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Analysis of Power Quality Based on Machine Learning Methods for Low-Voltage Electrical Distribution Lines

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Abstract: *The main objective of this paper is to propose two innovative monitoring methods for electrical disturbances in low-voltage networks. The two approaches present a focus on the classification of voltage signals in the frequency domain using machine learning techniques. The first technique proposed here uses the Fourier transform (FT) of the voltage waveform and classifies the corresponding complex coefficients through a multilayered neural network with multivalve neurons (MLMVN). In this case, the classifier structure has three layers and a small number of neurons in the hidden layer. This allows complex-valued inputs to be processed without the need for pre-coding, thus reducing computational cost and keeping training time short. The second technique involves these of the short-time Fourier transform (STFT) and a convolution neural network (CNN) with 2Dconvolutions in each layer for feature extraction and dimensionality reduction. The voltage waveform perturbations taken into consideration are: voltage sag, voltage swell, harmonic pollution, voltage notch, and interruption. The comparison between the two proposed techniques is developed in two phases: initially, the simulated data used during the training phase are considered and, subsequently, various experimental measurements are processed, obtained both through an artificial disturbance generator and through a variable load. The two techniques represent an innovative approach to this problem and guarantee excellent classification results.*

Keywords: convolution neural networks; electrical disturbances; short-time Fourier transform; multilayer neural networks with multivalve neurons; power quality.

I. INTRODUCTION

Power quality is a significant issue due to the increasing presence of nonlinear loads in power systems. For example, as shown in [1,2], electric vehicle charging stations and renewable energy production systems highly affect the power quality of the grid. Since these sectors are rapidly growing to contain the greenhouse gasses emission, several efforts have been made to minimize the impact of these power quality disturbances (PQDs).The fast and automatic classification of PQDs allows for properly taking counter measures to be able to maintain the stability of the grid, avoiding plant shutdowns and economic losses.TheEN50160[3],IEC61000[4],andIEEE-1159[5] standards provide a detailed description of all PQDs. A graphical representation is shown in Figure 1, while the main characteristics are summarized in Table 1.Several papers related to PQD detection and identification are available in the literature. A summary is shown in Table 2, where the type of identified disturbances and a brief description of the implemented technique is described. The identification process of the disturbances consists of the extraction of parameters by applying a

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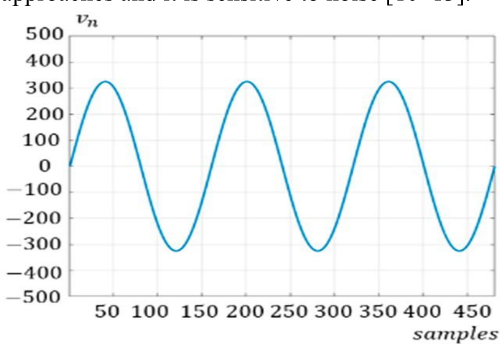
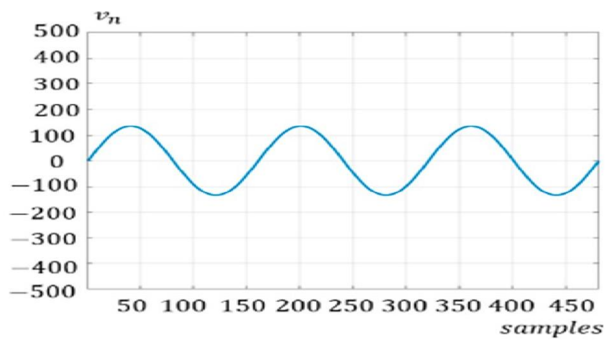
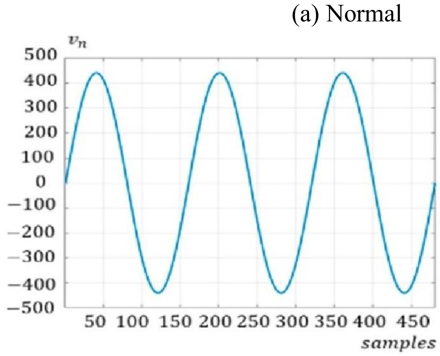
particular signal processing technique and then performing the classifications. The Fourier transform (FT) is the simplest technique for feature extraction from the sampled signal [6].This is a powerful technique for periodic time series where the characteristics of the signal do not change with time [7].In practice, the disturbances lead to non stationary signals. To overcome this issue, short-time Fourier transform (STFT) was used, introducing a sliding window to obtain time and frequency information [8]. Alternative techniques are based on Wavelet transform (WT). In this method, the sampling window is changed depending on the frequency content of the signal [9]. A short window is used for high frequencies, while a long window is used at low frequencies. This window adaptation makes this technique particularly suitable for monitoring transient behaviour and discontinuities in the signal, but it is more complex than FT base approaches and it is sensitive to noise [10–13].



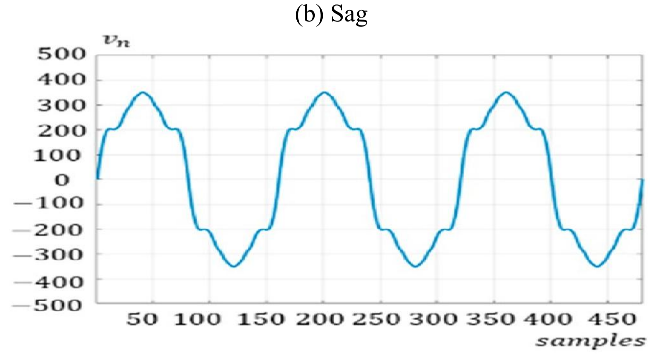
(a) Normal



(b) Sag



(c) Swell



(d) Harmonics

To improve the noise incentive, the S-transform (ST) technique was developed. Al- though this technique overcomes the limitations of FT, STFT, and WT, its adoption is limited due to high computational costs [14]. Additional techniques have been proposed over the years based on statistical approaches [15–18] or by including machine learning for feature extraction [19,20]

II. MACHINE LEARNING TECHNIQUES

This section presents the main theoretical aspects of the two proposed classifiers and highlights the characteristics of the learning procedures. The MLMVN employed here contains three layers and allows the use of a reduced number of neurons in a single hidden layer, thus speeding up the learning phase and limiting the computational cost. Thanks to its complex nature, it can be easily used in the solution of electrical problems, where all quantities are expressed by phasors. The CNN in this paper is used in conjunction with the STFT to convert the 1D signal into a 2D matrix and extract its time–frequency components as in [29]. Additionally, this is done so the signal can be treated as an image, to exploit the feature extraction capabilities of this architecture and obtain the desired results. Furthermore, in many recent applications, CNNs are used in real time to classify signals of different natures [30], diagnose faults in various electrical machines [31], and predict the evolution of numerous systems and electrical quantities [32].

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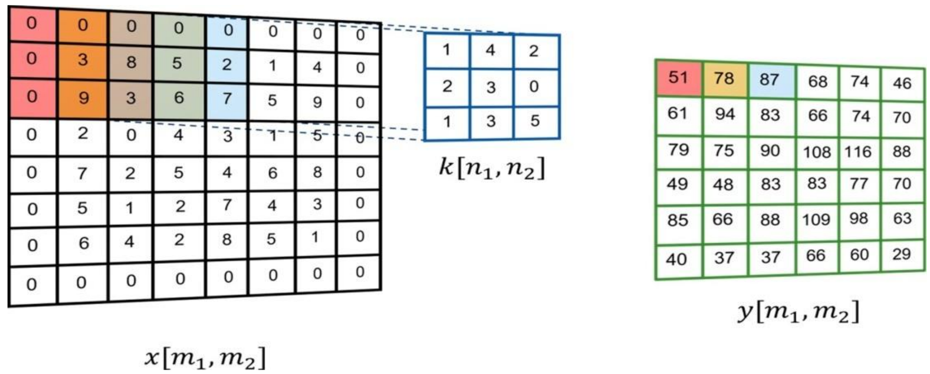
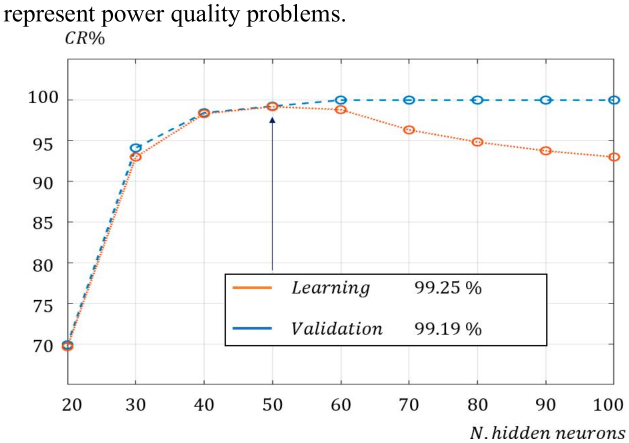


Fig: Convolutional layer example where x is the input, k is the kernel, and y is the output.

III. TRAINING RESULTS

This section presents the main results obtained during the training phase of the machine learning techniques described above. The data used during the training phase was generated by a simulation procedure on Matlab and Simulink environments. Therefore, a Matlab script was used to create a large variability in electrical disturbances in a very short time, starting from the sinusoidal function of the line voltage, which is characterized by a frequency of (50 Hz ±0.2%) and a root mean square value of 230 V. The amplitude and the frequency components of these signals were modified to create all the different disturbances following the formal definitions presented in Section 1.Starting from the normal sinusoidal signal shown in Figure 1a, the value of the maximum amplitude was chosen randomly in the interval (23 ÷207) V to simulate the presence of a voltage sag. This problem, in fact, causes a reduction in the phase voltage between 10% and 90% of the nominal value. Similarly, examples of voltages well were created by considering increases in the maximum amplitude from 10% to 50% of the nominal value. As for the harmonic disturbances, signals with frequencies multiple of the fundamental frequency (50 Hz) were generated up to the eleventh harmonic and then added to the line voltage. Notch is a condition when the magnitude of voltage decreases towards zero for a short period of time, usually microseconds. This condition was simulated in Matlab by adding impulsive components at specific instants of the nominal voltage waveform. Finally, interruptions were simulated by reducing the maximum voltage value below10%ofthenominalvalue. Note that the voltage frequency variations considered acceptable by the technical standard CEIEN50160 were included in the formation of the dataset, and this means that the classifiers are robust with respect to these perturbations, which do not represent power quality problems classifiers are robust with respect to these perturbations, which do not represent power quality problems.



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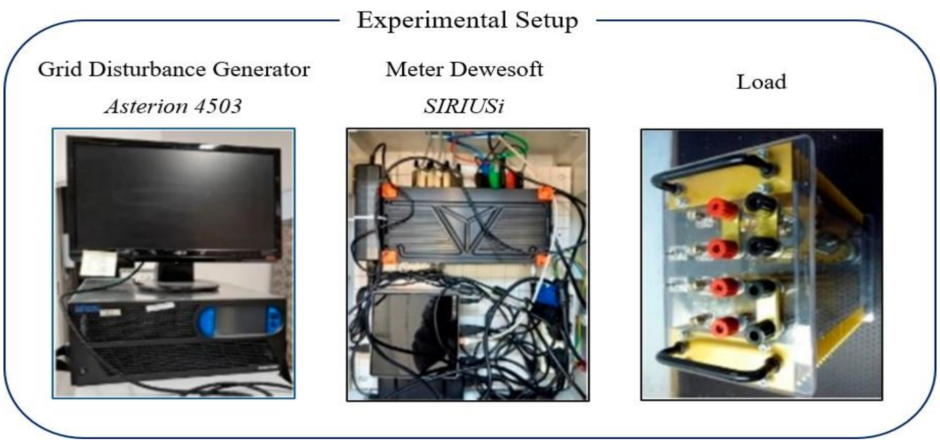
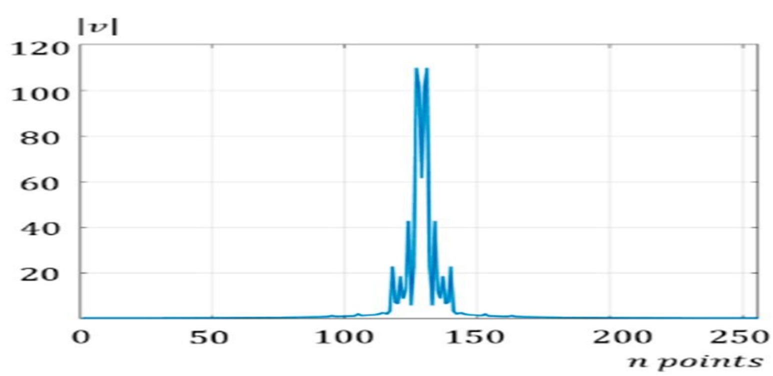
IV. EXPERIMENTAL SETUP

The experimental testing of the training results was carried out by generating an experimental dataset of the electrical quantities of interest. These datasets contain phase voltages and currents and some derived quantities that are needed for the disturbance recognition. Once the dataset was generated, it was fed to the classification algorithm for testing. The experimental setup is shown in Figure 12.The proposed setup can reproduce multiple network disturbances with different spectral contents, durations, and amplitudes, allowing us to evaluate the detection accuracy of the proposed neural networks. To simulate a grid with power quality disturbances, the Asterion 4503 A1/3PH by Ametek programmable AC source was used. It has a maximum power of 4500 VA and can generate arbitrary waveforms at a frequency of upto 5kHz. Its dynamic characteristics allow the simulation of any type of network disturbance. To acquire the current and voltage waveforms, a SIRIUSi-HS-4xHV-4xLV was used. The acquisition system can acquire eight channelsatamaximumsamplingrateof50kHz.Thepurposeoftheexperimentalsetupwas to reproduce most of the power quality disturbances that may affect industrial plant and to guarantee the repeatability of the electrical dynamics and accuracy of the measurements for each experiment so that the comparison is consistent. Moreover, thanks to the flexibility of the systems used, it can be adapted to any new configuration required for the testing of detection and classification algorithms.



These results were obtained considering real voltage measurements of 25 s, and they confirmed the excellent performance when the waveform is processed using a short time interval. On the other hand, the classification rate decreases as the number of periods pro- cessed simultaneously increases. It should be noted that the classification of the harmonic disturbance is slightly better than that of the other perturbations when using time intervals of 1 s and 2 s. The reason for this result is that the presence of a voltage component with frequency higher than 50 Hz introduces significant variation in the Fourier analysis.



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V. CONCLUSIONS

In conclusion, it can be stated that the two proposed techniques allow the monitoring of the power quality in a low-voltage distribution network with an excellent level of accuracy. The short training time and the use of common techniques, such as the Fourier transform, in the data processing phase make the two classifiers very versatile and easily adaptable for the recognition of other electrical disturbances. Compared to other techniques, they allow the analysis and classification of a voltage signal in time and frequency. This can further enhance the feature extraction capabilities due to the addition of the frequency dimension. The use of the STFT was to transform the 1D signal into a 2D matrix to exploit the CNN's feature extraction capabilities and its benefits for classification tasks. The STFT was chosen in this work because it uses a discrete Fourier transform, which is a simple algorithm to implement in a real-time application compared to other time–frequency transformation algorithms. Future developments could be focused on improving performance when processing a larger number of cycles per classification and introducing additional types of disturbances that are very frequent in industry. Furthermore, the real-time applications of these two approaches will certainly be studied in the future to develop an effective monitoring tool for electric grids. Therefore, the possibility of integrating the proposed techniques in embedded electronics and directly classifying the quality of the voltage waveform will be studied. This will certainly make the two techniques usable together with other systems for improving energy quality.

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