Event Classification in Non-Intrusive Load Monitoring Using Convolutional Neural Network

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Abstract— **The present paper addresses the event classification in the scope of non-intrusive load monitoring (NILM) through the use of Convolutional Neural Network (CNN), an artificial intelligence (AI) kind. Concepts of CNN and NILM are presented, as well as the methodology for the elaboration of signature appliances from the aggregate monitoring of energy for CNN training. A case study is performed considering 34 events of different devices to test the classification performed by CNN. At this, was possible to observe that the use of CNN is adequate for the event detection on the NILM approach, reaching 87% accuracy in the classification on the performed test. Through the tests carried out, it was observed that some confusions occurred in the classification process can be corrected through the improvement of the method of signature set formation, in order to reach a wider range of the signatures spectrum.**

***Index Terms*—Artificial Intelligence, Convolutional Neural Network, CNN, Non-Intrusive Load Monitoring, NILM.**

I. INTRODUCTION

Appliance Load Monitoring (ALM) has gained special attention because it is one of the elements that should be part of home energy management systems (HEMS) [1]. The ALM can provide an operation and consumption status of household appliances, allowing consumers to know their consumption profile in detail. Together with HEMS, ALM can enable demand response management applications through the optimized control of devices that have manageable consumption [2].

In the context of ALM, two approaches are used: Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). The advantage of NILM over ILM is due to the lower cost of installation, considering the need for only one sensor element to perform monitoring [3].

The NILM consists of obtaining appliances operation data from a single measurement point, requiring no additional equipment to be installed inside the residence. However, it presents a great challenge, because in this approach the complexity is in the algorithm that performs the energy disaggregation.

This study aims to show the methodology to create signatures from the aggregate energy monitoring, it is an important step for training the convolutional neural network to perform the event classification of appliances activation and deactivation in the NILM approach. A case study is performed to show the classification of 34 different types of events of 13 household appliances present in a residence. For this, Section II presents the characterization of non-intrusive load monitoring; Section III presents the convolutional neural network and CNN application on NILM; Section IV presents the methodology used to form event signatures; in Section V a case study is developed to verify the event classification from the proposed method; and finally in Section VI the conclusion is presented.

II. NON-INTRUSIVE LOAD MONITORING

The non-intrusive monitoring of electrical loads was presented by HART in 1992 [4], its discovery was based on the observation of the consumption patterns that allowed to recognize the device that was in operation from the visual observation of the residential load profile. The technique presented by HART has gained more importance in recent times due to the possible applications of this technique in the Smart Grid environment [1],[2]. According to [5], NILM monitoring presents the steps of signal acquisition, event detection, feature selection, learning, and inference. For a better understanding of the non-intrusive monitoring technique, the steps cited are described below:

A. Sign Acquisition

The signal acquisition process consists in measuring the electrical quantities of the network, and this process can be carried out at low or high sampling rates. Signals sampled at high frequency, with sampling rates over 10 kHz, require equipment with higher processing power and therefore have the disadvantage of having a high cost. However, it has the advantage of allowing analysis of harmonics and the waveform of the electrical network. Sampling at low frequency, typically 1Hz, is presented as more usual by the Smart Meters [5].

B. Detection of the appliance operation state

In the step of detecting the appliances operation state, there must be identification about the operation state of the appliances that are monitored. It is a step performed by the disaggregation algorithm and must be processed uninterrupted. The process of detecting the appliances operation state can be state-based detection or event-based detection. Methods based on event detection are pointed out as computationally more efficient [5]. In event-based detection, the variations in the electrical magnitudes of the aggregate signal are analyzed to detect which equipment may have been activated or deactivated.

C. Feature Selection

In the feature selection stage, the electric quantities used to define the electrical consumption pattern of each equipment, called the equipment signature, are made. The signatures should be in accordance with the sampling frequency of the electrical quantities.

D. Learning

In the learning phase, the NILM algorithm must learn the rules to recognize appliance signatures. In this process, learning techniques can be supervised or unsupervised. Supervised learning methods require a set of data (appliance signatures) duly identified, in order to allow the correlation between certain electrical signatures and the respective appliances.

E. Inference

In the inference step, the analysis of the aggregate signal is performed, so that based on the signatures of the known appliances, it is possible to estimate the operation state of the appliances in the monitored installation. From the detection of the operation status of each device, it is possible to count the operating cycles and the estimated energy consumption of each device.

III. CONVOLUTIONAL NEURAL NETWORK

The Convolutional Neural Network (CNN) is a type of Artificial Intelligence (AI) specially used for image classification [6]. The classification performed by CNN is based on the learning of parameters from a set of known data, called training samples. According to [7], in this learning process, features of the training samples are extracted so that the CNN weights are established automatically. In this way, CNN acquires the weights that allow the classification of new input data according to examples used in the learning phase, known as the training phase. Fig. 1 shows the basic structure of a CNN proposed by [8] for image classification, which consists of the input layer, convolution layer, filters, feature maps, pooling layer, fully connected layers and layer about to leave. More details on CNN can be found in [6] - [8].

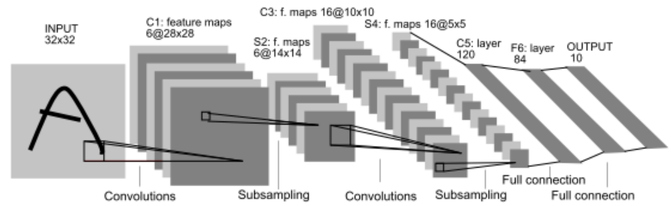

Figure 1. Convolutional Neural Network structure.

The use of convolutional neural networks in NILM has been used through different approaches. In [9] CNN is used to detect 12 event types of six appliances activation and deactivation events. In this approach, the transient waveforms of the electric current were used in the appliances activation and deactivation to represent their signatures. At the end of 500 training periods, the precision of 99.01% was reached. In the approach proposed in [9], it is observed the need for devices with high sampling capacity, due to sampling at high frequency.

In [10] high frequency sampled signatures were also used. In this, the signatures of the devices are composed of images formed by VI trajectories drawn from the electric current and voltage waves sampled in the permanent regime. The signatures are represented in images of dimensions 50x50 pixels and have the format shown in Fig. 2. In this approach, 33 devices were tested, with an average accuracy of 76%.

In [11] the appliance state is performing from the energy aggregate monitoring, in this approach, the signatures used are based on the active power sampled at fixed intervals of 1 second. One aspect of this proposed approach is that the signatures have different dimensions according to the time that each appliance usually stays connected, being necessary for this approach that the appliances complete its operation cycle so only after that its operation can be recognized, being this a limitation of the method for applications.

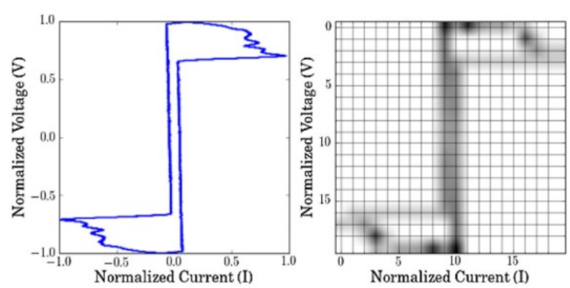

Figure 2. Signature model of VI trajectories.

IV. PROPOSED METHODOLOGY

In order to verify the use of signatures formed by components of active power (P) and reactive power (Q) of the appliance consumption using Convolutional Neural Network in the detection of NILM events, the methodology was adopted in this study uses the steps presented in Fig. 3.

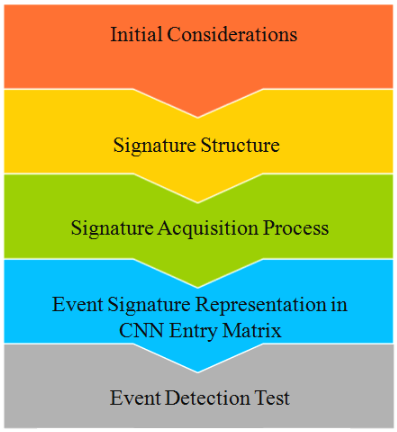

Figure 3. Structure of the proposed methodology.

A. Initial Considerations

The proposed signature model is based on the use of the active power (P) and reactive power (Q) components resulting from the activation and deactivation events of the monitored appliances. For this, such electrical quantities must be obtained from the aggregate monitoring, sampled at 1 Hz rate, that is, one sample of P and Q for each second of monitoring.

To perform the event detection from the proposed signature model it is defined that an activation or deactivation event occurs from the minimum variation of 50 W in the P in the aggregate monitoring. In this way, the detection of the activation and deactivation events can be defined according to the process shown in Fig. 4, where $P_{(i)}$ is the current sample of active power obtained in the aggregate monitoring and $P_{(i-1)}$ is the power sample active from the instant before the instant i.

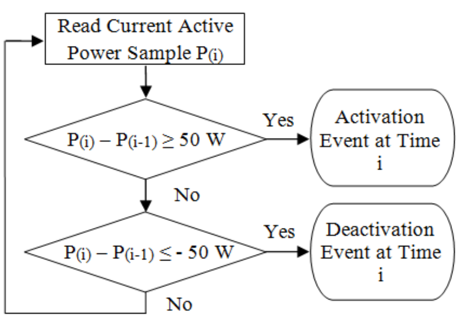

Figure 4. Flowchart of event detection process.

B. Signature Structure

The values that make up the signatures for each event must be obtained from the variations of P and Q the values from the aggregate monitoring. These signatures must be formed by two vectors of N positions, each one with P and Q components of the signature. Next, the process to form of activation and deactivation signatures is done after one activation or deactivation event is detected.

To realize the activation signature creation, the mean value of P and Q prior to the activation event, respectively P_{med} and Q_{med}, should be obtained, as shown in (1) and (2).

$$P_{med} = \frac{P_{(i-1)} + P_{(i-2)}}{2} \quad (1)$$

$$Q_{med} = \frac{Q_{(i-1)} + Q_{(i-2)}}{2} \quad (2)$$

The calculated P_{med} and Q_{med} values should be subtracted from the P and Q values obtained in the aggregate monitoring. The vectors with the P and Q components of the activation signature must be performed from (3) and (4).

$$P_{aa\,(x)} = (P_{(i-3+x)} - P_{med}) \quad (3)$$

where, $P_{aa\,(x)} = [P_{aa\,(1)} \ldots P_{aa\,(N)}]_{1xN}$.

$$Q_{aa\,(x)} = (Q_{(i-3+x)} - Q_{med}) \quad (4)$$

where, $Q_{aa\,(x)} = [Q_{aa\,(1)} \ldots Q_{aa\,(N)}]_{1xN}$.

Through (3) and (4) the P_{aa} and Q_{aa} vectors containing 2 values before the appliance activation are formed, with values close to zero, and more N-2 values resulting from the device activation.

To realize the deactivation signature creation, a process similar to that one carried out for the activation signature formation must be carried out. The values of P_{med} and Q_{med} should be obtained by (5) and (6).

$$P_{med} = \frac{P_{(i+1)} + P_{(i+2)}}{2} \quad (5)$$

$$Q_{med} = \frac{Q_{(i+1)} + Q_{(i+2)}}{2} \quad (6)$$

The calculated P_{med} and values should be subtracted from the values of P and Q obtained in aggregate energy monitoring. The vectors with the P and Q components of the deactivation signature must be performed from (7) and (8).

$$P_{ad\,(x)} = (P_{(i+2-N+x)} - P_{med}) \quad (7)$$

where, $P_{ad\,(x)} = [P_{ad\,(1)} \ldots P_{ad\,(N)}]_{1xN}$.

$$Q_{ad\,(x)} = (Q_{(i+2-N+x)} - Q_{med}) \quad (8)$$

where, $Q_{ad\,(x)} = [Q_{ad\,(1)} \ldots Q_{ad\,(N)}]_{1xN}$.

By means of (7) and (8), P_{ad} and Q_{ad} vectors are formed with 2 values after detection of the deactivation of the device, with values close to zero, plus N-2 values resulting from the deactivation of the device.

C. Signatures Acquisition Process

The process of signatures acquisition must be accomplished through the activation and deactivation of the appliances in all their operation states, repeating this action sometimes with the intention of obtaining a minimum number of curves capable of representing each type of event. Thus, through the steps for creating the signatures described above, it is possible to form a family of signatures for each type of event. These families of signatures created from the monitoring should be called the natural signatures. In Fig. 5 is showed the family of natural signatures of the compressor activation event of a refrigerator, in this, it is observed that the P_{aa} and Q_{aa} values of are within ranges of values that allow characterizing visually the pattern of activation of this appliance.

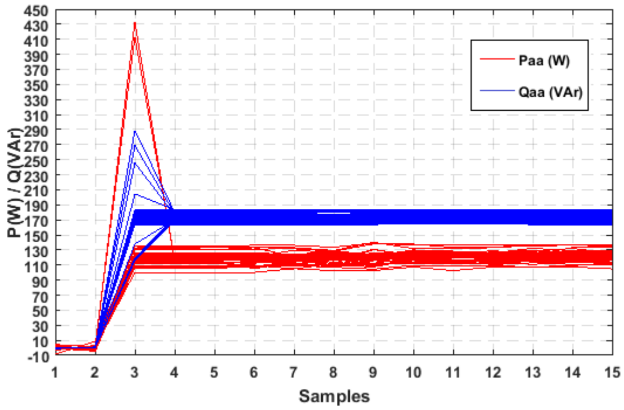

Figure 5. Natural signature family of the compressor activation event.

Given that CNN is able to detect patterns in images and that several images are needed for network training, this approach seeks to expand the signatures of natural events through the creation of synthetic signatures. Synthetic signatures must be created from natural signatures, and these should be scaled versions of natural signatures in order to: create new curves containing intermediate values to those covered by the natural curves; and increase the margin of the natural signatures values , considering a minimum limit of 10 W or 10 VAr between signatures of different events that have close values, in order to maintain all the different events with different values with respect to the components *P* and *Q* of the signatures.

D. Events Signatures Representation in CNN Entry Matrix

To carry out CNN training from the developed signatures set, it is necessary to transform this set of signatures into the CNN input format, which must be in matrix form. For this, the vectors with the *P* and *Q* components of the signatures must be converted into matrices through the steps described below.

- To observe among the *P* and *Q* vectors of the signatures of all events the largest and the smallest value that must be represented, respectively $S_{máx}$ and S_{min};
- Define the resolution (*R*) that will be used to represent the *P* and *Q* components of the signatures. The lower the resolution, the smaller the number of lines in the input matrix.
- The dimensions of the CNN input matrix $M_{(LxC)}$ must follow what is established in (9) and (10), where *L* is the number of lines of CNN input matrix, $S_{máx}$ is the highest value found among the components of *P* and Q that make up the signatures, $S_{mín}$ is the lowest value found between the components of *P* and *Q* that make up the signatures, *C* is the number of columns of the input matrix of CNN and *N* is the number of values of the components of *P* and *Q* of the signatures.

$$L = \frac{(S_{máx} - S_{mín})}{R} \tag{9}$$

$$C = N \tag{10}$$

- The representation of the values of P_{aa}, Q_{aa}, P_{ad} and Q_{ad} in the form of input matrix should be given from the creation of matrices of dimensions $M_{(LxC)}$, one to represent the values of *P* and another to the values of *Q*, containing all null elements.
- To represent the values of the components of *P* and *Q* of the signatures in the input matrix, one must establish the line in the input matrix that will represent the amplitude of zero value. Through (11) the line number that will be used to represent the zero value of the *P* and *Q* components of the signatures can be defined. In (11), L_0 is the reference line number to represent the zero value amplitude (0), $S_{máx}$ is the largest value found between the components of *P* and *Q* that make up the signatures and *R* is the resolution used to represent the values of the components of *P* and *Q* in the input matrix.

$$L_0 = \frac{S_{máx}}{R} \tag{11}$$

- The null elements of the CNN input matrix must be replaced by unit elements (value 1). The intention of this substitution is to represent through the unit value the activation of the pixel in the input matrix to represent the form of the signatures. The substitution of the input matrix elements $M_{(LxC)}$ must be performed as shown in (12). where, L_0 is the reference line number to represent the zero-value amplitude, $Y_{(x)}$ can be replaced by the values of $P_{aa(x)}$, or $Q_{aa(x)}$, or $P_{ad(x)}$, or $Q_{ad(x)}$ to form the respective input matrices to each component of *P* and *Q* of each event signature, and x represents the position of the elements of the vectors $P_{aa(x)}$, $Q_{aa(x)}$, $P_{ad(x)}$ and $Q_{ad(x)}$ and the column of matrix $M_{(LxC)}$.

$$M_{((L0-Y(x)),\, x)} = 1 \tag{12}$$

With the preparation of the necessary input matrices for CNN training, the CNN training can be done.

E. Event Detection Test

In order to verify if the trained CNN is able to perform the detection of the appliances activation and deactivation of the trained events, a set composed of 10 signatures of each event must be elaborated for testing. This set of samples for test must be constituted through a new phase of signatures acquisition next to the monitoring, and the signatures for the test should be constituted with the same premises with which the natural signatures were created.

To verify the CNN behavior in the test phase, the results of the predictions carried out by the CNN network must be placed in the form of a confusion matrix, as in [11], so that the precision and miss classifications of the test can be verified.

V. CASE STUDY

The case study performed is based on the monitoring of a residential electrical network where 13 devices were found that fit the proposed methodology, that is, theses appliances are ON/OFF states or multi-state. Of these 13 units, 10 are ON/OFF states and 3 are multi-state appliances. The multi-state appliances are the electric oven (6 states), air fryer (4 states) and garage door (4 states). From the observation of the 34 events, 1778 signatures were created to carry out the CNN training phase. In Fig. 6 and Fig. 7 are shown the distribution of the signatures of each event in the PQ plane, respectively the activation signatures in Fig. 6 and deactivation signatures in Fig. 7. From the signatures shown in Fig. 6 and Fig. 7 shows that none of the signatures have identical characteristics, which is necessary to distinguish them.

The CNN training was done from the signatures set elaborated using the Python language. The CNN model receives two matrices, one matrix with the component P of the event signature and another with the Q component of the event signature, thus a CNN of two input channels. Each of the matrices is formed by 400 rows and 15 columns, using a resolution of 5 W and 5 VAr for each line.

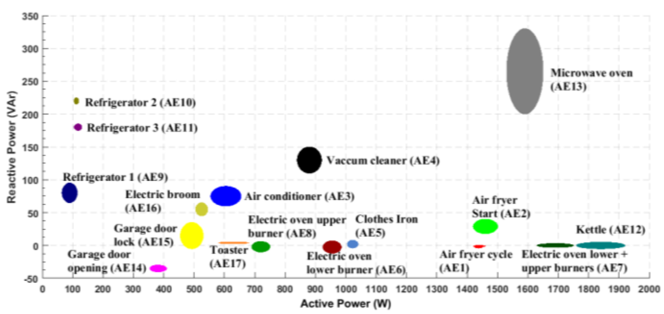

Figure 6. Activation signatures shown on the PQ plane.

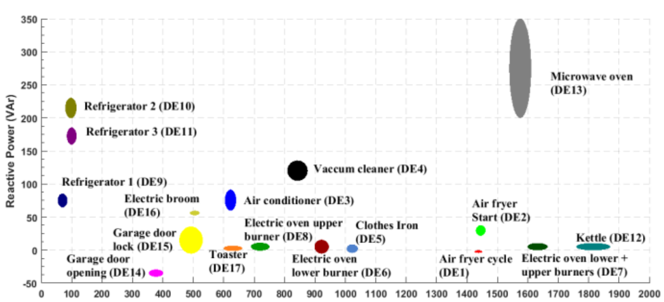

Figure 7. Deactivation signatures shown on the PQ plane.

The CNN training was performed by 50 training epochs, achieving 100% accuracy in the classification of the training samples. The 100% accuracy shows that CNN was able to establish its weights so that all the samples used in the training would be recognized by the network in a detection stage, demonstrating the learning capacity of the model.

To observe classification capacity of CNN, 340 new signatures for the test were sampled in the aggregate consumption monitoring, which were not used during the training phase of the network. In Fig. 8 the CNN confusion chart is shown for the test samples classification. In the main diagonal of the confusion matrix the number of correctly classified events appears, that is, the classified event corresponds to the event that was truly submitted to CNN. The values outside the main diagonal indicate detection errors, for example, AE12 event presented five of its events correctly classified and 5 erroneously classified as being confused with AE7 event.

From the 340 samples used in the test phase, CNN correctly classified 296 of these, reaching a precision of approximately 87% for this set of samples. In order to understand the reason for classification errors the samples where there were errors were analyzed. It was observed in all cases that the test samples presented values different from those that were used to train their respective classes, as can be seen in Fig. 8 where a test sample of DE12 is shown to compare with the family of signatures used for this event. Also, analyzing the voltage values during the collection of signatures, it was possible to observe that the signatures of tests that were wrongly classified all showed a voltage value lower than the voltage values observed in the training phase, which shows the need to normalize the values of P and Q as a function of the voltage.

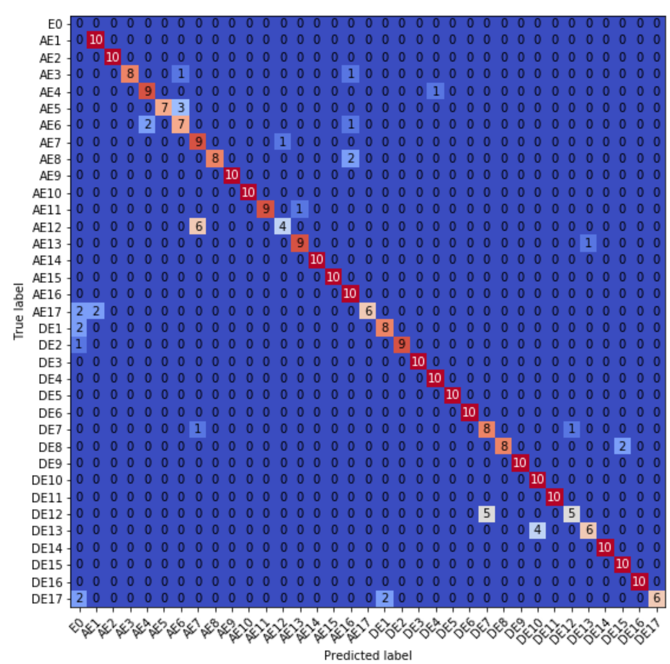

Figure 8. Test phase confusion matrix.

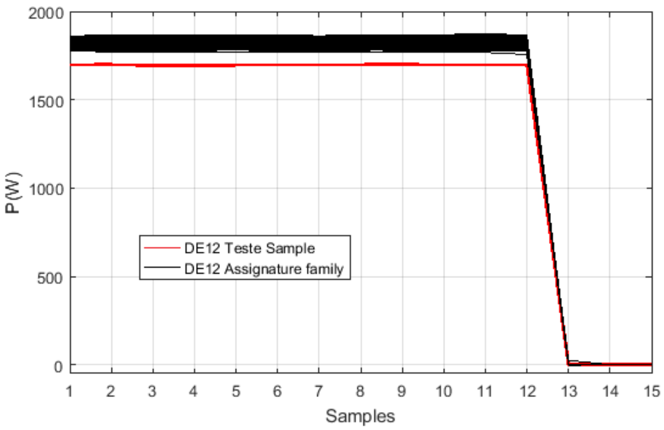

Figure 9. Active power (P) component of DE12 event deactivation signature.

VI. CONCLUSIONS

The study is conducted in the search for the development of techniques to be applied in the residential environment, mainly motivated by the expected advances from the creation of new charging models that will lead to the need for better energy management in the residential environment. The methodology proposed in this study points to the great potential of techniques that use artificial intelligence, especially CNN, applied to the event detection task in NILM approach.

The proposed case study aims to evaluate the use of signatures for events based on the values of active and reactive power, sampled together with the aggregate energy monitoring, performed at a low sampling frequency. The proposed methodology for signatures formation has the advantage of being generated from the aggregate monitoring of energy, that is, an individual appliance monitoring phase is not necessary for signatures acquisition.

The processed signatures were used as samples for training the CNN, where according to the training algorithm at the end of 50 training epochs 100% accuracy was reached for the classification of the training samples. This fact indicates both the consistency of the signatures used and the classification power presented by CNN. However, some classification errors were verified in the test phase that, according to the analysis of the tests samples, presented values outside the limits predicted in the signatures used in the training phase. This failure in detection indicates that there should be an improvement in the method used to train the set of samples for training, especially considering the variations of P and Q caused by the variation of the mains voltage.

Finally, it should be pointed out that the presented methodology can evolve from improvements evidenced, but certainly demonstrates the great possibility to be applied to event detection in non-intrusive monitoring applications.

ACKNOWLEDGMENT

The authors would like to thank the support from Federal University of Santa Maria, Santa Maria – RS, Brazil, funding from CAPES PROEX, CNPq PQ 1-D 310761/2018-2, CNPq process 465640/2014-1, CAPES process no. 23038.000776/2017-54 and FAPERGS 17/2551-0000517-1, support from CNPq, Brazilian National Council for Scientific and Technological Development – Brazil. This study was also financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES/PROEX) - Finance Code 001.

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