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ORIGINAL RESEARCH ARTICLE

Power grid monitoring based on Machine Learning and Deep Learning techniques

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ABSTRACT

Background: In this work, some application examples of machine learning and deep learning techniques in the monitoring of electricity distribution services and infrastructures are proposed. Three different fields of application are considered to highlight the use of techniques based on neural networks: detection and classification of power quality disturbances, monitoring of underground cables in medium voltage lines and diagnosis of joints in high voltage overhead power lines. **Methods:** In the field of power grid monitoring, this work proposes a classification method based on a complex valued neural network to assess working conditions of junction regions in high-voltage overhead lines and insulating materials in medium voltage underground networks. The purpose of this method is to prevent the rupture of joint structures and the abnormal degradation of underground cables via frequency response measurements. This approach allows the direct processing of complex measurements and to reduce the computational effort compared to other methods available in the literature. **Results:** The results obtained in the monitoring of underground cables and joints of high voltage lines guarantee an overall classification rate higher than 90%. In the field of power quality, several deep learning and machine learning methods are proposed to detect the most common voltage disturbances. **Conclusions:** In this paper, an innovative use of widespread algorithms such as convolutional neural networks is proposed with excellent results. Furthermore, the use of a complex-valued neural network in electrical infrastructure monitoring is presented, introducing a minimally invasive classification method that could be instrumental in the transition from corrective to predictive maintenance in the near future.

Keywords: power quality disturbances; machine learning; neural networks; medium voltage cables; fault diagnosis; high voltage systems

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1. Introduction

This paper proposes new approaches to monitor electricity distribution services, as this is one of the most important activities to ensure the continuity and quality of electricity grids. Electrical continuity is compromised by fault situations, while power quality is a problem that, in recent years, is becoming increasingly important[1]. One of the main causes is the growing use of electronic devices, which can be connected to the network both as loads and as energy injectors[2–4]. The integration of renewable energy generators significantly increases the complexity of electrical transmission and distribution systems, the maintenance of which requires the introduction of new techniques from other fields to detect and locate malfunctions[5–7]. Most of these new techniques use artificial intelligence algorithms to prevent catastrophic consequences; for example, in the research of Bindi et al.[8] and in the work of Hayder and Saidi[9], possible approaches to avoid failures in photovoltaic applications are presented. On the other hand, the widespread diffusion of electronic devices in any sector, from industry to the domestic, from commerce to the public sector, has improved the efficiency and accuracy of numerous services and the automation of many different processes. Unfortunately electronic devices have a nonlinear behavior that can produce distortions in voltage and current waveforms of the power grid with a consequent degradation of its quality. Detection and classification of these disturbances is important to avoid degradation of electrical components and power losses that lead to losses in revenue.

Another fundamental aspect to ensure the continuity of the electricity distribution service is the monitoring of underground cables. Medium voltage lines near urban centers generally consist of underground cables. Given the great difficulty of accessing these cables, the possibility of checking their state of health without removing them plays a fundamental role in organizing maintenance operations[10].

In the case of high voltage overhead lines are concerned, the prevention of catastrophic events and the rapid localization of the damage are essential to reduce recovery times and organize maintenance interventions. This is not easy due to the length of this kind of lines[11].

Depending on the problem to be treated, it is necessary to apply the most appropriate computational technique. For example, in order to detect and classify disturbances affecting grid power quality, various techniques are currently exploited such as Kalman filters[12] and wavelet transforms[13].

There are several fault location techniques in underground lines, but many of them cannot be used online during normal network operation[14,15]. One of these methods[16] is based on the measurement of dielectric losses due to the degradation of the insulating material, but requires measurements to be performed in the laboratory. Other methods are based on the reflection of the measurement signals and are able to locate the point of the conductor with an impedance value different from the nominal one[17,18]. This group of techniques, called Time Domain Reflectometry (TDR), does not require pulling out cables, but it does not prevent insulation problems.

Regarding the transmission lines, there are various methods that can be used to monitor the operational state of overhead conductors, such as Load Flow analysis and state estimators[19–21]. Although these methods can identify incorrect behavior, they may not be able to determine the type and location of the malfunction. Given that joints are one of the most critical components, it is essential to have knowledge of their level of deterioration. In order to achieve this, TDR techniques can be employed to remotely detect the impedance of the joint by analyzing signals that are reflected from the areas of the conductor where there are discontinuities[22,23]. However, the accuracy of this technique can be affected by measurement errors, environmental noise, line length, and any changes to the environmental conditions along the line.

One effective approach to addressing the issues mentioned earlier is to utilize machine learning methods. In addition to automating grid monitoring, these techniques can help resolve problems associated with conventional procedures, such as those for underground cables and overhead transmission lines. They employ an adaptive pattern classification mechanism, which enables them to perform a robust classification even in the presence of unclear system models and noisy environments. Following an initial training phase, a neural network can extrapolate the acquired information to make generalizations.

The main innovative contributions of this paper can be summarized as follows:

- propose the use of Long Short-Term Memory (LSTM) algorithms, Convolutional Neural Networks (CNN) and the mixed architectures LSTM-CNN to detect the most common electrical disturbances in low voltage electrical grids;
- present a possible configuration of a complex neural network to obtain the detection and localization of insulation problems in medium voltage underground cables;
- improve a minimally invasive monitoring method for assessing the health of joints in high voltage overhead

lines.

The paper is organized in the following way. The problem of power quality disturbance detection and classification is faced in Section 2. The monitoring of underground cables in medium voltage lines is considered in Section 3, and the diagnosis of joints in high voltage electrical lines in Section 4. Finally, Section 5 contains the conclusions and some ideas for future work.

2. Power quality analysis

Power quality is a critical aspect of modern electrical systems, with implications for the safe and reliable operation of all types of electrical equipment. The IEEE defines Power Quality (PQ) as: “The concept of powering and grounding sensitive equipment in a matter that is suitable to the operation of that equipment" In other words, power quality refers to the consistency and reliability of the voltage, frequency, and waveform of the electrical power delivered to a facility or device. Any variations or disturbances in power quality can result in equipment damage, data loss, or even system failure, leading to significant economic costs and potential safety risks. As our reliance on electronic devices and sensitive equipment continues to grow, the need to maintain high power quality has become increasingly important[24,25]. Optimal power quality implies standard voltage and current values and a non-deviation from frequency of voltage and current signals in the grid. Power quality disturbances can affect the normal functioning of electrical components such as transformers, capacitor banks, power lines, electric motors, household electronics, etc. This in turn affects everyday life as well as industrial processes. These disturbances include frequency component injection, amplitude deviation, waveform and symmetry distortion of the three-phase voltages and currents. Their identification and classification are important in order to counteract and find the origin of the distortion. This can be achieved by using specialized instrumentation for data acquisition of voltage and current signals on the power grid. In the context of power quality, machine learning algorithms can be used to identify patterns and anomalies in electrical power systems. They have proved to be accurate and precise when dealing with detection and classification of disturbances. Several of these algorithms, using different architectures and feature extraction in the time domain and/or the frequency domain, are currently exploited to carry out this task[26,27].

The most frequent power quality disturbances in low voltage electrical networks can be divided into three main groups: amplitude fluctuations, sudden transients and steady state harmonic pollution. A more detailed classification of disturbances includes voltage sag, voltage swell, harmonic disturbances, interruption, notch and transient. For each kind of these disturbances a specific machine learning algorithm can be more efficiently used, so a comparison among different kinds of techniques is very useful. For example, in the study of Iturrino et al.[28] the effectiveness of three deep learning architectures for power quality disturbance detection and classification is investigated. They are the Long Short-Term Memory (LSTM), the Convolutional Neural Networks (CNN) and the mixed architecture LSTM-CNN. To compare the different techniques, the work proposed by Iturrino et al.[28] focuses on the different feature extraction techniques of the different architectures and their effectiveness on classifying power quality disturbances.

Also, deep learning architectures trained with simulated data have proven to be successful in detecting and classifying different types of disturbances in an experimental setup. For this reason, a Matlab®/Simulink model has been built to simulate the voltage and current time signals on a micro grid including several different industrial loads (a three-phase dynamic load, connected to an electrical engine with variable load, a linear load, a nonlinear load injecting disturbances). Through the simulation, a current and voltage dataset was created for training and validating the classification algorithms. These disturbances include: under voltage (sag), over voltage (swell), harmonics distortions, transient, notching and interruption. To create a balance dataset and optimize the performance of deep learning algorithms it is necessary to reproduce different disturbances by varying amplitude, duration, and intensity of the signal window. To improve the performance of classification and converge to a generalized result, the data in the simulated dataset was augmented. After training with the augmented dataset, the algorithms have been tested using experimental voltage measurements containing the disturbances previously mentioned. For testing to be successful, an experimental testbench has been created in order to reproduce and measure several real-time disturbances. In **Figures 1–4**, the results of the classification using experimental data of the different classifiers previously mentioned are shown.

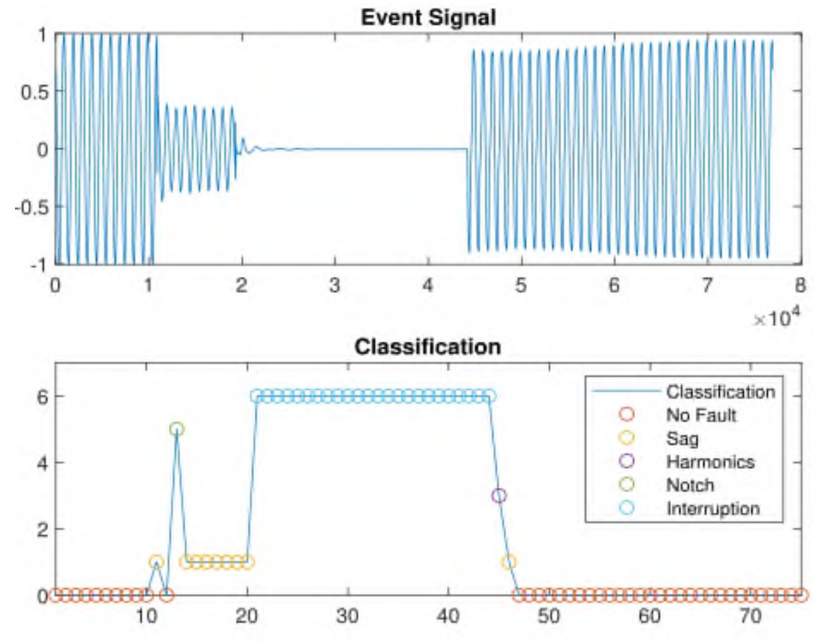


Figure 1. Classification results. LSTM real time classification.

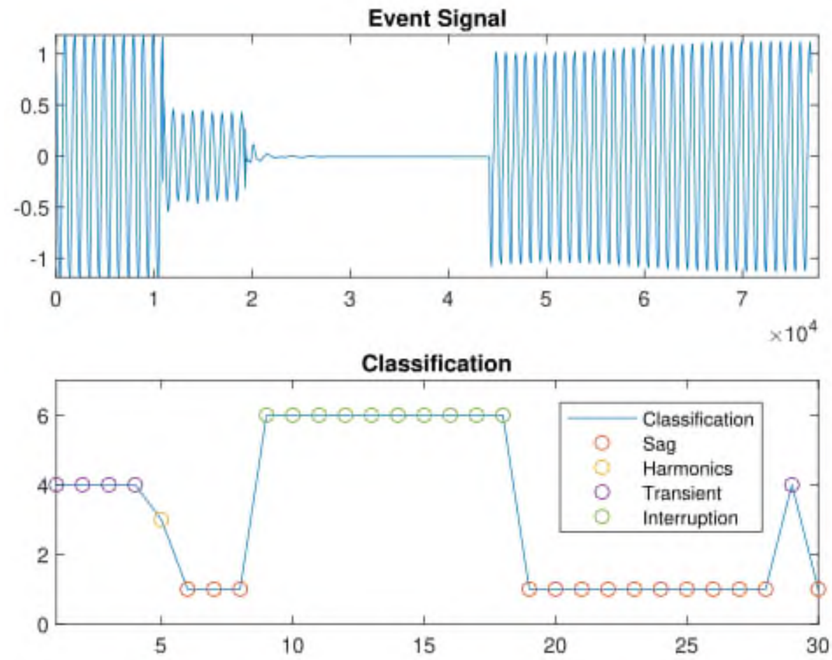


Figure 2. Classification results. CNN real time classification.

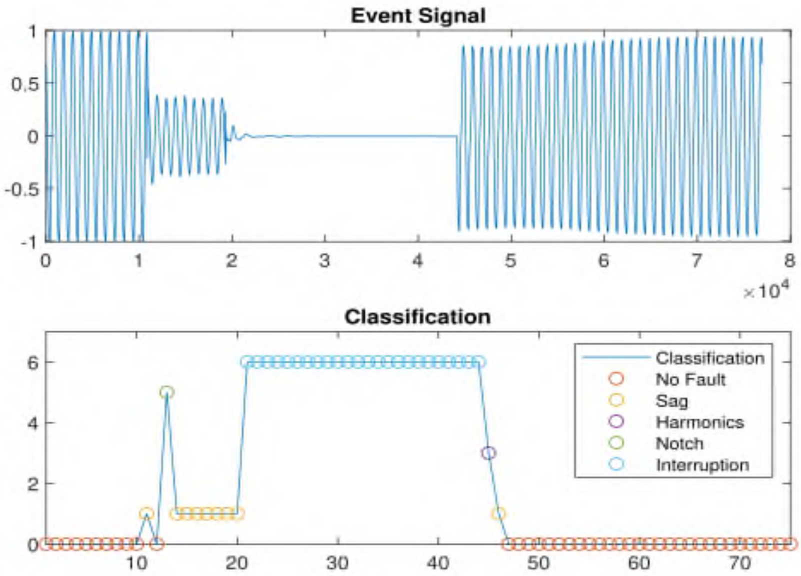


Figure 3. Classification results. LSTM-CNN real time classification.

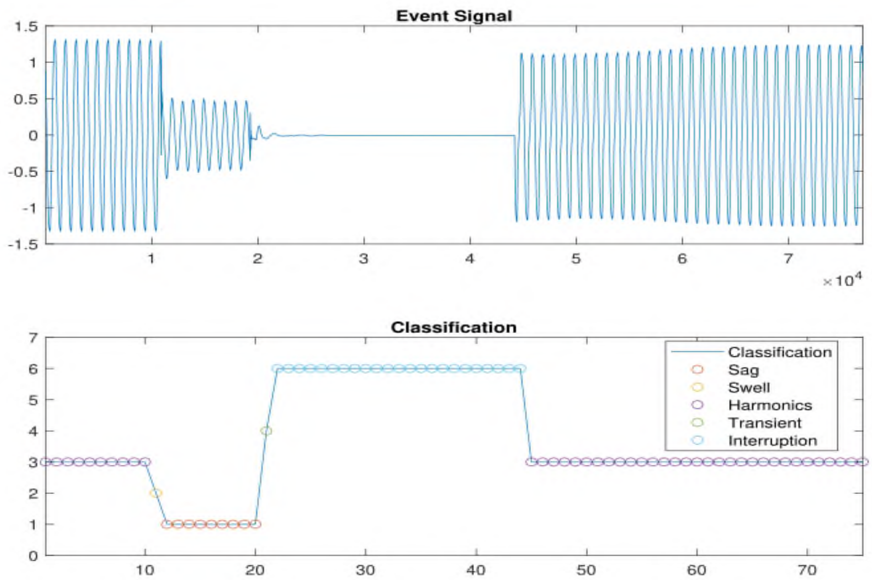


Figure 4. Classification results. LSTM-CNN with optimized hyperparameters real time classification.

This experiment was executed using a sliding window method and classifying sections of the measured signal in an orderly fashion. In **Figures 5** and **6**, a bar chart containing the recall and precision of the different deep learning architectures classifying different power quality disturbances is shown. In this test, the different classifiers are compared using the measured recall and precision.

In the research of Iturrino et al.[29] a new type of algorithm was developed called the Single Shot Power Quality Disturbance Detection (SSPQDD) algorithm. This algorithm is based on an object detection algorithm for image detection and classification. Voltage signals can contain a sequence of disturbances in a single window frame of a certain duration. The SSPQDD is a pretrained VGG-16 architecture modified with two outputs in order to accurately detect and classify multiple disturbances in a single window frame. In **Figure 7**, a comparison of the SSPQDD with different classical deep learning architectures is shown. It shows the SSPQDD was able to correctly detect and classify the sequence of disturbances in a single window frame where the other architectures misclassified.

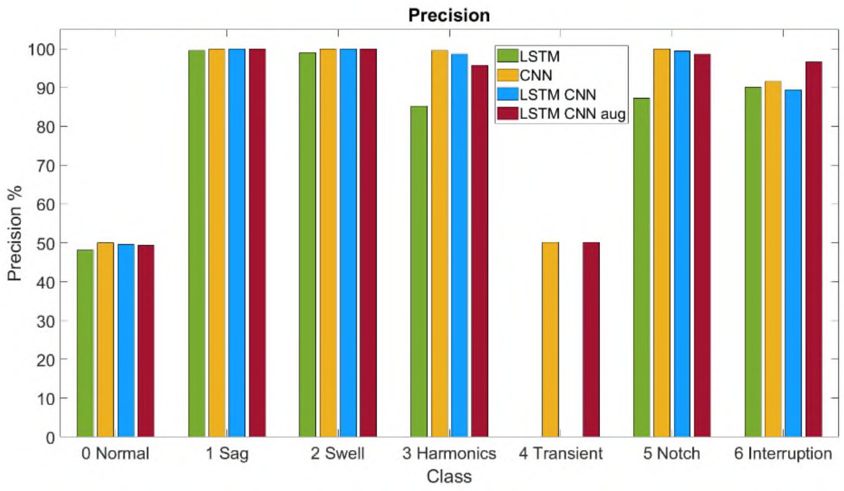


Figure 5. Comparison. Precision chart of the classifiers.

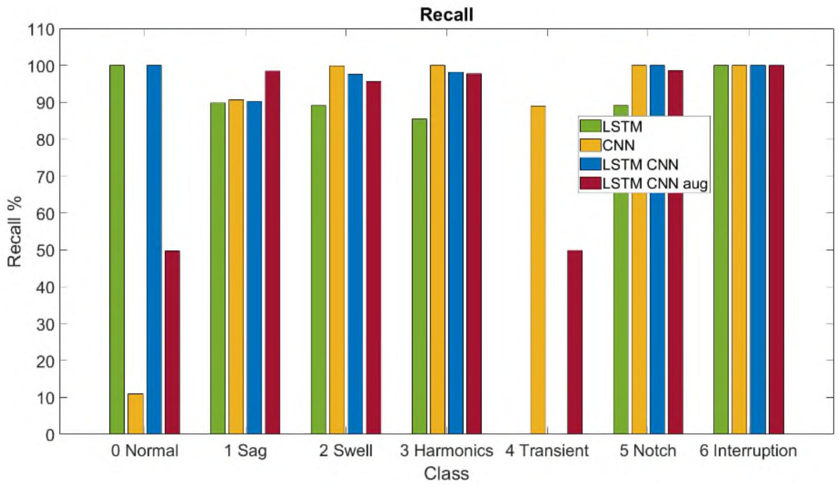


Figure 6. Comparison. Recall chart of the classifiers.

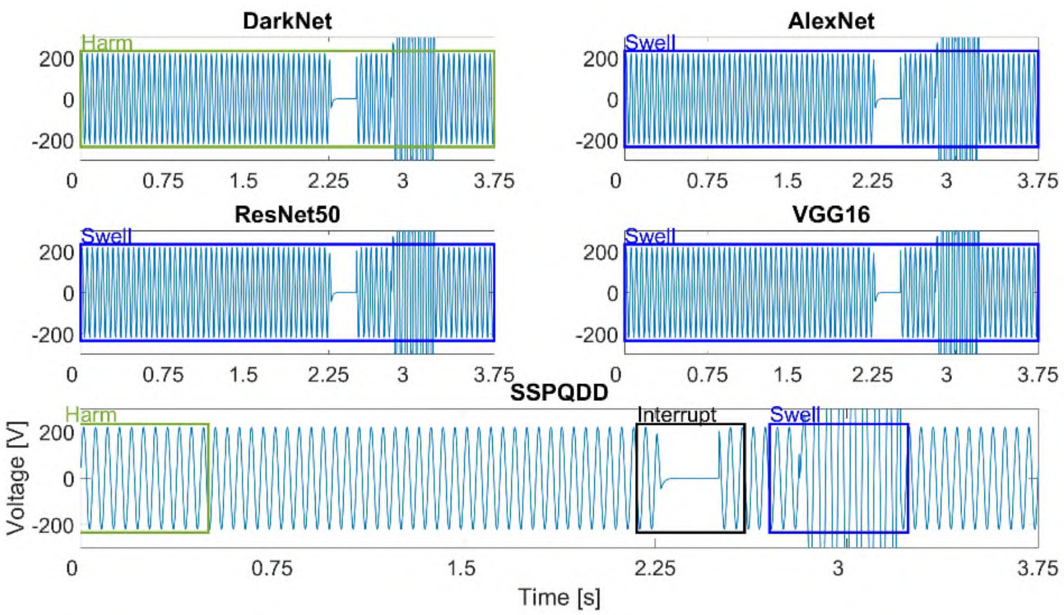


Figure 7. Test results. Classification results of the SSPQDD of a signal with three disturbances.

3. Localization of malfunctions in underground cables

Monitoring medium voltage lines can prevent power outages for thousands of users. Given the underground position of the cables, it is necessary to adopt specific techniques, usually based on artificial intelligence techniques, to prevent catastrophic failures. This can be achieved by monitoring the working temperature of successive cable sections, as temperature increases can indicate insulation problems[30]. Malfunctions can be localized by identifying the section with a higher temperature. If current overload and/or an unusual increase in ambient temperature occur, their duration must be monitored to prevent degradation of the cable insulation[31]. A complex neural network can be used to identify the working temperature of several cable sections by measuring the frequency response of the line[32]. In this paper a possible application of the complex classifier is proposed, processing measurements of the line voltage gain for different frequencies. To achieve the purpose of monitoring and locating the part of the line in the worst conditions, the network branch is divided into successive sections. Each of these sections is represented by a π-model shown in **Figure 8**.

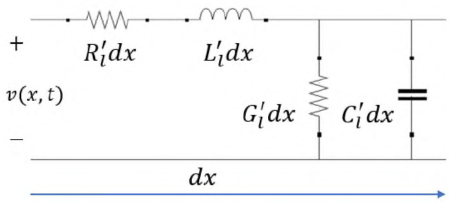


Figure 8. Equivalent circuit. Lumped circuit of a single cable section.

Since the resistance of the conductor increases with temperature and the change in resistance introduces a corresponding change in the frequency response, its measurements contain all the information about the working temperature. Thus, the neural classifier processes the magnitude and phase of the transfer function measurements.

The dataset matrix required for the classifier training phase contains numerous samples of each fault class obtained by randomly varying the temperature of the cable sections. These changes are converted to resistance values using Equation (1) and Equation (2). Subsequently, the values of the resistors are used in the model of the line.

$$\rho_T = \rho_{20}[1 + \alpha(T - 20)] \tag{1}$$

where the resistivity ρ_{20} refers to the conductor material at 20°C, T is the working temperature and ρ_T is the corresponding resistivity. Finally, α is the thermal coefficient of the conductor material.

$$R'_{lT} = \frac{\rho_T}{S} \tag{2}$$

where S represents the cross-section of the cable. The dataset used during the training phase contains several samples of each possible fault class. Assuming a maximum level of working temperature equal to 105 ℃[33] and considering the phase current approximately equal to the rated current of the cable, with the ambient temperature equal to 25 ℃, the operating temperature of the cable is approximately 70 °C[34]. Two possible working conditions are considered for each cable section: an operating temperature below 70 ℃ represents the nominal condition, while a cable temperature above 70 ℃ indicates the presence of a thermal malfunction. The minimum cable temperature considered in this paper is 30 ℃ and describes the minimum load condition. The overheat situation is 135 ℃ and indicates that there is a problem.

3.1. Case study

A 900-meter medium voltage (20 kV) underground line consisting of three RG7H1M1 single core cables with a 35mm^2 section represents the case study analyzed here. This cable has a rated current of 205 A and the whole line is theoretically divided into three successive sections. Furthermore, the hypothesis of a single fault is assumed and this means that overheating can only affect a single section at a time. This means that there are four error classes: the first (class 0) describes the nominal operating condition of each part of the cable, the other 3 classes describe the thermal malfunction of each section of the line (n = 1, 2, 3). **Table 1** summarizes the characteristics of a single piece of cable and **Figure 9** shows the case study.

Table 1. Characteristics of a single cable part.

Cable length [km]	**Conductor radius [mm]**	**Sheath radius [mm]**	**Outer radius [mm]**
0.3	7	17	23.2
Line-line spacing [mm]	Line formation	Insulation relative permittivity	Cable section [mm^2]
46.4	Flat	2.4	35

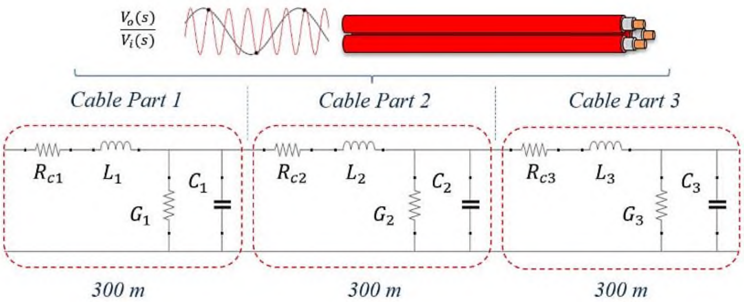


Figure 9. Underground line. Medium voltage underground line divided into three sections.

As previously mentioned, the main physical phenomenon considered in this application is the relation between the working temperature and cable resistance (only the longitudinal resistance is the variable element): as the operating temperature increases, the resistance of the conductor also increases. When a large change in conductor resistance occurs, there is also a change in frequency response. This means that the transfer function contains all the information on the working temperature of the cable. To obtain the frequency response measurements it is necessary to inject high-frequency signals into the line using the typical tools of Power Line Communication. Magnitude and phase of the voltage transfer function are processed by the neural classifier to detect any thermal malfunctions.

In this application, dataset creation is completely done on Matlab/Simlinks. SapWin software is used to verify Testability of the overall circuit[35], and the result obtained indicates the possibility of distinguishing the four fault classes through the selected measure.

3.2. Simulation procedure

Once all the possible working conditions have been defined, it is necessary to create the dataset matrix. As previously mentioned, a Simulink model is used, where the transmission of signals is simulated by introducing a PLC system. The turn ratio of the matching transformers is fixed to adapt the transmitter/receiver resistance with the characteristic line impedance. The coupling circuit used in this case is capacitive and presents a fourth order high pass filter with a minimum bandwidth frequency of 3 kHz. The injection of signals in the (3 ÷ 50) kHz band is considered. To simulate all the possible fault classes, the Simulink/Simscape scheme is managed by a Matlab script, which varies the resistance values. The corresponding voltage transfer function is measured in magnitude and phase for n_f test frequencies belonging to the band taken into consideration.

In this procedure, two different approaches are compared: the first involves the selection of 4 test frequencies while the second is based on a Principal Component Analysis (PCA). In the first case, 4 frequencies obtained by dividing the total bandwidth into three equal parts are used in the Simulink/Simscape diagram to extract the transfer function measurements and create a dataset containing 300 random samples for each fault class. Next, 100 frequencies are considered and a PCA is applied to reduce the number of inputs. In this way it is not necessary to choose the test frequencies beforehand. Again 1200 examples are generated from the four failure classes at the test frequencies. A linear PCA is applied to the dataset matrix containing the measurements relating to 100 frequencies, maintaining the 98% of the informative content. This produces the reduction of the dimensionality of each input from 100 complex numbers to 4. This means that two dataset are available to classify the state of health of the line using four complex numbers for each input. In the first case, these numbers correspond to magnitudes and phases of the measured transfer function. In the second case they are obtained following the projections of the measurements obtained for 100 frequencies in a space with reduced dimensionality. In the new coordinate system, the physical meaning of the measurements is not maintained, but a certain percentage of the information content is preserved (98% in this case).

3.3. Neural network setup and results

In this case, the output configuration of the complex neural network is based on the single failure hypothesis. Therefore, three binary neurons are used in the output layer, one for each cable section taken into consideration. **Figure 10** illustrates the structure of the output layer of the neural network.

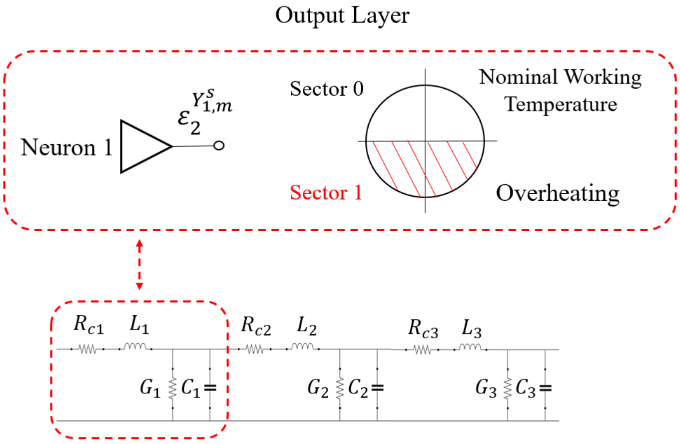
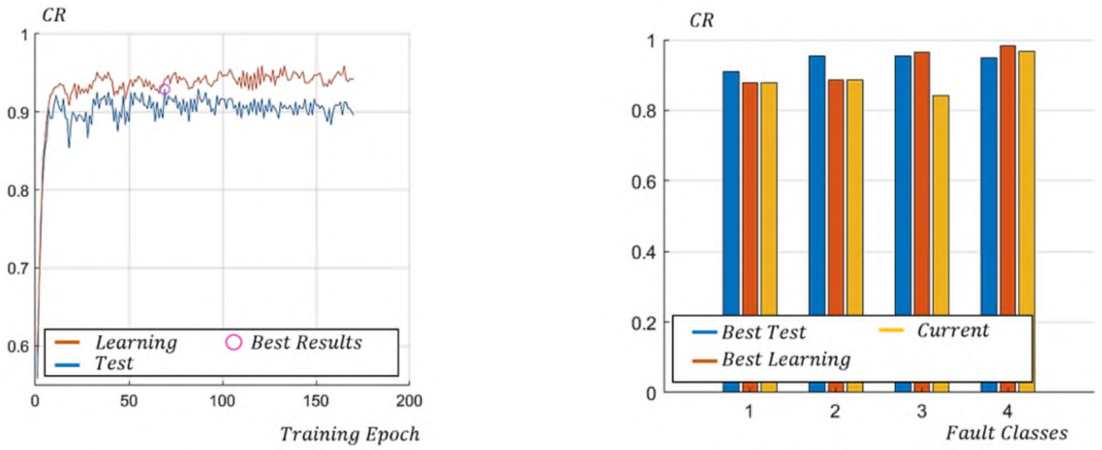


Figure 10. Neural network structure. Configuration of the output layer of the complex neural network: use of a binary neuron for each section of cable.

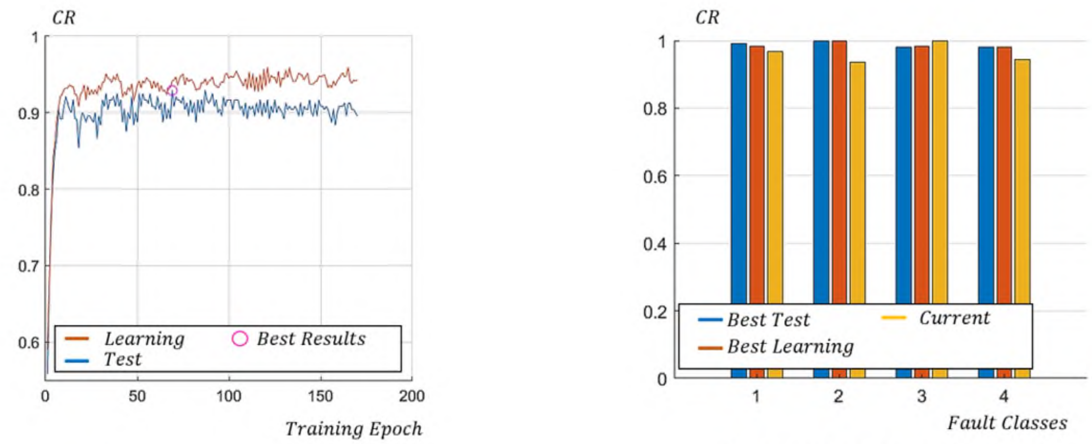
These neurons are used to distinguish the nominal condition of the corresponding cable section from the over temperature situation. In particular, the value 0 corresponding to the beginning of the upper half plane is used to indicate the nominal working temperature, while the lower border of the second sector indicates the overheating. As previously mentioned, two datasets are used in this case to evaluate the performance of the classifier. In the first case, the transfer function measurements obtained at 4 test frequencies are used. The results obtained in terms of the overall classification rate are shown in **Figure 11a**, while **Figure 11b** presents the performance of the complex neural network for each class separately. Initially, hold out validation is used to evaluate the classification results: this means that 80% of the data is used to modify the weights of the neural network (learning) while the remaining 20% is used to verify performance (testing). Note that the results presented are obtained by setting 20 neurons in the hidden layer. In **Figure 11a**, the red line is used to describe the classification rate obtained during the learning phase, while the blue one refers to the testing phase. Finally, the training procedure is repeated by applying a linear PCA to the simulated measurements obtained at 100 frequencies. By maintaining 98% of the information content, the results shown in **Figure 12a,b** are obtained. The performance obtained by keeping 20 neurons in the hidden layer is slightly better than that obtained in the previous case. Therefore, the use of a linear PCA can be considered a valid alternative to the frequency selection. Instead of implementing a rather complex mathematical method, it is possible to perform measurements at multiple frequencies and then reduce the dimensionality of the inputs to avoid a heavy structure of the neural classifier. To obtain a comparable result using all the measurements obtained at 100 frequencies, it is necessary to use a number of neurons in the hidden layer 3 times higher. **Table 2** summarizes these considerations, where No PCA indicates the use of four test frequencies selected through the mathematical method, Linear PCA indicates the use of a linear PCA to the dataset containing simulated measurements at 100 frequencies and 100 Frequencies indicates direct use of this dataset.



(a) global classification rate

(b) classification rate for each output neuron

Figure 11. Classification results. Results obtained using 4 specific frequencies: **(a)** global classification rate; **(b)** classification rate for each output neuron.



(a) global classification rate

(b) classification rate for each output neuron

Figure 12. Classification results. Results obtained by PCA: **(a)** global classification rate; **(b)** classification rate for each output neuron.

Table 2. Classification results obtained by selecting 4 frequencies and using a linear PCA.

Configuration	Classification rate (CR%)	N. hidden neurons	N. complex inputs
No PCA	92.92	20	4
Linear PCA	98.75	20	4
100 Frequencies	96.70	60	100

4. Prognosis of joints in high voltage electrical lines

To identify the operating state of high-voltage overhead transmission lines, it is important to focus on the joints (as shown in **Figure 13**), which are responsible for maintaining electrical continuity along the phase conductor. Joints are among the most vulnerable components of the line, and problems such as voltage drops, power losses, and decreased power quality may be caused by their deterioration. The physical characteristics of the joints are described through three terms: Δ_λ is the length, d is the thickness and H is the height. Then, when a partial break occurs, the term x is used to indicate the thickness of the break and the h term for its height.

For high voltage electrical lines, predictive maintenance requires assessing the health of the joints and taking preventive measures to avoid any potential failures. A multi-layer feedforward neural network based on multi-valued neurons[32] can be employed[36] for this purpose. The voltage transfer function is still used as input for the neural network. Once nominal ranges have been established for the electrical parameters of the line pattern, any deviation can be used to indicate a possible fault.

The monitoring action consists in the comparison between the theoretical frequency response and the simulated measurements at multiple frequencies. The variation obtained from the comparison describes the change in the parameters of the joints and therefore the departure from the nominal condition.

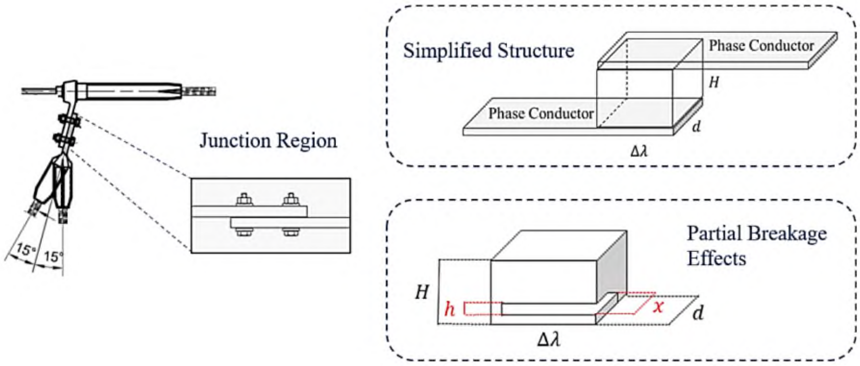


Figure 13. Joint structure. Joint modelling in nominal condition and in the case of a partial breakage.

The neural network is responsible for performing the task of classifying the severity of joint degradation. The procedure for assessing the health of the joints can be summarized as follows.

First, the model of the elementary section of the line, consisting of the cascade connection of the conductor model and the joint model (**Figure 14**), must be introduced. Indeed, the infrastructure can be seen as a sequence of joints and sections of conductor. The conductor equivalent circuit typically used in the literature is the canonical π model[21], whose parameters depend on the mechanical characteristics of the conductor and are considered constant per unit length[37]. The variation of interest is that of the junction regions. Among the three parameters of the joint model (R_{sj}, L_{sj}, and C_{sj}), the resistance parameter is most affected by the formation of oxide, as this modifies the resistivity, while L_{sj} and C_{sj} account for any breakage in the joint[38]. Once the model is established, the neural network can perform the task of evaluating the health of the joints.

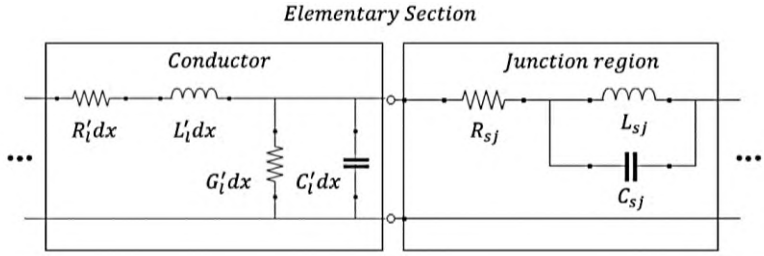


Figure 14. Equivalent model. Elementary section of an overhead line.

The second step involves determining the potential health conditions of each joint region, which can be categorized into three possible classes: nominal, structure oxidation, and partial breakage. The ranges for each joint parameter can be calculated based on the information extracted from the research of De Paulis et al.[22], as shown in **Table 3**.

Table 3. Fault classes.

Nominal conditions	
R_{sj} $[\Omega]$	$60 \cdot 10^{-6} \div (4.78 \cdot 10^{-5}\sqrt{f} + 7.77 \cdot 10^{-4})$
L_{sj} $[H]$	$(1.3 \div 1.7) \cdot 10^{-6}$
C_{sj} $[F]$	$(0.0099 \pm 0.011) \cdot 10^{-12}$
Oxidation conditions	
R_{sj} $[\Omega]$	$(4.78 \cdot 10^{-5}\sqrt{f} + 7.77 \cdot 10^{-4}) \div 2$
L_{sj} $[H]$	$(1.3 \div 1.7) \cdot 10^{-6}$
C_{sj} $[F]$	$(0.0099 \pm 0.011) \cdot 10^{-12}$
Partial breaking conditions	
R_{sj} $[\Omega]$	>2
L_{sj} $[H]$	$(1 \div 1.3) \cdot 10^{-6}$
C_{sj} $[F]$	$(0.011 \pm 0.16) \cdot 10^{-12}$

The third step is focused on selecting an appropriate set of frequencies based on the procedure outlined in the study of Grasso et al.[39]. The voltage transfer function of the model can be calculated using SAPWIN[40], which provides its symbolic formulation and allows the calculation of the response at specific frequencies within reasonable time limits. Next, a training set is created. The symbolic network function can be handled in MATLAB to generate the training samples. In fact, a specific MATLAB script calculates the analytical expressions of magnitude and phase and evaluates their values for each test frequency and for each line health state. This is achieved by replacing symbolic parameters with their numeric values. Therefore, all training samples are obtained by randomly varying the parameters of each joint in the respective classes. During this operation, the parameters of the conductor sections are changed randomly within a range of 10% of their nominal value. In this way, the effects of ambient conditions and load current can be taken into account.

Case study and results

The complex neural network used to obtain the classification results has two layers and uses a pair of binary output neurons for each junction region. The first neuron of each pair detects the oxidation process while the second the partial breakdown mechanism. **Figure 15** shows the global structure of the neural network-based classifier.

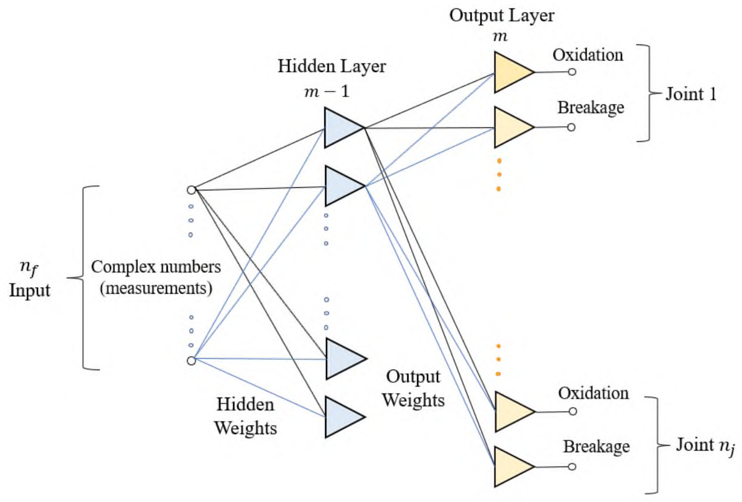


Figure 15. Complex-valued neural network. Overall structure of the complex neural network.

Since these neurons have two possible levels of output, the low value is used to describe nominal conditions. When the output of the first neuron is high and that of the second is low, the combination represents joint oxidation. If, on the other hand, both outputs have a high level, the corresponding junction region has partial damage. Since the hypothesis of the consequentiality between the oxidation mechanism and partial failure is assumed, the remaining combination is not taken into consideration. In general, there are $N_c = 3^{N_g}$ possible output combinations, since each junction region can be oxidized, broken or fully functional (where N_g is the total number of joints,). **Figure 16** illustrates the case study considered.

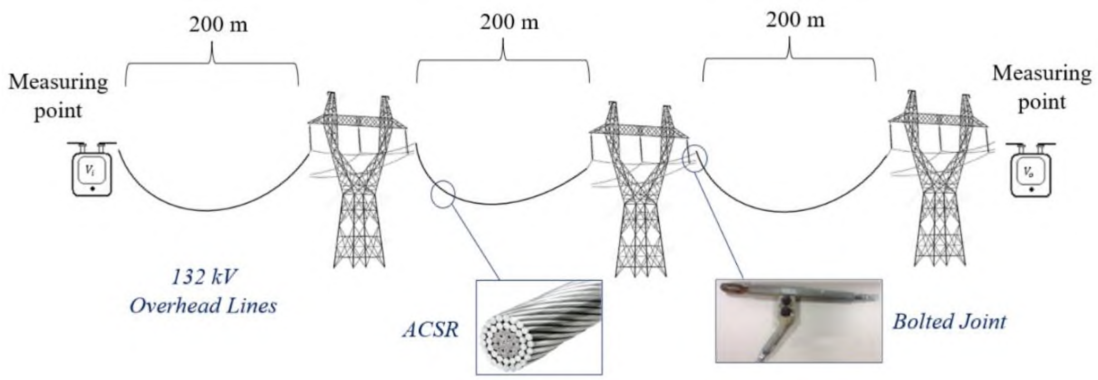


Figure 16. Case study. Overhead line with three junction regions.

The results reported in **Table 4** are obtained for a line with three junction regions and show that the classification method identifies the operating conditions of each joint with an accuracy level higher than 90%.

Table 4. Characteristics of a single cable part.

Fault classes	Neuron	CR% for each neuron	Joint	CR% for each joint
Oxidation	1	95.11	1	94.07
Partial breakage	2	99.37		
Oxidation	1	92.85	2	91.30
Partial breakage	2	99.22		
Oxidation	1	97.89	3	96.70
Partial breakage	2	99.81		

5. Conclusion

The use of machine learning algorithms has shown significant potential for detecting power quality disturbances in electrical systems. The research presented in this article has explored different machine learning techniques for power quality analysis. They can accurately classify different types of power quality disturbances, including voltage sags, swells, interruptions, harmonics, and transients. Moreover, the localization and classification of power quality disturbances using the SSPQDD have been also considered.

The results of our study suggest that machine learning-based approaches can provide an efficient and reliable way to monitor power quality and detect disturbances in real-time. By analyzing the electrical signals from power systems, these algorithms can identify patterns and anomalies that may indicate power quality issues. Moreover, the ability to detect and classify power quality events can provide valuable information for power system operators to take preventive measures and improve system performance.

Despite the promising results, there are still challenges to overcome in implementing machine learning-based power quality analysis in practice. These challenges include data availability and quality, and interpretability. Further research is needed to address these challenges and optimize machine learning models for power quality analysis.

In summary, the use of machine learning for power quality analysis has significant potential to improve the safety, reliability, and efficiency of electrical systems. As the demand for high-quality power continues to grow, machine learning can provide an effective solution for power quality monitoring and detection, enabling early detection and mitigation of disturbances and reducing the risk of equipment damage and system failures.

Furthermore, the theoretical results presented in this paper offer a possible approach for the detection and localization of malfunctions in transmission and distribution lines. The goal of the simulations performed was to demonstrate that the MLMVN-based classifier allows the identification of the state of the line using measurements of its frequency response. In the case of the prognosis of joints on overhead lines, the hypothesis of multiple failure with multiple severities was adopted. In this situation, the method allows the correct monitoring (classification rate higher than 90%) of the joints contained in a branch of 800 meters. Exceeding this limit, the performance in recognizing the operating conditions of all joints decreases. It is still possible to study a single joint with good accuracy, but the overall performance is not sufficient. As regards the monitoring of underground lines, the single failure hypothesis was assumed and the prognostic method was focused on the detection of overheating. In this case, the classifier allows the correct monitoring (accuracy greater than 95%) of approximately 1 km of line divided into three successive sections. The increase in the length of the line branch considered and therefore in the number of successive sections determines the reduction of the classification rate and requires further developments.

Author contributions

Conceptualization, MB; methodology, CIG; software, MB and CIG; validation, AL, FG and LP; formal analysis, MCP; investigation, LP; data curation, LP and CIG; writing—original draft preparation, MB; writing—review and editing, MCP; supervision, AL and FG. All authors have read and agreed to the published version of the manuscript

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Conflict of interest

The authors declare no conflict of interest.

Abbreviations

TDR	Time Domain Reflectometry
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Networks
SSPQDD	Single Shot Power Quality Disturbance Detection
PQ	Power Quality
PCA	Principal Component Analysis
MLMVN	Multi-Layer neural network with Multi-Valued Neurons

References

1. Bindi M, Luchetta A, Paolucci L, et al. Applications of machine learning techniques for the monitoring of Electrical transmission and distribution lines. In: Proceedings of the 2022 18th International Conference on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design (SMACD); 12–15 June 2022; Villasimius, Italy. pp. 1–4.
2. Wang L, Qin Z, Slangen T, et al. Grid impact of electric vehicle fast charging stations: trends, standards, issues and mitigation measures—An overview. *IEEE Open Journal of Power Electronics* 2021; 2: 56–74, doi: 10.1109/OJPEL.2021.3054601
3. Rafiqi IS, Bhat AH. Role of UPQC in addressing power quality issues in the power grid connected with renewable energy sources. In: Proceedings of the 2022 1st International Conference on Sustainable Technology for Power and Energy Systems (STPES); 4–6 July 2022; Srinagar, India. pp. 1–4.
4. Kanjiya P, Khadkikar V. Enhancing power quality and stability of future smart grid with intermittent renewable energy sources using electric springs. In: Proceedings of the 2013 International Conference on Renewable Energy Research and Applications (ICRERA); 20–23 October 2013; Madrid, Spain. pp. 918–922.
5. Auler LF, d'Amore R. Power quality monitoring controlled through low-cost modules. *IEEE Transactions on Instrumentation and Measurement* 2009; 58(3): 557–562. doi: 10.1109/TIM.2008.2005264
6. Cappelli I, Carli F, Fort A, et al. Enhanced visible light localization based on machine learning and optimized fingerprinting in wireless sensor networks. *IEEE Transactions on Instrumentation and Measurement* 2023; 72: 1–10. doi: 10.1109/TIM.2023.3240220
7. Farhoodnea M, Mohamed A, Shareef H, Zayandehroodi H. Power quality impacts of high-penetration electric vehicle stations and renewable energy-based generators on power distribution systems. *Procedia Technology* 2013; 11: 11–17. doi: 10.1016/j.protcy.2013.12.156
8. Bindi M, Corti F, Aizenberg I, et al. Machine learning-based monitoring of DC-DC converters in photovoltaic applications. *Algorithms* 2022; 15(3): 74. doi: 10.3390/a15030074
9. Hayder AN, Saidi L. Applications of artificial neural networks with input and output degradation data for renewable energy systems fault prognosis. In: Proceedings of the 2021 12th International Renewable Energy Congress (IREC); 26–28 October 2021; Hammamet, Tunisia. pp. 1–6.
10. Ozbuber S, Bagriyanik M. A smart grid integration platform developed for monitoring and management of energy systems. In: Proceedings of the 3rd International Istanbul Smart Grid Congress and Fair (ICSG); 29–30 April 2015; Istanbul, Turkey. pp. 1–5.
11. Belardi R, Bindi M, Grasso F, et al. A complex neural classifier for the fault prognosis and diagnosis of overhead electrical lines. In: Proceedings of the 2020 International Conference on Advanced Electrical and Energy Systems; 18–21 August 2020; Osaka, Japan.
12. Kwan KH, So PL, Chu YC. An output regulation-based unified power quality conditioner with kalman filters. *IEEE Transactions on Industrial Electronics* 2012; 59(11): 4248–4262. doi: 10.1109/TIE.2012.2193852
13. Kumawat PN, Verma DK, Zaveri N. Comparison between wavelet packet transform and M-band wavelet packet transform for identification of power quality disturbances. *Power Research* 2018; 14(1): 37–45. doi: 10.33686/pwj.v14i1.142183
14. Pugach VN, Polyakov DA, Nikitin KI, Yurchuk DA. XLPE-insulated cables temperature monitoring for the determination of their residual life. In: Proceedings of the Dynamics of Systems, Mechanisms and Machines (Dynamics); 14–16 November 2017; Omsk, Russia. pp. 1–6.
15. Shafiq M, Kiitam I, Taklaja P, et al. Identification and location of PD defects in medium voltage underground power cables using high frequency current transformer. *IEEE Access* 2019; 7: 103608–103618.

16. Heider MZ, Rahman MM, Al-Arainy AA. Study of frequency variant tan delta diagnosis for MV cables insulation status assessment. In: Proceedings of the 2019 5th International Conference on Advances in Electrical Engineering (ICAEE); 26–28 September 2019; Dhaka, Bangladesh. pp. 260–264.
17. Rahim NH, Chairul IS; Ghani SA, et al. Simulation of TDR circuit for the analysis of wave propagation in XLPE cable model. In: Proceedings of the IEEE International Conference on Power and Energy (PECon); 2–5 December 2012; Kota Kinabalu, Malaysia. pp. 796–801.
18. Xun L, Shungui L, Ronghui H, et al. Study on accuracy traveling wave fault location method of overhead line—Cable hybrid line and its influencing factors. In: Proceedings of the Chinese Automation Congress (CAC), 20–22 October 2017; Jinan, China. pp. 4593–4597.
19. Andersson G. *Modelling and Analysis of Electric Power System* [PhD thesis]. ITET ETH Zurich 2008.
20. Davoudi M, D'Antona G, Berizzi A. *Sensitivity Analysis of Power System State Estimation Regarding to Network Parameter Uncertainties* [PhD thesis]. Politecnico di Milano-Electrical Engeneering Department-Doctoral Program In Electrical Engineering; 2009–2012.
21. Monteiro JS, Neves WLA, Fernandes D, et al. Computation of transmission line parameters for power flow studies. In: Proceedings of the Canadian Conference on Electrical and Computer Engineering 2005; 1–4 May 2005; Saskatoon, SK, Canada. pp. 607–610.
22. de Paulis F, Olivieri C, Orlandi A, et al. Exploring remote monitoring of degraded compression and bolted joints in HV power transmission lines. *IEEE Transactions On Power Delivery* 2016; 31(5): 2179–2187. doi: 10.1109/TPWRD.2016.2562579
23. Jaffrey NA, Hettiewatte S. Corrosion detection in steel reinforced alluminium conductor cables. In: Proceedings of the 2014 Australasian Universities Power Engineering Conference (AUPEC); 28 September–1 October 2014; Perth, WA, Australia. pp. 1–6.
24. Shi X, Yang H, Xu Z, et al. An independent component analysis classification for complex power quality disturbances with sparse auto encoder features. *IEEE Access* 2019; 7: 20961–20966. doi: 10.1109/ACCESS.2019.2898211
25. Liu Y, Jin T, Mohamed MA, Wang Q. A novel three-step classification approach based on time-dependent spectral features for complex power quality disturbances. *IEEE Transactions on Instrumentation and Measurement* 2021; 70: 1–14. doi: 10.1109/TIM.2021.3050187
26. Mohan N, Soman KP, Vinayakumar R. Deep power: Deep learning architectures for power quality disturbances classification. In: Proceedings of the 2017 International Conference on Technological Advancements in Power and Energy (TAP Energy); 21–23 December 2017; Kollam, India. pp. 1–6.
27. Khokhar S, Mohd Zin AA, Memon AP, Mokhtar AS. A new optimal feature selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network. *Measurement* 2017; 95: 246–259. doi: 10.1016/j.measurement.2016.10.013
28. Iturrino GC, Grasso F, Luchetta A, et al. A comparison of power quality disturbance detection and classification methods using CNN, LSTM and CNN-LSTM. *Applied Sciences* 2020; 10(19): 6755. doi: 10.3390/app10196755
29. Iturrino-García C, Patrizi G, Bartolini A, et al. An innovative single shot power quality disturbance detector algorithm. *IEEE Transactions on Instrumentation and Measurement* 2022; 71: 1–10. doi: 10.1109/TIM.2022.3201927
30. Sturchio A, Fioriti G, Salusest V, et al. Thermal behavior of distribution MV underground cables. In: Proceedings of the 2015 AEIT International Annual Conference (AEIT); 14–16 October 2015; Naples, Italy. pp. 1–5.
31. Sturchio A, Fioriti G, Pompili M, Cauzillo B. Failure rates reduction in SmartGrid MV underground distribution cables: Influence of temperature. In: Proceedings of the 2014 AEIT Annual Conference—From Research to Industry: The Need for a More Effective Technology Transfer (AEIT); 18–19 September 2014; Trieste, Italy. pp. 1–6.
32. Aizenberg I, Belardi R, Bindi M, et al. Failure prevention and malfunction localization in underground medium voltage cables. *Energies* 2020; 14(1): 85. doi: 10.3390/en14010085
33. Available online: https://www.latrivenetacavi.com/it/cavi_categorie.aspx (accessed on 20 October 2023).
34. Gatta FM. *Electrical Installations* [Italian]. Esculapio; 2019.
35. Bindi M, Piccirilli MC, Luchetta A, et al. Testability evaluation in time-variant circuits: A new graphical method. *Electronics* 2022; 11(10): 1589. doi: 10.3390/electronics11101589M
36. Bindi M, Aizenberg I, Belardi R, et al. Neural network-based fault diagnosis of joints in high voltage electrical lines. *Advances in Science, Technology and Engineering Systems Journal* 2020; 5(4): 488–498. doi: 10.25046/aj050458
37. Hashmi GM, Lehtonen M. Covered-conductor overhead distribution line modeling and experimental verification for determining its line characteristics. In: Proceedings of the 2007 IEEE Power Engineering Society Conference and Exposition in Africa—PowerAfrica; 16–20 July 2007; Johannesburg, South Africa. pp. 1–7.
38. Bindi M, Grasso F, Luchetta A, et al. Smart monitoring and fault diagnosis of joints in high voltage electrical transmission lines. In: Proceedings of the 2019 6th International Conference on Soft Computing & Machine Intelligence (ISCMI); 19–20 November 2019; Johannesburg, South Africa. pp. 40–44.
39. Grasso F, Luchetta A, Manetti S, Piccirilli MC. A method for the automatic selection of test frequencies in analog

fault diagnosis. *IEEE Transactions on Instrumentation and Measurement* 2007; 56(6): 2322–2329. doi: 10.1109/tim.2007.907947

40. Grasso F, Luchetta A, Manetti S, et al. SapWin 4.0—A new simulation program for electrical engineering education using symbolic analysis. *Computer Applications in Engineering Education* 2015; 24(1): 44–57. doi: 10.1002/cae.21671