturbance analyzed is the voltage sag. It was generatedat a depth of 60% of the rated voltage (230V) on phase A and over a periodfrom 0.1s to 0.5s as shown in fig. 13. This figure presents the sinusoidal waveform of the voltage on phase A, its RMS value and the MLP output respectively. The ANN output indicates with level “1” the disturbance occurrence. It returns to “0” as soon as the voltage sag disappears. The second electrical disturbance analyzed is a swell, generated at 180% of the nominal value (230V) of the voltage of phase A over a duration from 0.1s to 0.5s. The results are shown in fig. 14. The sinusoidal voltage waveform, its RMS value and the ANN output are also shown. The overvoltage reaches a value of 414 V on the same phase over the interval 0.1s to 0.5s. In this figure, we can clearly observe the transition of the neural output to “1” in





Time (s)

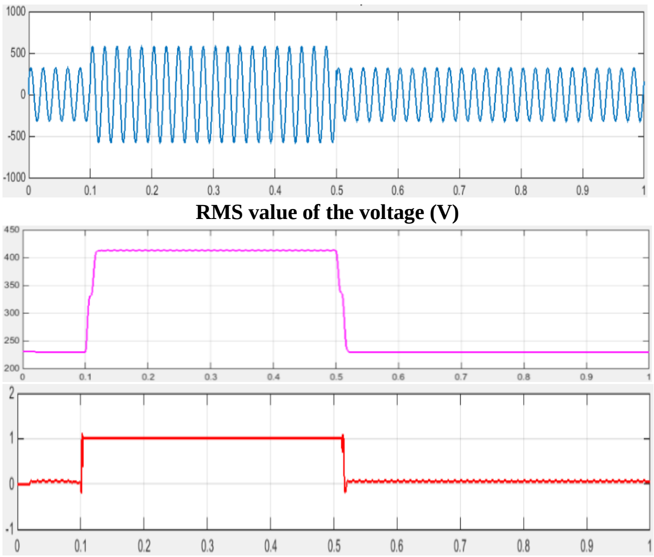
Figure 13. Detection of a voltage dip on phase A

the presence of the disturbance and its returning to "0" as soon as it disappears.

B. Classification of electrical disturbances

In this section, the performance of the LM-MLP used for the detection and classification of combined disturbances is evaluated. The input vector for the neural network has a dataset of 1000 samples in which we find the amplitudes for voltage sag, swell and normal voltage generated from the power grid. The neural network made up of two similar architectures for sag/swell detection, will then have two outputs for the voltage sag and swell respectively. The desired values at the output of the neural networks are "1" for both types of disturbances and "0" for the normal signal (voltage at 230V RMS).

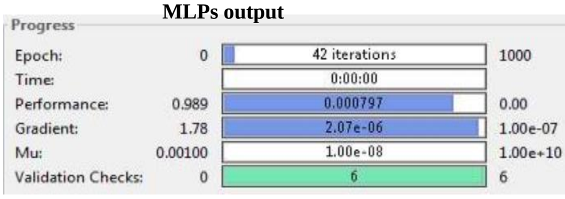
In the same way, 60% of the input samples are been used for the learning process, 20% is for the validation process and the remaining 20% for the test process. After multiple simulation operations, we came to a 3-layer neural network



Time (s)

Figure 14: Swell detection on phase A

MLPs output



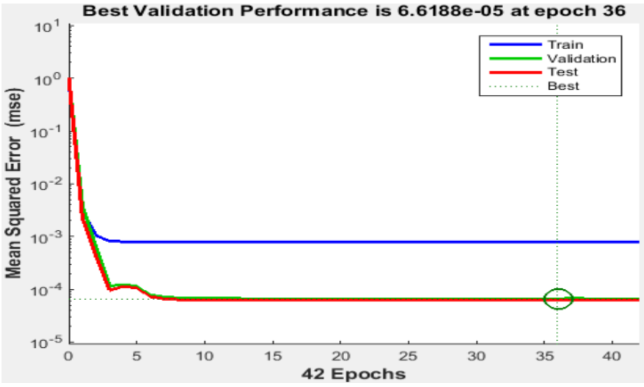
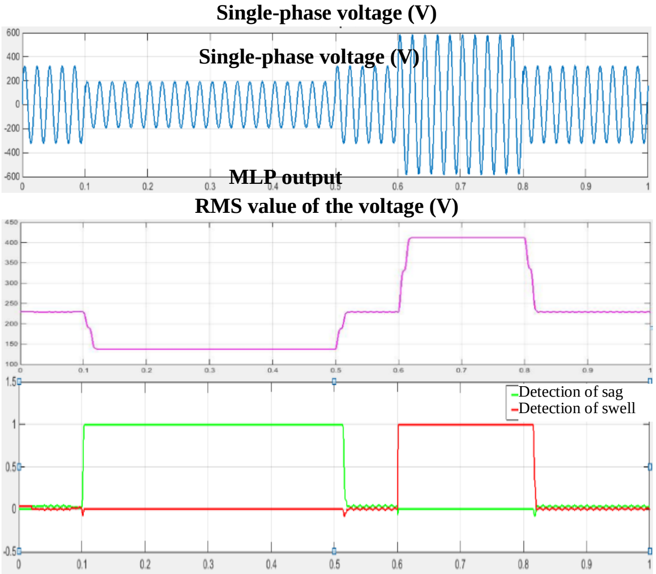


Figure 15: Network Performance for sag and swell detection and classification

having 20 neurons on the hidden layer, providing better performance. The learning process stops at 36 iterations with a MSE at 6.6188e-5 s. The increase in the number of iteration compared to the number of iteration (05 iterations) obtained in the detection of simple perturbations is due to the presence of a larger learning data (1000 samples).

After the learning phase, from a distribution model in Simulink, we generated on phase A, a signal having a normal voltage of 230V RMS, a voltage sag in the interval 0.1s to 0.5s whose depth is 60% of the nominal value and a short swell between 0.6 and 0.8 rising to a level of 180% of the nominal value. The outputs of the neural networks are shown in Figure 16. As we have said a little more high, the desired network outputs are "1" for voltage sag / swell and "0" in the absence of perturbation. The analyzed instantaneous voltage on phase A,its RMS value and the ANN outputs are then shown respectively. As observed, the voltage sag appears from 0.1s to 0.5s and the swell between 0.6s to 0.8s. This

Single-phase voltage (V)



Time (s)

Figure 16: Detection and classification of voltage sag and swell on phase A

reflects a good classification of the voltage sag and swell by the neural network.

International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-2, July 2019

On the other hand, Table IV shows a comparison between the obtained results in this paper and other research studies reported in [20]. The other methods are defined as follows:

- SCGB: scaled conjugate gradient descent,
- RB: resilient backpropagation,
- OSS: one step secant (OSS).

Table IV: Performance comparison in terms of percentage of correct classification results

Algorithms	Parameters			
	No. of neurons in the hidden layer	Epochs	MSE in training set	Percent of accurate cases
SCGB	20	40	$2.59*2^{-5}$	98
LM	20	329	0.00891	84
BR	20	1000	0.013254	74
OSS	100	132	0.03367	63
LM-MLP	20	36	6.6188*10-5	96

As shown in the table, the proposed method offers the smallest MSE and 96% of accurate cases, quite close to 98% obtained for the SCGB. The detection and classification of voltage sags and swells are effective. Therefore,the proposed neural network provides a better performance.

V. CONCLUSION

This study successfully presented the application of the LM-MLP approach for the detection and classification of power quality disturbances as sags and swells, as well as its comparison with some other backpropagation algorithms. The comparative study is made according to criteria such as the number of neurons, the number of epochs, the mean squared error and the percentage of accurate cases. The data set for the neural networks was realized using generated sag / swell signals. Some are used for the learning process and others for the tests. Learning performance and test results are tabulated and presented. The comparison shows that the proposed Levenberg-Marquardt multilayer perceptron is the best choice for detecting and classifying energy quality disturbances especially in terms of mean square errors, number of epochs and particularly the accuracy.

REFERENCES

1. R. C. Dugan, M. F. McGranaghan, and H. W. Beaty, Electric Power Systems Quality, McGraw-Hill, 1996.
2. M. H. J. Bollen, Understanding Power Quality Problems Voltage Sags and Interruptions, IEEE Press, 2000.
3. E. Arrais ; V. O. Roda ; C. M. S. Neto ; R. L. A. Ribeiro ; F. B. Costa, FPGA versus DSP for Wavelet transform based Voltage Sags detection, in Proc. Of the IEEE International Instrumentation and Measurement Technology Conference (I2MTC) , 12-15 May 2014
4. J. de J. Rangel-Magdaleno, M. Valtierra-Rodriguez, J. P. Amezquita-Sanchez , D. Granados-Lieberman, J. F. Gomez-Aguilar, J. R. Razo-Hernandez, Homogeneity-PMU-Based Method for Detection and Classification of Power Quality Disturbances, electronics, 2018, 7, 433 pp 1-13
5. M. Valtierra-Rodriguez, R. de J. Romero-Troncoso, R. A. Osornio-Rios, A. Garcia-Perez, Detection and Classification of Single and CombinedPower Quality Disturbances Using Neural Networks, IEEE Transactions On Industrial Electronics, Vol. 61, No. 5, May 2014
6. Granados, D.; Romero, R.; Osornio, A.; Garcia, A.; Cabal, E. Techniques and methodologies for power quality analysis and disturbances classification in power systems: A review. IET Gener. Transm. Distrib. 2011, 5, 519–529
7. Khokhar, S.; Zin, A.; Mokhtar, A.; Pesaran, M. A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances. Renew. Sustain. Energy Rev. 2015, 51, 1650–1663.
8. Mahela, O.; Shaik, A.; Gupta, N. A critical review of detection and classification of power quality events. Renew. Sustain. Energy Rev. 2015, 41, 495–505.
9. Alhelou, H.; Hamedani-Golshan, M.E.; Zamani, R.; Heydarian-Forushani, E.; Siano, P. Challenges and Opportunities of Load Frequency Control in Conventional, Modern and Future Smart Power Systems: A Comprehensive Review. Energies 2018, 11, 2497.
10. Alhelou, H.H.; Golshan, M.H.; Askari-Marnani, J. Robust sensor fault detection and isolation scheme for interconnected smart power systems in presence of RER and EVs using unknown input observer. Int. Electr. Power Energy Syst. 2018, 99, 682–694.
11. Bollen, M.; Gu, I. Signal Processing of Power Quality Disturbances, 1st ed.; John Wiley & Sons: Hoboken, NJ,USA, 2006; ISBN 13.
12. Heydt, G.T.; Fjeld, P.S.; Liu, C.C.; Pierce, D.; Tu, L.; Hensley, G. Applications of the windowed FFT to electricpower quality assessment. IEEE Trans. Power Deliv. 1999, 14, 1411–1416.
13. Santoso, S.; Grady, W.M.; Powers, E.J.; Lamoree, J.; Bhatt, S.C. Characterization of distribution power qualityevents with Fourier and wavelet transforms. IEEE Trans. Power Deliv. 2000, 15, 247–254.
14. Barros, J.; Diego, R.I.; Apráiz, M. Applications of wavelets in electric power quality: Voltage events. Electr. Power Syst. Res. 2012, 88, 130–136.
15. Zhao, C.; Li, K.C.; Li, Y.Z.; Wang, L.Y.; Luo, Y.; Xu, X.B.; Ding, X.J.; Meng, Q.X. Novel method based onvariational mode decomposition and a random discriminative projectionextreme learning machine formultiple power quality disturbance recognition. IEEE Trans. Ind. Inform. 2018.
16. R. C. Dougan, M. F. McGranagham, S. Santoso, and H. W. Beaty, Electrical Power Systems Quality, 2nd ed. New York, NY, USA: McGraw-Hill, 2004.
17. IEEE Recommended Practices for Monitoring Electric Power Quality, IEEE Std. 1159-2009, 2009.
18. [18] Voltage Characteristics of Electricity Supplied by Public Distribution Systems, Eur. Std. EN 50160, 2002.
19. Electromagnetic Compatibility (EMC) Part 4–7: Testing and Measurement Techniques-General Guide on Harmonics and Interharmonics Measurements and Instrumentation, for Power Supply Systems and Equipment Connected Thereto, IEC Std. 61000-4-7, 2002.
20. Chetan B. Khadse, Madhuri A. Chaudhari, Vijay B. Borghate «Comparison of seven backpropagation algorithms for three phase power quality assessment», TENCON - IEEE Region 10 Conference 5-8 Nov. 2017

AUTHORS PROFILE

Serge Raoul DZONDE NAOUSSI is born in 1971 at Mbo'o (Cameroon). He received the M.Sc. degree from the National Advanced School of Engineering of Yaoundé, Cameroon, and the Ph.D. degree in microelectronics from the University of Strasbourg, France in 1994 and 2011, respectively. Since 2011, he has been with the LTSA Laboratory, University of Douala, where he is a Senior Lecturer. His current research interests are adaptive control systems, FPGA implementation and renewable energy. His research works also include artificial neural networks applied to harmonic compensation and active power filters

Jean Paul Ngon is born in 1987 in Cameroon. He received the M.Sc. degree from the Postgraduate school for pure and applied sciences of the University of Douala, Cameroon in 2016. He is also graduate from the high school teacher of technical education and is actually working at the Ministry of Employment and Vocational Training, Douala, Cameroon. For few years, he has been with Laboratory of Electronics, Power Engineering, Automation and Telecommunication (LEEAT), University of Douala. His current research interests is Automation and control in power systems.