A NOVEL LEARNING METHOD FOR THE CLASSIFICATION OF POWER QUALITY DISTURBANCES USING THE DEEP CONVOLUTIONAL NEURAL NETWORK

METODĂ PENTRU ÎNVĂȚAREA CLASIFICĂRII PERTURBAȚIILOR CALITĂȚII ENERGIEI FOLOSIND REȚELE NEURONALE CONVOLUȚIONALE PROFUNDE

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Abstract: *Since a multitude of power systems are integrated into a single interconnected system, there is a growing risk of deteriorating electricity quality at all stages of electricity generation (production, transportation, distribution and in the final stage of its use. Automatic classification of energy quality distortions is the starting point for solving the problem of power quality. From the outset, the process of identifying power quality disturbances should be stratified into three independent levels, namely: analyzing the disturbances, selecting them, and classifying the signal characteristics. However, some defects that may occur are inherent in the signal analysis and thus requires a procedure of manual selection of characteristics which is demanding and inaccurate, which leads to low accuracy in the classification of multiple disturbances and poor immunity to electromagnetic noises. from the network.*

Keywords: Power quality disturbances, Deep convolutional neural networks, Distributed energy.

Rezumat: *Din momentul în care sunt integrate o multitudine de sisteme electroenergetice într-un singur sistem interconectat, din acel moment apare un risc ce crește în amplitudine legat de deteriorarea calității energiei electrice*

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în toate etapele și stadiile în care se găsește energia electrică (producție, transport, distribuție și în etapa finală cea de utilizare a sa. Clasificarea automată a distorsiunilor calității energiei electrice este fundamentul de la care se pleacă pentru a rezolva problema calității energiei electrice. Din start, procesul de identificare a perturbațiilor calității energiei electrice ar trebui stratificat pe trei nivele independente acestea fiind: analiza perturbațiilor, selectarea acestora și clasificarea caracteristicilor semnalului. Însă, unele defecte ce pot apărea sunt inerente în analiza semnalului și astfel este nevoie de o procedură de selectare manuală a caracteristicilor ceea ce este solicitant și imprecis, ceea ce duce la o precizie redusă în clasificarea multiplelor perturbații și la o imunitate slabă la zgomotele electromagnetice din rețea.

Cuvinte cheie: Perturbații ale calității energiei, Rețele neuronale convoluționale profunde, Energie distribuită.

1. Introduction

This paper contains and details a proposal for a new approach in a closed loop for classification but also for detecting problems caused by power quality disturbances, an approach based on the principles of new deep convolutional neural networks. Considering the characteristic of power quality disturbances problem, a unit construction which consists of an 1-D convolutional, pooling, and batch-normalization layers is designed to capture multi-scale features and reduce overfitting.

The integration of multiple energy sources can lead to efficient operation of energy systems but also to the reduction of pollutant (mainly carbon) emissions. The access, to such a system, of the new renewable energy sources but also the optimization of the connections from the nodes of the system of some sources such as, but not limited to, combined sources (cooling, heating and power known as CCHP, microgrid etc.) have become an important form of integration of multiple energy sources.

PQDs (Power Quality Disturbances) means deviation / disturbances of voltage, current or frequency from the standardized value. From the production stage, some renewable energy sources such as solar and wind show a predominant feature of randomness, fluctuation and intermittent. An important source of power quality pollution is the volatility of generation but also the converters needed for renewable energy sources, these sources easily lead to energy imbalances and variations in electrical voltage. Regarding the next stage of the electricity cycle, the transformation stage, with the help of the extra brought by the energy storage sources in batteries but also with the help of the charging stations of electric vehicles (EV) from the composition of the microgrids, the wide use a power electronic device such as solid-state switches and electronic inverters have caused significant harmonic pollution.

In the last stage of the energy cycle, that of energy consumption, the problem of integrating multiple other energy sources (such as but not limited to asynchronous motors, electronic measurements, control devices but also other non-linear loads), and their operation aggravates the level voltage and current distortion. In addition to the situations already presented, another problem is the coordination and optimization of the regional systems operation of multiple microgrid systems that make the PQDs of these microgrids overlapped, which will lead to multiple and complex compound disturbances that are extremely difficult to manage.

Meanwhile, with the integration of power system and other energy systems, the PQDs problem also has adverse impacts on the coordinating control and safe operation of multi-energy systems. Problems with power quality can easily spread to other power systems due to the easy transformation of energy but also its long-distance transport. A good example is the conversion of energy into heat, the fluctuation of electrical voltage will affect the efficiency of heat production, resulting in an imbalance in the supply of heat. In addition to problems already known in the system, a new problem is caused using computers, programmable logic controllers, and other sensitive electronic equipment for measurement and control has also brought a higher requirement for power quality, because PQDs will result in failure or malfunction of electrical / electronic equipment, misoperation of automatic protection device and equipment damage such as overheating, motor failures.

Given that different PQDs have different effects and consequences on different energy systems, and in line with the PQDs already identified and detected, we can say that we can adopt new targeted and efficient methods for solving power quality problems otherwise, there is an urgent need to determine and classify these disturbances and to improve power quality and from an economic point of view, to avoid damage and especially the destruction of used equipment. The lack of feedback causes that the features extracted in the first step may not always be conducive to identifying different PQDs and sometimes may even have an adverse effect, especially when the sample data contain noise. Because of this we come to the conclusion that rather than continue to use, and be limited only to traditional processes (signal processing, feature optimization, classification) we better evolve, from a technological point of view, and use a novel closed-loop analysis framework for to classify PQDs [4] and to simplify the analysis process and improve accuracy.

Deep learning has a dramatic performance in image classification, speech recognition and machine translation from its feature extraction through multiple levels of abstraction. Through special layers and supervised training of multiple samples, Deep Neural Networks (DNNs) can perform automatic extractions of spatial and temporal features from input data without following the traditional steps of signal processing, then completing tasks such as classification and regression [1]. That being said, the use of DNN in the issue of PQDs is not limited to improving the accuracy of the classification but can reduce the need for people by simplifying the process. The process by which DNN improves the PQD problem involves transferring PQD input data into a 2-D matrix similar to image data, and then going through a typical 2-D CNN process in order to identify the types of PQD. I mention that the PQD data in the 1-D time series, but also 2-D CNN are designed for image classification and are not entirely suitable with the issues brought by PQD [8].

2. Problem definition

i ∈ I, j ∈ J which are the indices of disturbances and types, and $y_{i,j}$ is the categorial variable, and j-th type label of the i-th disturbance sample. E(x) represent a future extraction and selection function and it is used before the classification to extract feature vector $S_{i,j}$ from the original waveform data w_i:

$$S_{i,j} = E\ (w_i)\ , \tag{1}$$

F(x) is a classification model which is need to be trained, and it denote the mapping relationship between waveform data to the j-th label. For the given $\{S_{i,j}, y_{i,j}\}$, the j-th label of the i-th sample can be estimated [6]:

$$y_{i,j}^{'} = F(S_{i,j}) \tag{2}$$

And w_1 și w_2 are the optimal trained parameters of Neural Network used for feature extraction and classification [1].

$$CE\ (w_1, w_2) = -\frac{1}{n}\sum_{i=1}^{n}[y_i' \ln y_i + (1 - y_i')\ln (1 - y_i)]\ , \tag{3}$$

The raw data required for this DNN in the learning process are obtained from mathematical models of the PQD-us.

Learning and testing sets are obtained / generated using parametric equations based on 16 types of PQD signals, including 10 singular types such as pure sine waveform, sag, swell, interruption, harmonics, impulsive transients, oscillatory transients, flicker, notch, spikes and 6 multiple types such as harmonic sag, harmonic swell, harmonics interrupt, harmonics,

harmonics flicker, sag flicker and swell flicker (all of these parameters are in line with the IEEE-1159 standard) [3].

3. Classification method based on deep CNN

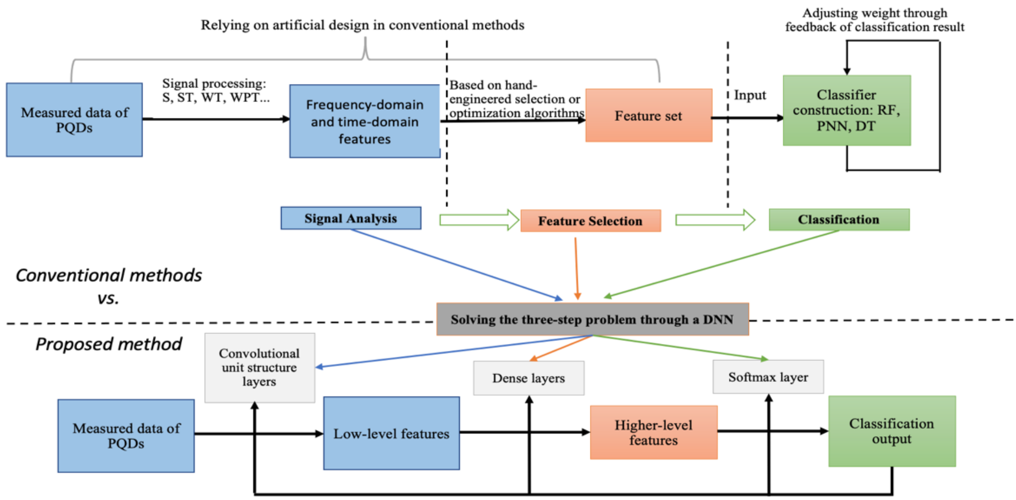

Figure 1 – Difference between traditional and proposal fmethod framework [6]

As shown in Figure 1, and compared to the traditional framework, the classification framework of the rationale for applying a CNN in this issue is as follows:

[1]. Automatic feature extraction: learning is the most important feature of a deep learning, and learning allows a DNN to be permanently fed with raw data and after this data have been processed allows the discovery of new data that are needed to classify PQDs because the implementation of a deep learning can independently and automatically perform the extraction, selection and combination of PQDS features [7].

[2]. A closed-loop feedback: through a DNN such a deep CNN, the problems and classification of PQDs is a unified whole that can be solved automatically by a universal DNN. In the process of supervised training, each layer’s weights will be updated automatically by the feedback of classification performance. Thus this process is a completely closed loop type feedback without the need for any manual intervention [1].

The architecture of a deep CNN includes three stacked units that have the role of extracting features which consist of 1-D convolutional layers, pooling layers, and batch-normalization (BN) layers. The 2nd unit and especially its outputs are connected to a few fully connected layers, and for the last unit this is a softmax layer.

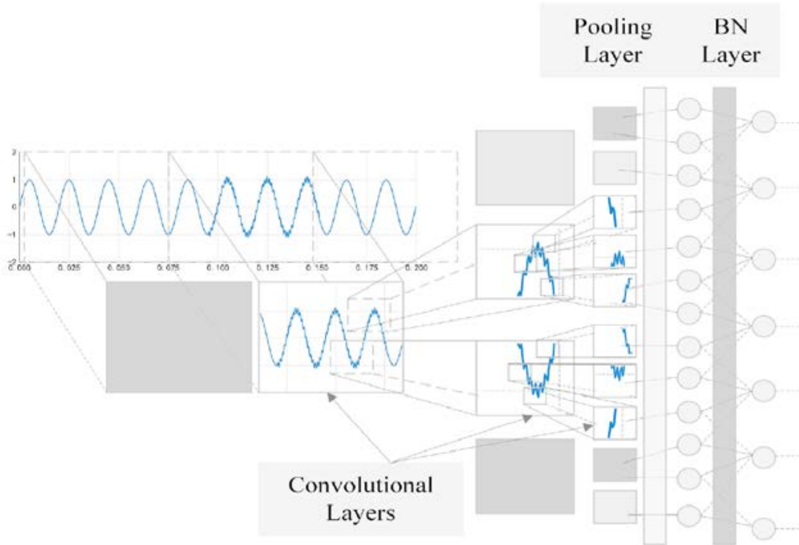

Figure 2 – The construction of the proposed unit and his extracting characteristics [4]

The structure of the unit is composed of 2 convolutional layers that have a small stride are stacked with a role in capturing features of the disturbances waveform from the whole period. As for the PQD samples they are in the form of 1-D signals which are very different from the 2-D image data, so there is a 1-D filter is mounted in each layer. To consider both local and overall features, the kernel size of the filter is designed small and plenty of filters with short stride are employed. A pooling layer is mounted by inserting behind each set of convolutional layers in order to reduce dimensionality and highlight the features of disturbances. Finally, the batch-normalization layer is able to greatly reduce the overfitting and enchance the generalization ability [2]. Figure 2 shows the process of extracting and transforming features from the disturbance sample by means of the proposed unit construction.

4. Exemple of state-of-the-art DNNs what competing with our unit proposed

Currently, there are four developed examples that have the status of technologically advanced DNNs that are able to be compared, in terms of performance, with the method proposed in this paper. A brief description of them can be found below:

1) *Stacked Auto-encoder (SAE):* It is an unsupervised method, which is used to compare the characteristics of PQD. The principle of operation but also the key idea behind the SAE is for the network to learn the characteristics of the input data in a clear, easy way but most importantly in an unsupervised way [1-4]. Thus, this learning takes place following an unsupervised training that takes place in the SAE network with the greedy layer-wise training method in order to obtain the features of PQDs. The next step in the self-learning process is to connect the SAE training with a softmax layer in order to classify the types of disturbances referring to features outputted by the SAE [5].
2) *Long short-term memory (LSTM)*: this method has been applied in order to facilitate speech recognition and machine translation, which has been successfully applied. This method is a typical Recurrent Neural Network (RNN) that consists of a memory cell, comprised of a gated input, gated output and gated feedback loop. In the comparison underlying this chapter, a stacked-LSTM structure was used to classify PQDs [3-7]. The model used uses three stacked LSTM layers in order to achieve the ability to learn higher-level temporal representations.
3) *ResNet50:* Residual networks (ResNet) allow, through a structure called block, the training of a network that consists of up to 1000 layers. 3.6×10^9 parameters are used to increase the speed of training, a training called fine-tunning is carried out on the basic of a trained ResNet50 netwotk. The original purpose of ResNet was to classify images, the input signal size was changed from a value of 640+36 (an insufficient number) up to a 26 x 26 and a softmax layer consisting of 16 neurons that replace the output layer [2].
4) *Gated Recurrent Unit (GRU)*: whisch is also a RNN. Its principle of operation is to cancel the separate memory cells, and to reduce the time-consuming training process within Long short-term memory. As they are dependent on each other, there are no deadlines for a comparison between GRU and LSTM, so their choice depends only on the task and its dataset.

GRU and LSTM are similar, and stacked-GRU is similar to stacked-LSTM except that LSTM layers are replaced with GRU layers.

The competing DNNs proposed for the classification of PQDs are summarized in the following table.

Table 1 – *Comparison between the proposed DNN types [6]*

Name of the network	Number of layers	Type
RestNet50	49 conventional 2-D layer 1 dense layer	Convolutional Neural Network
GRU	3 GRU layer, 32 unit and tanh activation 1 dense layer and softmax activation	Recurrent Neural Network
Stack Auto-encoder	5 dense layer	Auto-encoder
LSTM	3 LSTM layer with 32 unit and tanh activation 1 dense layer with softmax activation	Recurrent Neural Network
Deep CNN	6 conventional 1-D layer 3 Dense layer	Convolutional Neural Network

5. Results and discussion

Firstly, 768.000 samples have been generated using the method described in Chapter 2. However, there is always noise in data collected from the real sensor. To enhance the robustness of the proposed method, Gaussian white noise is added randomly to the synthetic PQDs data at different levels.

Some of the parameters, such as signal-to-noise ratio (SNR), vary with values between 20 and 50 dB. Then 10-fold cross validation is applied to these samples so 10% of the training data is shared as a validation set. Last but not least, 1000 samples are generated for each type of disturbance as a test set, in order to test the performance of all training and instruction models presented in the previous chapter. In order to be able to compare the results obtained with the existing methods, noise signals with values of 20, 30 and 40 dB are added.

5.1. The case of a single microgrid and simulation of PQDs in it

The concept of microgrid allowed a new approach that expanded on a large scale and came to the possibility of integrating renewable energy sources in a distributed way, concepts that some time ago seemed difficult to achieve. They are also indispensable elements of smart grids.

Given the development potential of microgrids but also the complexity of power quality issues, a key to the future causes of PQD problems are microgrids and validation of the effects of the proposed method, which are built using PSCAD / EMTDC power system simulation software, which has photovoltaic generator, wind turbine generator, gas turbine generator and energy storage unit. On the other hand, in a microgrid, there are a multitude of loads such as: resistive load, inductive load and other nonlinear loads [8].

Line faults and some special operating events will cause PQDs in the microgrid, which is not the same as traditional power system. Here are some examples:

1) Voltage interruption – is a drop of 90-100% of the voltage into a microgrid for the period of 1 to 9 cycles. Two faults which will generate an apparent voltage interruption are line-to-ground (LLG) faults and three-phase (LLL) faults. Besides, foar a microgrid operating in island mode, the tripping of a heavy-load DG will also cause the voltage interruption [2].
2) Voltage sag - is a drop of 10-90% of the voltage into a microgrid for the period of 1 to 9 cycles. The single line-to-ground (SLG) faults happened on the bus or at the end of transmission line will generate the voltage sag events. Into a microgrid, a possible cause of voltage sags is also a sudden startup of wind turbines and switching on large load [5].
3) Voltage swell – is a rise of 10-90% of the voltage into a microgrid for a period of 1 to 9 cycles. A possible source of voltage swell is a line-to-line (LL) faults or the switching off heavy load in a short time. In the simulating system, voltage swell samples are generated by adding LL faults at PCC and switching off the most of microgrid loads [6].
4) Voltage spike, impulsive and oscilatory transient – the main reason of appearance of the spikes and impulsive in power system is the switching of a large capacitor bank in distribution system. For a microgrid operating in the grid-connected mode, the switching of capacitor bank in distribution system also have an adverse effect on the connected microgrid. In order to prove this situation, in the simulation system, is connected a large capacitor bank into the distribution system near the PCC of microgrid, and the voltage of PCC is monitored when the

capacitor bank is switched. Din experiență se știe că mai multe oscilații tranzitorii au loc în microrețele în comparație cu sistemul de distribuție, due to the change of microgrid island switch-over process [4].

5) Harmonics, flicker and notches disturbances – this power quality disturbances is possible to be created by connecting the non-linear power electronic based converters such as six pulse rectifiers and simulating the occurrence of some special line faults. Usual anf typical waveform can be seen into Figure 3.

Generarea PQDs compuse poate fi și prin aplicații simultane ale defectelor pe linie (line faults), loads switching and operation mode changing in the simulation microgrid. În contrapartidă, sunt șanse mai mici posibilități de apariție, ale diferitelor PQDs, în același timp pentru un singură microrețea din exploatare. Astfel, pentru a putea simula cât mai exact o situație reală vom genera o mostră pentru fiecare tip de PQDs through changing different combinations of DG outputs and microgrids loads.

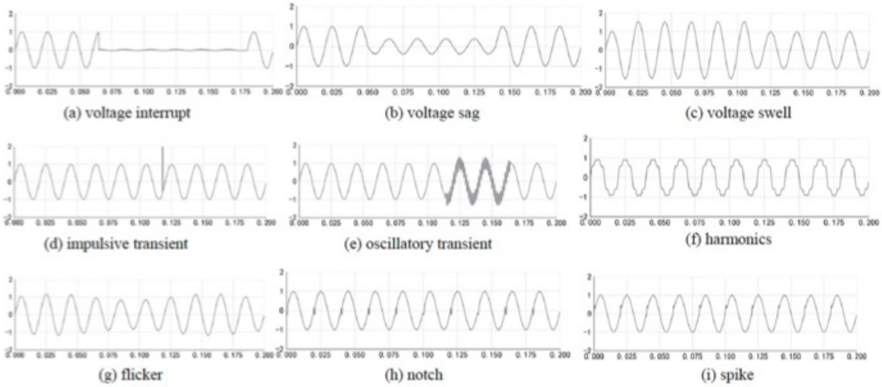

Figure 3 – Usual PQDs waveforms [6]

5.2. The case of multi-microgrid system and the field data validation of PQDs in it

A multitude of microgrids placed next to each other can create a multi-microgrid in cooperative operation mode. In addition to what has already been said, the integration of other forms of energy can increase the efficiency of the entire network created. A total of 27 single-phase measuring devices located in different locations of a multi-microgrid can be used for the purpose of an identified test. In fact, a multi-grid can also include equipment such as photovoltaic generators, wind turbines, gas turbines, energy storage units, boilers and bromide refrigerating machines. And its operation can be organized and responsibly using a dispatching model of multiple CCHP microgrids [1].

As the simulations performed over time show, the interaction in micro-networks generates complex composite disturbances and further aggravates the problems with the quality of electricity. For the original 35 groups of measured data labeled standard signals, after the identification of deep CNN, 30 groups are identified as standard signals and 4 groups are identified as harmonics. The further signal analysis is carried out for these 4 groups signals, and it is found that there are indeed small harmonic components. It's no doubt that with the development of distributed energy and microgrid, PQDs will become more complicated and diversified [8]. Due to these disturbances, the service life of these equipments will be short, and sometimes these disturbances can lead to the deterioration of the equipments in serious cases, and can bring potential risks on the operational reliability of the multi-energy systems.

In all these cases presented, the so-called artificial methods of differentiating the features of different types of disturbances will become more and more tedious and difficult. A DNN can automatically show / display and extract the features used for differentiation and can more easily cope with the incredibly complex power quality environment in the future multi-energy system, as another goal is to improve process reliability. multi-energy system through targeted solving measures [5].

6. Conclusions

The proposal of this scientific paper was a deep convolutional neural network consisting of constructive units and their application in order to classify the disturbances of electricity quality. After the supervised training stage, the presented DNN will perform an automatic extraction and selection of features. The three steps (signal process, feature selection and classifier establishment) existing in conventional methods are merged and replaced by a global closed-loop-feedback training process, which is helpful to enhance power quality and ensure operational reliability in multi-energy systems.

The comparison between DNN and the 4 advanced deep neural networks led to the conclusion that the proposed solution has higher accuracy but also lower training costs compared to the others, which proves that it's more suitable for the PQD classification problem.

Compared to existing methods, DNN has a significant advantage that can easily be called a considerable advantage in terms of classification accuracy, noise immunity and computational speed. DNN is also suitable as a solution for big data analysis of PQD data taking into account the rapid growth of monitor devices in multi-energy system.

R E F E R E N C E S

[1] *GK Singh* „Power system harmonics research: a survey" Eur Trans Electr Power 2009;19:151-72. https://doi.org/10.1002/etep.201

[2] *OP Mahela, AG Shaik, N. Gupta* „A critical review of detection and classification of power quality events.," Renew Sustain Energy Rev 2015 ;41 :495-505. https://doi.org/10.1016/j.rser.2014.08.070

[3] *S. Khokhar, AA Zin Mohd, AP Memon, AS Mokhtar* „A new optimal features selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network" Measurement 2017; 95:246-59, https://doi.org/10.1016/j.measurement.2016.10.013.

[4] *M. Drouineau, N. Maïzi, V. Mazauric,* „ Impacts of intermittent sources on the quality of power supply: the key role of reliability indicators" Appl Energy 2014, https://doi.org/10.1016/j.apenergy.2013.11.069

[5].*M. van der Kam, W. van Sark,* "Smart charging of electric vehicles with photovoltaic power and vehicles-to-grid technology in a microgrid; a case study", Appl Energy 2015, https://doi.org/10.1016/j.apenergy.2015.04.092

[6] *S. Wang, H. Chen,* „A novel deep learning method for the classification of power quality disturbances using deep convolutional neural network", Applied Energy number 235, 2019, 1126-1140, https://doi.org/10.1016/j.apenergy.2018.09.160

[7] *N. Mohan, KP. Soman, R. Vinayakumar,* "Deep power:Deep learning architectures for power quality disturbances classification.", In:Proc 2017 IEEE int conf technol adv. Power energy explor energy solute an intel power grid, TAP energy 2017; 2018. P. 1-6, https://www.doi.org/10.1109/TAPENERGY.2017.8397249

[8] *Ray PK, Kishor N, Mohanty SR*. "Islanding and power quality disturbance detection in grid-connected hybrid power system using wavelet and S-transform. IEEE Trans Smart Grid 2012;3:1082–94. https://doi.org/10.1109/TSG.2012.2197642.