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Chapter

Novelty Detection Methodology Based on Self-Organizing Maps for Power Quality Monitoring

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Abstract

The inclusion of intelligent systems in the modern industry is demanding the development of the automatic monitoring and continuous analysis of the data related to entire processes, this is a challenge of the industry 4.0 for the energy management. In this regard, this chapter proposes a novelty detection methodology based on Self-Organizing Maps (SOM) for Power Quality Monitoring. The contribution and originality of this proposed method consider the characterization of synthetic electric power signals by estimating a meaningful set of statistical time-domain based features. Subsequently, the modeling of the data distribution through a collaborative SOM's neuron grid models facilitates the detection of novel events related to the occurrence of power disturbances. The performance of the proposed method is validated by analyzing and assessing four different conditions such as normal, sag, swell, and fluctuations. The obtained results make the proposed method suitable for being implemented in embedded systems for online monitoring.

Keywords: condition monitoring, power quality, novelty detection, self-organizing feature maps, feature extraction

1. Introduction

The development and application of intelligent systems in the modern industry lead to the implementation of improved devices capable of acquiring, processing, storing, and sending any kind of information from any process to perform its continuous assessment. These novelty systems and devices lead to the industry 4.0 and aim to increase the value of the work developed to handle the complexity of all the available data from industrial processes. Indeed, this information is not only directly related to the sensors that are installed in the equipment involved in processes, but the information could also be the electrical consumption that the equipment, the supply to the machinery. Due to an adequate electrical supply has a lot of inference in all the processes in the industrial, commercial, and residential equipment [1].

Therefore, the monitoring of Power Quality (PQ) has been increased and reached its importance to ensure the appropriate functioning of the electrical equipment in the industrial processes, avoiding unexpected interruptions which may cause and lead to the loss in the production or utilities. Moreover, the importance of developing new strategies and methodologies for monitoring PQ has gained more interest in the scientific field in recent years [2]. The increase in the electrical power system and the loads connected to supply sources highlight the importance of the availability of monitoring systems to detect and face the occurrence of anomalies presented in the system [3]. Despite in the literature has been identified that problems related to PQ are caused by the supply system or non-linear behaviors of the loads, the opportunity of detecting the occurrence of electrical power disturbances represent a critical challenge to the monitoring systems [4].

In this regard, condition monitoring strategies focused on the assessment of PQ are mainly related to data-driven approaches. In these cases, the acquisition and processing of electrical power signals are performed in order to estimate a useful and meaningful set of features. These, in turn, allow a high-performance characterization of different kinds of electrical power disturbances that may be presented in electrical power systems. In this sense, most of the classical approaches focused on the identification of electrical power disturbances are related to the use of signal processing that transforms the original space of electric power signals through processing techniques such as Fourier Transform, Hilbert Transform, Wavelet Transform, among others [5–7].

Additionally, these proposed approaches focused on obtaining a useful set of features, then use common machine learning-based classification structures to carry out the pattern recognition and classification of assessed power disturbances. Indeed, the most used classifier structures are represented by Support Vector Machines (SVM), Artificial Neural Networks (ANN), infrared Fuzzy Classifiers, among others [8, 9]. On the other side, self-organizing maps (SOM) is a well-studied technique that is based on a grid of neurons and by a procedure performed under unsupervised learning, the topology of an input data space is represented by a discrete distribution [10]. In this regard, the application of SOM as a part of a monitoring strategy focused on PQ, may lead to extend its application to solve different tasks such as feature reduction, multiple class classification, remaining life prediction, and even novelty detection [11, 12].

Thereby, the main contribution of this chapter lies in the proposal of novelty detection methodology based on Self-Organizing Maps (SOM) for the monitoring of Power Quality (PQ). The proposed methodology faces the occurrence of power disturbances from the viewpoint of detecting novel events that do not belong to pre-established normal conditions. Thus, the originality of this proposal includes the characterization of different electric power signals by means of calculation a meaningful set of statistical time domain-based features and, then, its posterior data distribution modeling through individual SOM neuron grid models to perform the diagnosis and novelty evaluation. The effectiveness of the proposed methodology is evaluated by analyzing synthetic electric power signals that consider the normal condition, sag, swell, and fluctuations. The obtained results make the proposed method a suitable option for being implemented in embedded systems for online monitoring purposes.

2. Theoretical basis

2.1 Electric power disturbances

The ideal electric power signals have specific parameters such as fundamental frequency and a specific range of amplitudes that are also known as nominal values. Thus, any deviation from these values is determined as an electric power disturbance and its occurrence may be detected through PQ monitoring [13]. According to the IEEE Std 1159 [14], a sag is defined as a decrease of the rms value of the voltage for durations that comprises 0.5 cycle to 1 minute with typical decreases of 0.1 per unit (pu) to 0.9 pu. On the other side, a swell is defined as an increase of the rms value and it may occur for values up to 1.1 pu with a duration of 0.5 cycles to 1 min. Otherwise, fluctuations are defined as a series of voltage changes that may appear randomly in the envelope of the signal with typical values between 0.95 pu to 1.05 pu. In the category of waveform distortions are included the harmonics, which are sinusoidal voltages or currents with frequencies that are integer multiples of the fundamental frequency. In addition, other kinds of disturbances are known as transient, which depicts a phenomenon that presents variations between two consecutive steady states, that is, during a short interval of time and can be a unidirectional impulse or an oscillatory wave [15].

2.2 Self-organizing maps

Machine learning represents a suitable tool that may be considered in condition assessment methodologies applied to the monitoring of PQ to detect the occurrence of electric power disturbances. In this regard, the SOM is an unsupervised technique based on a neural network that has been used with multiple purposed, such as clustering, classification, prediction of novelty detection. The main objective of SOM is based on the non-linear projection of an original and high-dimensional input data space into a low-dimensional space represented by a pre-defined number of neurons. Through this mapping, the data distribution of the input space, which commonly is represented by a defined number of features, resembles the mapped neurons since the topology of the data is preserved. In this regard, the consideration of SOM for PQ monitoring may lead to detecting the occurrence of power disturbance from a novelty detection viewpoint. Until now, other reported methodologies used for PQ analysis require to be continuously supervised and they use a predefined topology of the data, meanwhile, the SOM automatically adjusts to different data topologies. These are important advantages since they allow to be trained only once, while other techniques are retrained every time the conditions change. This is possible of being implemented whether the available data distribution related to the normal condition is initially modeled and then, eventual novelty patterns are detected due to the topological characteristics of the initial data distribution are highly associated with the normal condition. Indeed, SOM performance is qualitatively measured in terms of the average quantization error, $\bar{E}q$, that also provides information to the degree of novelty detection (Nd) described by Eq. (1) [12]:

$$N_d = \begin{cases} E_q \le \bar{E}_{\text{q}-training}, & 0 \\ d_{\max} > E_q > \bar{E}_{q-training}, & 1 - \dfrac{E_q - \bar{E}_{q-training}}{d_{\max-training} - \bar{E}_{q-training}} \\ E_q > d_{\max-training}, & 1 \end{cases} \tag{1}$$

3. PQ-based novelty detection method

The proposed novelty detection methodology for PQ is composed by five different steps as **Figure 1** depicts. Thus, in the first step, a complete database composed

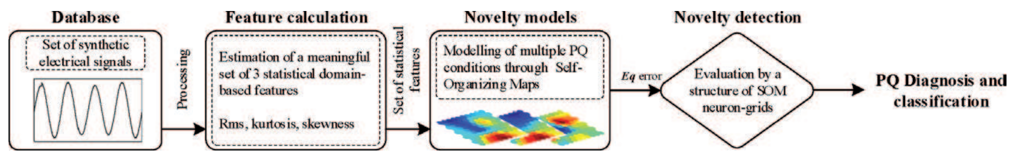

Figure 1.
Proposed novelty detection strategy based on SOM for monitoring and detecting different PQ events.

Root mean square	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(1)
Kurtosis	$Ku = \frac{\sum_{k=1}^{n} \left[(x_k - \bar{x})^4 \right]}{\sigma^4}$	(2)
Skewness	$S_k = \frac{\sum_{k=1}^{n} \left[(x_k - \bar{x})^3 \right]}{\sigma^3}$	(3)

Table 1.
Statistical time domain-based set of features.

by several synthetic signals is generated. The database is generated in Matlab following the corresponding definitions established by the IEEE Std 1159 [13]. In this regard, the synthetic signals are related to different power signals including normal conditions and different disturbances such as sag, swell, and fluctuations.

Subsequently, in the second step, a meaningful set of 3 statistical time domain-based features is estimated from all the synthetic signals, this set of features is composed by the rms value, kurtosis, and skewness [16]. Indeed, the calculation of a numerical set of statistical-time domain features allows obtaining a significant characterization due to its capability for characterizing trends and eventual changes over these trends in the analyzed signals [12, 15]. The mathematical equations of the considered statistical time domain features are listed in **Table 1**.

Then, in the third step, the modeling of all considered power signals is carried out through different SOM neuron grid structures. Thereby, in this modeling stage, the data distribution of each one of the events is modeled and represented by a unique and specific SOM neuron grid model, i.e. the normal condition is represented by SOM_1, and the power disturbances such as sag, swell, and fluctuations are represented by SOM_2, SOM_3, and SOM_4, respectively.

Afterward, the continuous assessment of electric power signals and the detection of events is performed by a novelty detection stage, such detection is carried out by analyzing the resulting $\bar{Eq}$ value of each one of the considered SOM's neuron grids. Specifically, the $\bar{Eq}$ values are successively analyzed by each SOM neuron grid. That is, a measurement is assessed, first, through the SOM_1 in order to analyze its normal condition. Subsequently, a novel event is detected if an abrupt change in the $\bar{Eq}$ value is obtained. In this regard, the electric power signal under inspection is subsequently analyzed by a second, third and fourth SOM's neuron grids aiming to find the SOM model that best represents such power signal in Eq terms. Indeed, the increase of the $\bar{Eq}$ value lies to achieve a novelty detection. Such increase is due to the topological characteristic of the database considered during the modeling of each SOM neuron grid and its difference with the topological characteristics of the measurement under inspection.

Finally, the diagnosis and classification of different power disturbances follows. Synthetic signals with multiple power disturbances are analyzed in this step, in order to validate the effectiveness of the proposed fault detection and identification methodology.

It worth mentioning that the PQ monitoring problem is addressed by the novelty detection technique since changes in the Eq values would be analyzed to conclude if effectively a power disturbance occurs, or if simply the electrical equipment reaches a new condition that falls between an operating range that stills remains normal. In counterpart, techniques focused on outlier/anomaly detection could lead to misclassifications.

4. Results

The proposed novelty detection methodology has been implemented in Matlab, a software platform used to develop multiple engineering applications such as condition monitoring of industrial systems.

4.1 Synthetic signal database

As it has been aforementioned, a database composed of different synthetic signals is generated by taking into account the corresponding definitions established by the standards. In this sense, it should be highlighted that any power disturbance must fulfill specific characteristics for being considered as a specific disturbance, otherwise, there will be no appropriate category to which it could belong. Thus, all synthetic signals are generated by considering a sampling frequency of 8 kHz and 50 Hz as fundamental frequency; additionally, different levels of noise are also considered with the aim of increasing the variability of the database.

Consequently, a database with four different patterns is generated, such patterns are related to different electric power conditions representing the normal condition and, three disturbances such as sag, swell, and fluctuations. Hence, for each one of the considered electric power conditions, twenty synthetic signals are produced with a signal duration of 5 seconds.

4.2 Signal processing and data modeling

Subsequently, as it has been described, all synthetic signals are processed by estimating a set of statistical time-domain based features. The proposed feature estimation is considered attempting to highlight the most meaningful characteristics that may describe the incidence of unexpected electric power disturbances.

In this regard, due to there exist specific disturbances that may appear instantly, the statistical set of features is individually estimated for each one of the cycles that compose a complete electric power signal; indeed, a zero-crossing detector is considered to identify the beginning and end of each cycle. Thus, for each one of the considered conditions, twenty synthetic signals with 250 cycles are subjected to this feature estimation, as a result, a feature matrix with 5000 files (samples) and 3 columns (features) is obtained for each specific condition.

Then, the data distribution of each one of the electric power signals, represented by its corresponding feature matrix, is modeled and represented by a unique and specific SOM neuron grid model. Thereby, the considered SOM's neuron grids consist basically of a predefined number of neurons (10 x10) which is known as the Matching Unit (MU). Subsequently, during a training process, each SOM neuron grid is randomly initialized and consecutively is adapted to the data distribution under evaluation aiming to retain as much as possible its topological properties.

Furthermore, the performance achieved for each SOM neuron grid model may be quantitatively defined in terms of its quantization error. Specifically, the average quantization error, $\bar{E}q$, represents the mean distance from each measurement to the nearest neuron that is activated (Best Matching Unit-BMU). Thus, after modeling the data distribution of the electric power signal in normal conditions, the first SOM_1 neuron model achieves a mean quantization error equal to 0.0016.

4.3 Novelty detection and PQ diagnosis

In order to demonstrate the effectiveness of this first SOM_1 neuron grid for modeling the normal condition and to evaluate its achieved performance, three different electric power signals, with an electric disturbance, are assessed through the SOM_1 model. Thus, in **Figure 2** is shown the mean quantization, $\bar{E}q$, obtained by the first SOM_1 model during the evaluation of the first electric power signal that includes a power disturbance. From **Figure 2**, it should be clarified that each sample of the horizontal axis represents each analyzed cycle from the electric power signal under evaluation. In this regard, it is possible to observe that an abrupt increase of the $\bar{E}q$ is achieved between samples 89 and 93, this increase depicts the sudden occurrence of an abnormal condition, indeed, such occurrence is also known as novel detection.

Due to a novelty detection is performed by the SOM_1, the electric power signal under evaluation has to be analyzed in order to confirm the occurrence of disturbances. Hence, in **Figure 3a** is shown the complete electric power signal and, through visual inspection, it is possible to identify an abnormality on the signal (amplitude reduction), where, such abnormality describes a sag. A detailed visualization of the affected part of the power signal is shown in **Figure 3b**, thus, from **Figure 3b**, and by following the definitions established by the IEEE Std 1159, it may be determined that three cycles of the power signal are affected by the occurrence of sag.

Afterward, a second and a third electric power signal that also includes power disturbance are also assessed under the SOM_1 model. In this sense, the $\bar{E}q$ value achieved during the evaluation of the second signal is graphically represented and shown in **Figure 4**. For this electric power signal, the novelty detection is placed between samples 175 and 178, on the other hand, when this electric power signal is visually inspected an instantaneous amplitude increase is detected. In **Figure 5a** is shown the complete electric power signal evaluated and, in **Figure 5b** is shown a detailed visualization of the affected part of the second power signal, that, according to the established definitions represents the occurrence of swell and affects the power signal during two cycles.

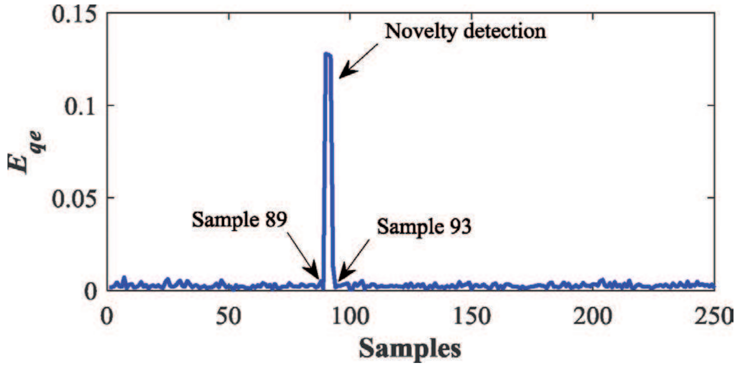

Figure 2.
Graphical representation of the resulting mean quantization error ($\bar{E}q$) that is obtained during the evaluation of an electric power signal that includes an unknown power disturbance (sag), in the first SOM_1 model.

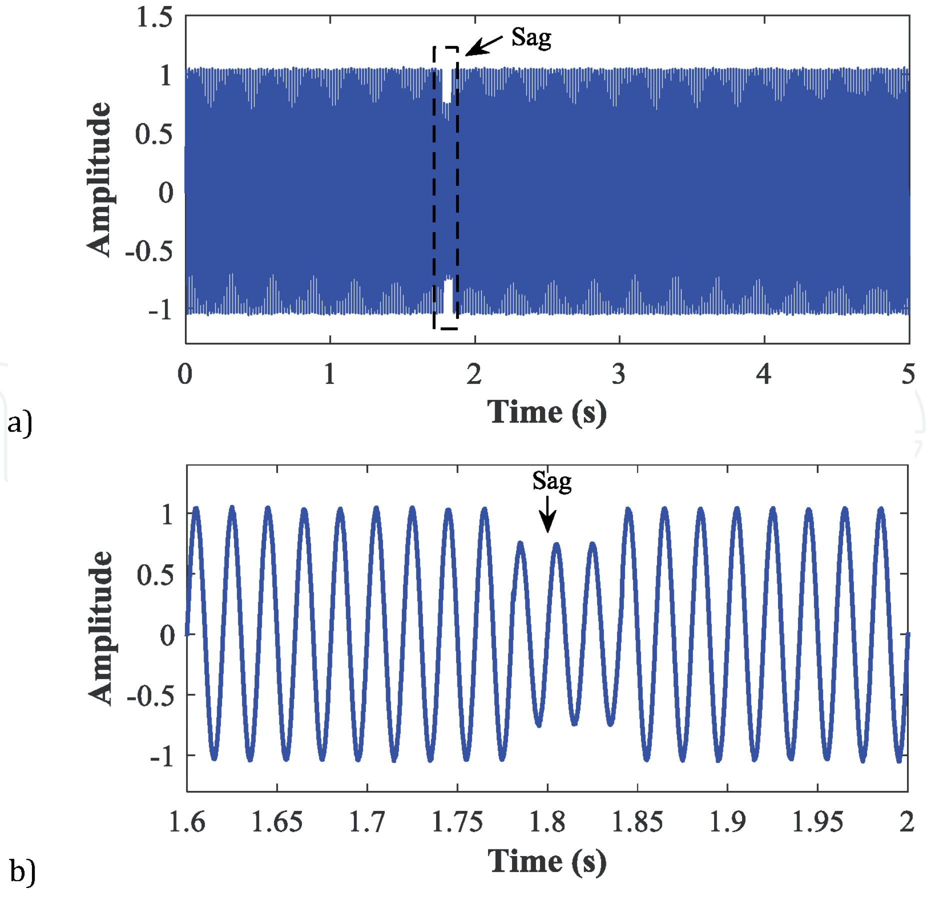

Figure 3.
Electric power signal with a power disturbance, SAG, evaluated under the first SOM_1 model. (a) Complete signal with 5 seconds of duration and, (b) zoom of the detailed signal that shows the signal affectation.

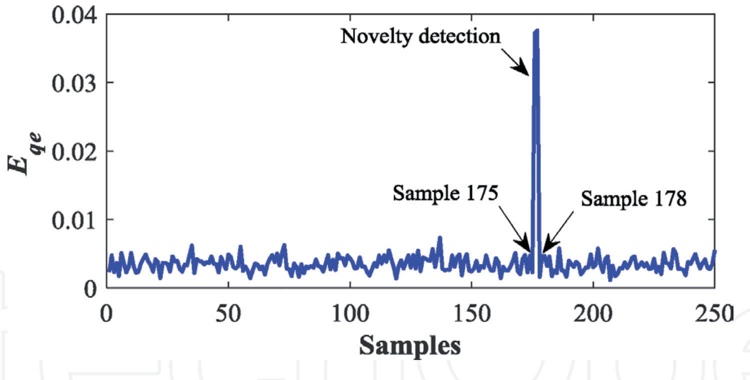

Figure 4.
Obtained mean quantization error during the evaluation of an electric power signal that includes an unknown power disturbance (swell), in the first SOM_1 model.

Later, the third electric power signal is finally evaluated through the first SOM_1 model, the $\bar{E}q$ value obtained during its evaluation is graphically represented in **Figure 6**, where, the novelty detection is performed between samples 21 and 32. Thus, when this electric power signal is visually inspected, it is noted that several amplitude variations appear over the power signal, as in **Figure 7a** is shown. In **Figure 7b** is shown a detailed visualization of the affected part of the third power signal, that, in terms of the established definitions, such amplitude variations represent the occurrence of fluctuations. Thereby, through the evaluation of these three electric power signals, which include power disturbances such as sag, swell, and fluctuations, is validated the effectiveness of considering a specific SOM neuron grid to model and represent the data distribution of electric power signals in normal conditions.

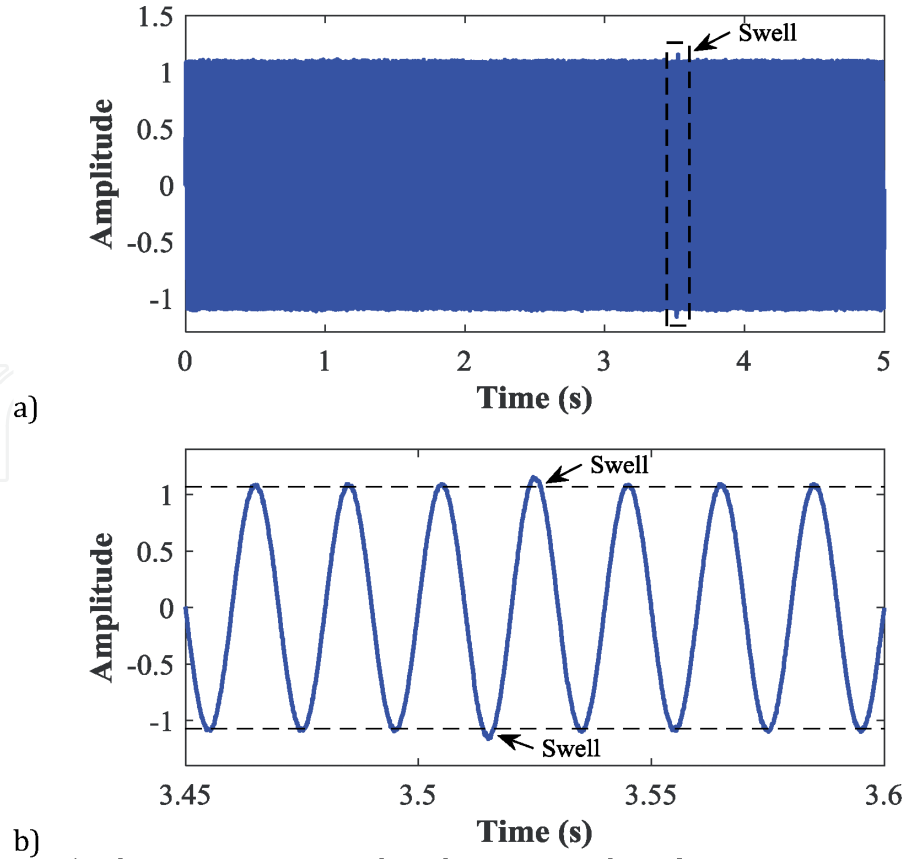

Figure 5.
Electric power signal with a power disturbance, SWELL, evaluated under the first SOM_1 model. (a) Complete signal with 5 seconds of duration and, (b) zoom of the detailed signal that shows the signal affectation per two cycles.

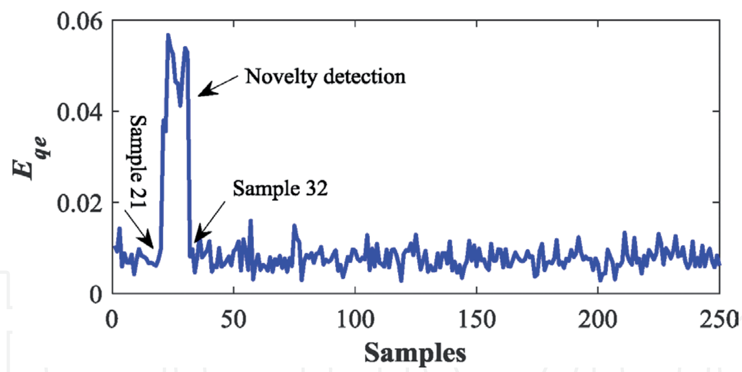

Figure 6.
Achieved mean quantization error obtained during the assessment of an electric power signal that includes an unknown power disturbance (fluctuations), in the first SOM_1 model.

Regarding the proposed methodology, the modeling of the data distributions related to synthetic electric power signals with different disturbances such as sag, swell and fluctuations, is also performed by three individual SOM neuron models, SOM_2, SOM_3 and SOM_4 respectively. Thereby, SOM_2 represents the sag power disturbance, SOM_3 represents the swell power disturbance and, SOM_4 represents the fluctuation power disturbance. The mean quantization error, $\bar{E}q$, achieved during the training of each SOM neuron model is 0.003, 0.0023 and 0.0016, for each one of the considered disturbances, sag, swell and fluctuations, respectively.

Accordingly, in order to evaluate the performance achieved by each modeled SOM neuron model, an electric power signal that includes all considered conditions, normal, sag, swell and fluctuations, is evaluated through the four SOM

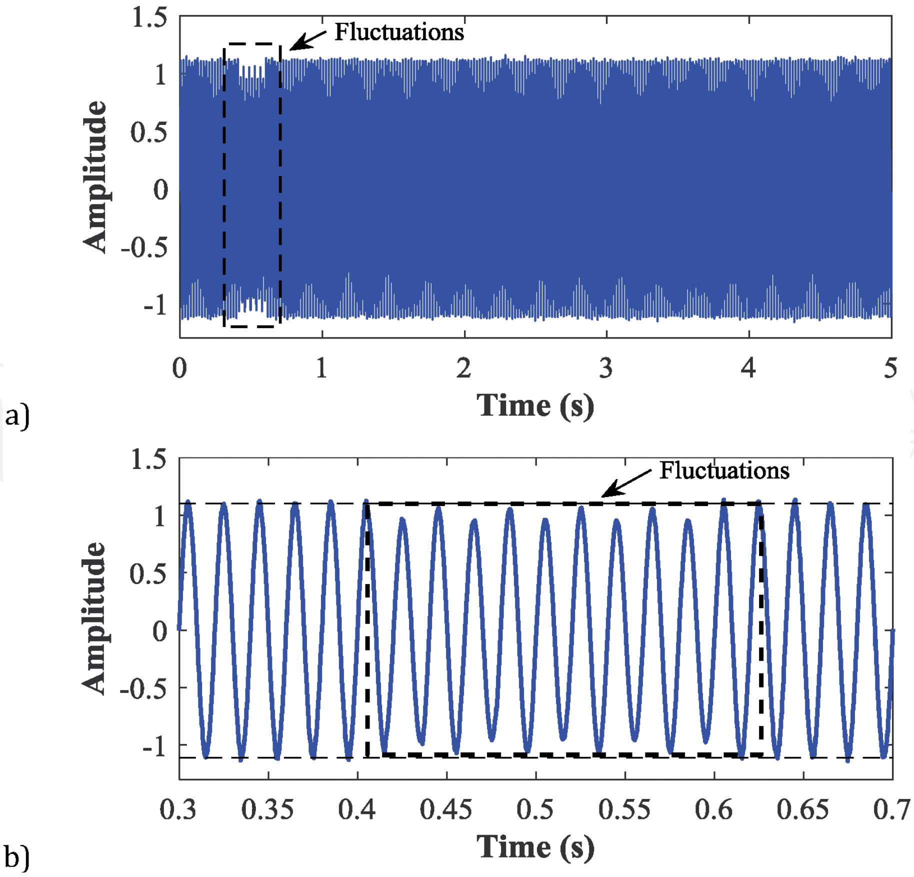

Figure 7.
Electric power signal with a power disturbance, fluctuations, evaluated under the first SOM_1 model. (a) Complete signal with 5 seconds of duration and (b) zoom of the detailed signal that shows the signal affectation.

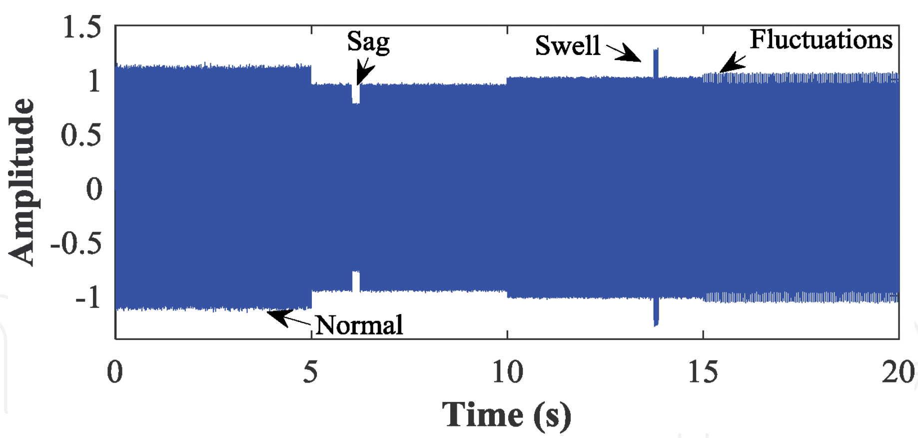

Figure 8.
Electric power signal with three power disturbances, sag, swell and fluctuations, used by the subsequent evaluation through SOM_1, SOM_2, SOM_3 and SOM_4.

neuron models, SOM_1, SOM_2, SOM_3 and SOM_4. Thus, as it has been mentioned, the electric power signal is first evaluated through the SOM1 neuron model and, in case of novelty detection, such electric power signal is subsequently analyzed by SOM_2, SOM_3 and SOM_4 neuron grids aiming to find the SOM model that best represents such power signal in terms of its $\bar{E}q$ value. In **Figure 8** is shown the electric power signal used to evaluate the SOM neuron grid structure, this electric power signal is composed by concatenating an electric power signal in a normal condition of 5 seconds of duration with the electric power signals shown in **Figure 3a**, **Figure 5a** and **Figure 7a**.

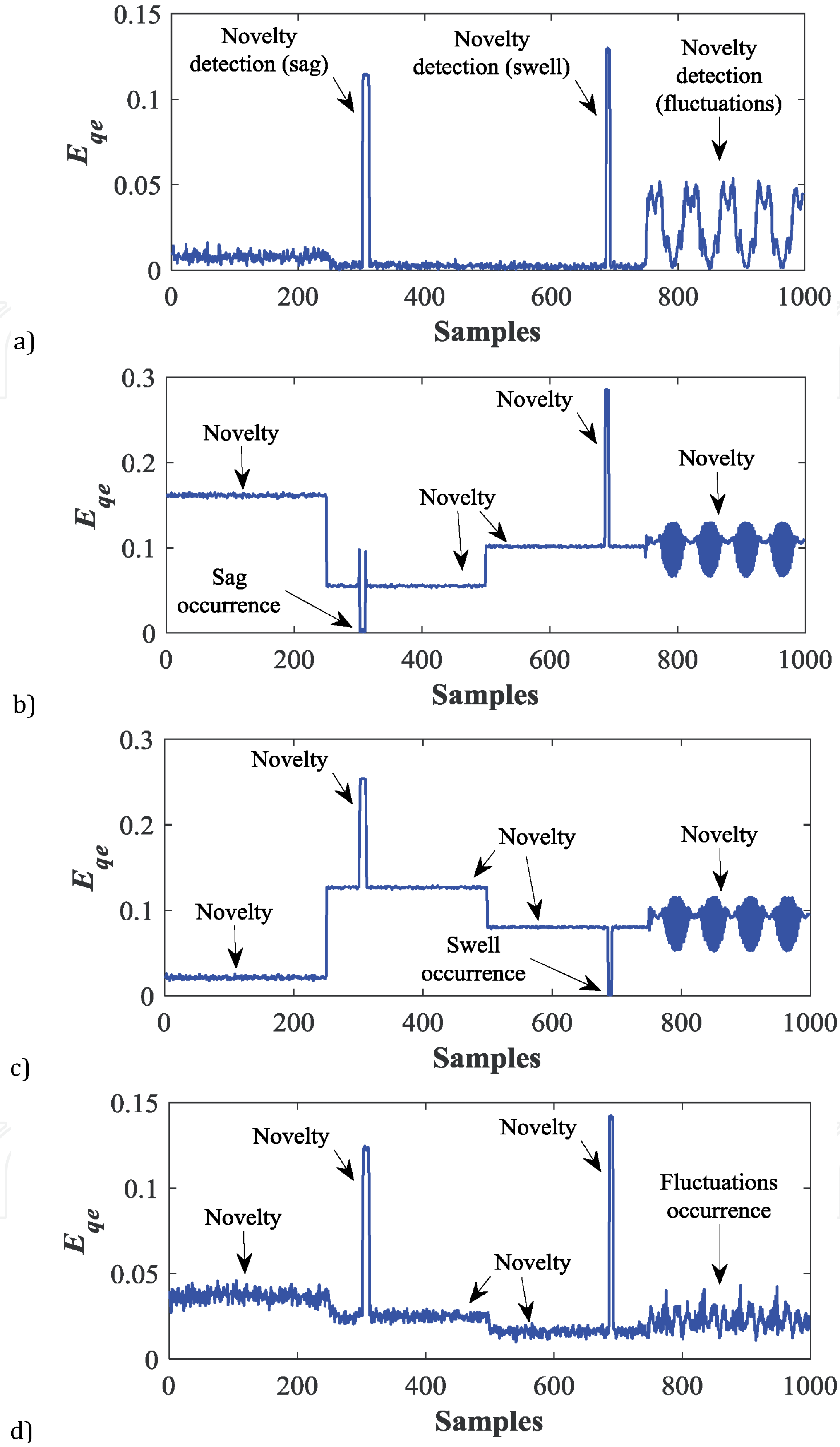

Figure 9.
Mean quantization error achieved by each SOM neuron model during the evaluation of an electric power signal that includes power disturbance such as sag, swell, and fluctuations. (a) SOM_1, (b) SOM_2, (c) SOM_3 and (d) SOM_4.

The $\bar{E}q$ values achieved by each SOM neuron model are individually shown from **Figure 9a-d**, for SOM_1, SOM_2, SOM_3 and SOM_4, respectively. Therefore, by analyzing the $\bar{E}q$ value of **Figure 9a**, from SOM_1, it is possible to notice the occurrence of different events detected as novelties. In this regard, when the first novelty detection occurs, the $\bar{E}q$ values of the following SOM's neuron models have to be analyzed. That is, while a novelty detection is performed by the SOM_1 neuron grid, for these specified number of samples, in the second SOM neuron grid, SOM_2, is achieved the lowest $\bar{E}q$ value; whereas, the rest of SOM's neuron models present an abrupt increase of the $\bar{E}q$ value. Consequently, the first novelty detection of SOM_1 belongs to the appearance of sag.

Subsequently, when the second novelty detection appears over the $\bar{E}q$ value of SOM_1 (**Figure 9a**), in the SOM_3 is achieved the lowest $\bar{E}q$ value; while the rest of SOM's neuron models the abrupt increasing and change of the $\bar{E}q$ value is described; thus, the occurrence of swell produces the second novelty detection. Finally, the third novelty detection that occurs in the $\bar{E}q$ value of SOM_1 trend to produce abrupt and variable changes of the $\bar{E}q$ value, indeed, this variable behavior also appears over the $\bar{E}q$ values of SOM_2 and SOM_3 neuron grids, and, the unique SOM neuron model that do not present these abrupt and variable changes in the $\bar{E}q$ value is the SOM_4 neuron grid. Hence, the third novelty detected by the SOM_4 neuron grid depicts the occurrence of fluctuations.

Therefore, the obtained results prove the effectiveness of the proposed methodology to perform the PQ monitoring and for detecting the occurrence of electric power disturbances. In fact, the proposed diagnosis methodology also has the advantage of considering additional disturbances for being modeled through additional SOM's neuron grids models. Definitely, this proposed structure is suitable to be implemented in embedded systems such as field-programmable gate arrays (FPGA) for online monitoring purposes.

Moreover, aiming to summarize the obtained results in **Table 2** are shown the resulting classification ratios that were achieved during the training and validation of each SOM neuron grid model; thus, three test cases are evaluated. As in **Table 2** is observed, the test case 1 consists on evaluating the available data related to the Normal and Sag conditions through the first SOM_1 model and, in the case of the Normal (evaluated as the known condition) condition is achieved 100% of the global classification ratio; whereas, in the case of Sag (evaluated as the unknown condition) or novelty detection 100% of the global classification is also obtained. Subsequently, for the second test set, the conditions considered as known are the Normal and Sag conditions and, the occurrence of Swell is evaluated as the known condition; in the third test case, the known conditions are Normal, Sag and Swell; while the Fluctuation represents the unknown condition. Therefore, it should be highlighted that all the samples that were evaluated have been correctly identified and diagnosed to its corresponding class (assigned condition) with a membership probability higher than 97% for all cases.

Regarding other novelty detection methods, one-class support vector machine (OC-SVM) remains as the most classical approach that has been implemented under condition monitoring strategies to perform novelty detections. In this sense, the consideration of OC-SVM with classical feature reduction techniques, such as PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis),

Test case	*Known class* (%)	*Unknown class* (%)
1	Normal (100%)	Sag (100%)
2	Normal (100%), Sag (100%)	Swell (>98%)
3	Normal (100%), Sag (100%), Swell (100%)	Fluctuation (>97%)

Table 2.
Resulting diagnosis and novelty detection ratios for each SOM neuron grid model.

are used to evaluate the available data to detect novelties during the PQ monitoring. Thus, by evaluating the available data by means of such approach a global classification ratio about 62% is approximately obtained for each evaluated condition. Therefore, it must be mentioned that the consideration SOM neuron grids as a part of a novelty detection structure leads to obtain advantageous results over classical approaches such as OC-SVM.

4.4 Experimental validation by analyzing a photovoltaic generation system

Additionally, the proposed method is evaluated under a real scenario in order to highlight the effectiveness and performance during the novelty detection of PQ disturbances. In this regard, experimentation is performed in a 30-MW wind farm located in northwest Spain. A proprietary data acquisition system (DAS) is used for collecting and storage the electrical signals. This DAS is based on field programmable gate array (FPGA) technology and it is able to acquire data from 7 channels simultaneously. Three of these channels are devoted to collect the voltage signals, whereas the four remaining channels are intended to receive current signals. The FPGA-based DAS operates at a sampling rate of 8000 samples per seconds and has a 16-bit analog to digital converter that ensures the proper representation of the acquired data. Finally, the DAS incorporates a 128 GB SD memory that allows performing the uninterrupted data storage for periods up to 11 days. When the memory is full, it can be easily replaced to continue with the acquisition process. The DAS is located at the substation of the windfarm, which means that the production of the complete farm can be monitored. The measurements are taken from a measuring transformer, so the DAS must measure voltages up to 110 Vrms. The commercial current clamps SCT-013-010 from YHDC are used to perform the current measurements in this location.

Therefore, the proposed novelty detection method for detecting the occurrence of PQ disturbances is applied to real data acquired from a real scenario as follows:

1. One of the voltage signals that was acquired during the monitoring of the transformed is processed as is described in Section 3, this processing is performed in order to compute the proposed set of 3 statistical features.

2. Subsequently, the set of statistical features that represent the voltage signal is evaluated though all the SOM neuron grids models that were obtained during the training procedure, in which, the synthetic signals were considered. Specifically, such set of statistical features is evaluated through the neuron grid model: SOM_1, SOM_2, SOM_3 and SOM_4, which represent the normal condition, the occurrence of sag, swell, and fluctuations, respectively.

3. The mean quantization error, $\bar{E}q$, is analyzed aiming to determine the novelty detection and aiming to determine whether the occurrence of a PQ disturbance is detected by one of the SOM models.

In this regard, after evaluating the set of the statistical features through each one of the SOM neuron grid models, SOM_1, SOM_2, SOM_3, and SOM_4, the $\bar{E}q$ value is obtained. Thereby, the $\bar{E}q$ value achieved by each SOM model is represented and show from **Figure 10a-d**, respectively. From these obtained results it should be highlighted that the graphical representation of the $\bar{E}q$ value of **Figure 10a, c** and **d**, presents an abrupt increase. This increase is produced due to the neuron grid models SOM_1, SOM_3 and SOM_4 detect a novelty; on the other hand, the $\bar{E}q$ value achieved by the SOM_2 neuron grid does not show the increase since it could be considered that the novelty detection belongs to the occurrence of sag.

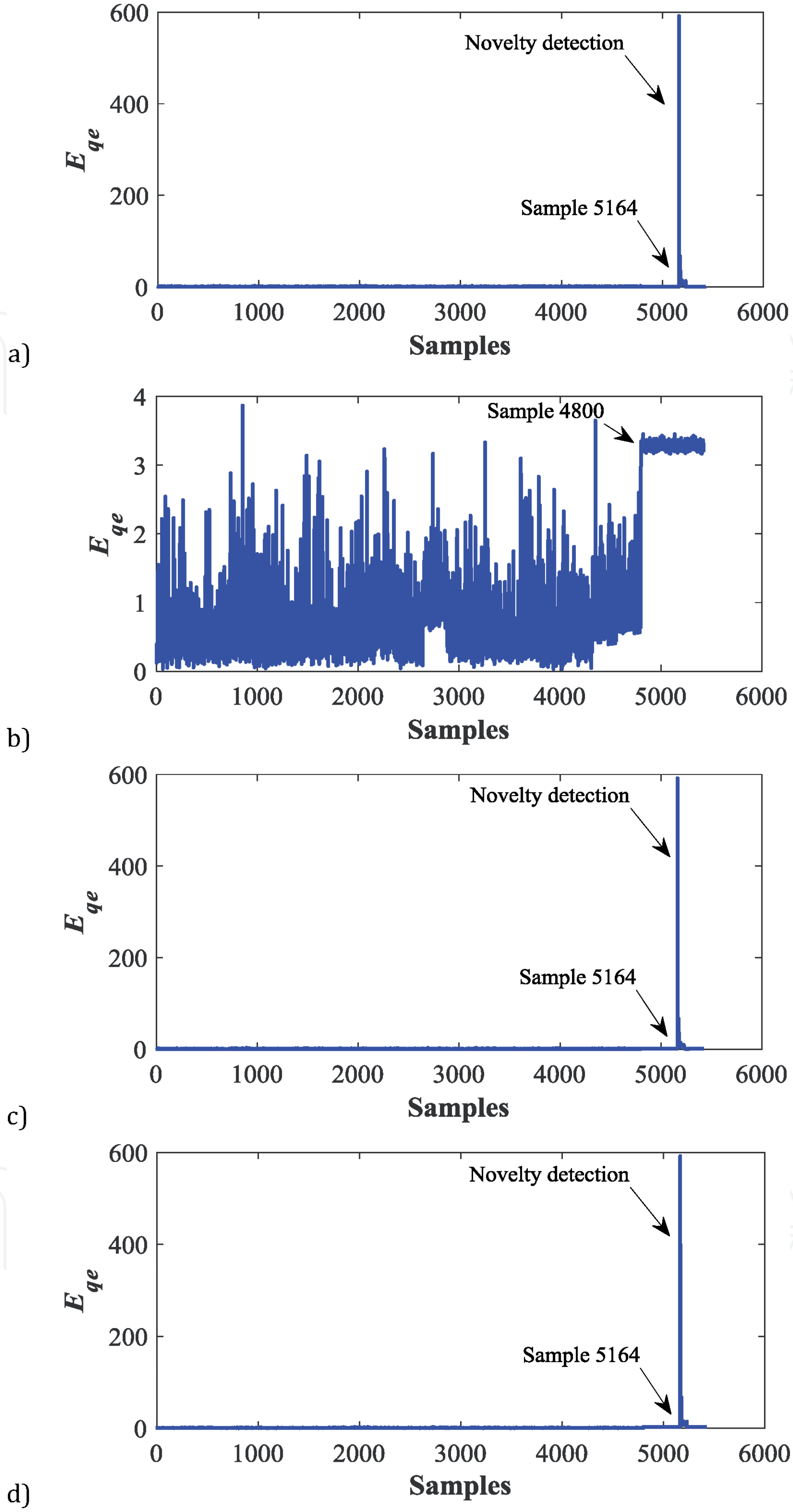

Figure 10.
Achieved mean quantization error by each SOM neuron model by evaluating the electric power signal of a transformer in: (a) SOM_1, (b) SOM_2, (c) SOM_3 and (d) SOM_4.

Afterward, in order to validate the occurrence of the sag, the voltage signal is analyzed by visual inspection to find and detect such PQ disturbance; in this sense, in **Figure 11a** is shown the voltage signal and it may be observed that

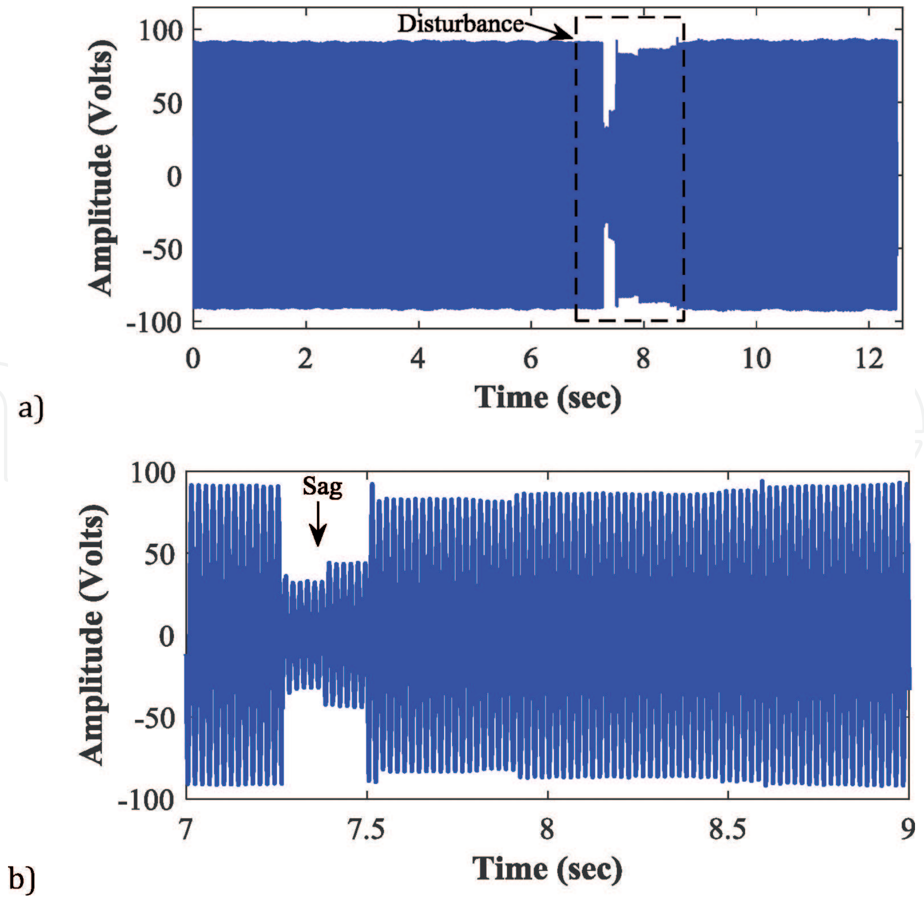

Figure 11.
Voltage signal acquired during the monitoring of the electric transformer in which a novelty detection is detected. (a) Complete voltage signal, (b) zoom over the specific area in which the disturbance is detected and identified as sag.

around the eight-second a disturbance is presented. Also, in **Figure 11b** is shown a zoom of such specific area in which the disturbance is presented and, it can be appreciated that the disturbance has the specific characteristics that belong to the occurrence of sag. In this sense, it should be highlighted that the effectiveness of the proposed novelty detection methodology has been proved by analyzing real data acquired from a real scenario that includes the monitoring of a transformer.

5. Conclusions

This chapter proposes a novelty detection methodology based on Self-Organizing Maps to perform the monitoring of Power Quality. The obtained result proves the effectiveness of the proposed method for detecting the occurrence of unexpected and undesirable electric power disturbances such as sag, swell, and fluctuations.

Thus, two main important key points must be highlighted from this proposal. First, the characterization of the electric power signals through statistical time-domain based features leads to achieving a high-performance representation of the data distribution. Second, the modeling of the available data by means of SOM's neuron grids allows preserving the topology of the data, which is a key feature that leading the detection of novelty events. Additionally, the consideration of a collaborative SOM neuron structure based on the analysis of the mean quantization error effectively detects all novel electric power disturbances considered.

Finally, the proposed method is evaluated under a synthetic database of electric power signals that considers the occurrence of four conditions, normal, sag, swell, and fluctuations. In fact, the proposed PQ monitoring structure may be extended to other power disturbances. The obtained results depict that this proposal is a suitable option to be implemented in embedded systems, such as field-programmable gate arrays (FPGA), as a tool for online monitoring with application in industrial processes.

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Conflict of interest

The authors declare no conflict of interest.

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