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Multi-State Appliances Identification through a NILM System Based on Convolutional Neural Network

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***Abstract*— Electrical loads have a unique energy consumption pattern, often referred to as a "signature", which allows disaggregation algorithms to distinguish and recognize the operations of different users from aggregate load measurements. Both in the case of civil users and in that of commercial and industrial users, the presence of multi-state appliances is extremely common. The disaggregation algorithms must be able to correctly identify the consumption patterns of such devices from the aggregate load measurements. In this paper we will illustrate a NILM algorithm, based on a convolutional neural network, able to identify the electrical loads connected to a house, starting only from the measurement of the total electrical current. Furthermore, the algorithm provides information on events in real time through a process of simultaneous detection and classification of them, without having to perform a double processing, thus reducing calculation times. Then we will focus on the algorithm's ability to manage multi-state devices, analyzing a specific case and commenting on the possibilities of the system.**

Keywords—Non-intrusive load monitoring (NILM), disaggregation algorithm, load signatures, energy management, load identification, machine learning (ML), Convolutional Neural Network (CNN).

I. INTRODUCTION

The development of industrialized countries has led to a continuous growth in the world demand for energy which, in the last two decades, has recorded a further acceleration due to the economic development in emerging countries. About 80% of this world energy requirement is met through the use of exhaustible fossil resources. An important negative aspect of this energy policy is that related to the impact on the environment, which is no longer sustainable.

There are several actions that can be taken to reverse this trend. A significant reduction in energy consumption can be achieved by monitoring consumption and communicating this information to consumers, to implement appropriate corrective actions. A detailed review [1] of over 60 studies suggests that maximum energy savings can be achieved using direct feedback mechanisms (i.e. real-time equipment-level consumption information) rather than indirect feedback mechanisms (e.g. monthly bills) . The fields of application are the most diverse, including domestic, civil and industrial ones, and in general all those in which it is possible to improve electrical energy efficiency and performance.

Load monitoring and identification allows you to determine the electricity consumption and operating conditions of individual equipment, based on the analysis of the composite load measured by the overall power meter in a building. These systems can provide information such as: the type of load, details of electricity consumption and the operating conditions of the appliances for both the consumer and the distributor. This information can be used to formulate load plan strategies that enable optimal energy use.

Intrusive load monitoring provides accurate results and allows to measure the energy consumption of each individual load, using a supervisory and data acquisition system (SCADA). To adequately monitor the various loads, a transducer must be installed on each device to be monitored. The cost of installation and maintenance of this system is high. Furthermore, intrusive load monitoring is often too complicated to implement in an existing plant, especially due to space problems (required by transducers and communication systems).

The non-intrusive load monitoring (NILM or NIALM), on the other hand, starts from the measurement of the total consumption, carried out by means of a single transducer, and then "disaggregates" (break it down) into the individual contributions relating to each load. This technique provides an alternative solution to the more traditional intrusive one and enables innovative approaches to energy savings and efficiency. NILM requires a reduced number of equipment and less space occupied, even if it presents greater complexity in terms of processing the acquired data.

Research on load disaggregation began by Hart [ ] in the early 1990s. Over the years, significant improvements have been made with respect to event detection and feature extraction techniques. Various techniques have been proposed in the literature, often based on complex processing techniques.

In the last decade, interest in this research topic has undergone a significant increase, mainly due to the spread of machine learning techniques such as Artificial Neural Networks (ANN) or Deep Learning (DL). For example, Kelly et al. [3] proposed three different architectures of ANN to address the problem of energy disaggregation. Subsequently, Zhang et al. [4] proposed an improvement using a sequence to sequence and a sequence to point learning model. Other valid techniques have been proposed besides those based on artificial neural networks: Kolter et al. they used a sparse

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coding that approximates the original energy matrix by representing it as a product of over-complete bases and their activations [5], another possibility is to use a factorial hidden Markov model (FHMM) [6-8]. In an FHMM, each appliance is represented by a hidden Markov model. The parameters of FHMM are learned using the training data.

In this work, a monitoring system installed inside a house is proposed. This system is capable of acquiring and processing the overall user current. The proposed solution is a DL-based NILM system, which adopts a particular type of ANN, namely, the convolutional neural network (CNN) [4],[9],[10]. This CNN is suitable for processing complex inputs such as multidimensional arrays. In the proposed application, the CNN processes the short-time Fourier transform (STFT) of the total current. In particular, the spectral content analyzed by our CNN-based algorithm allows us to keep track of the events that occur within the monitored system as they occur, unlike other algorithms such as those above which analyze the aggregate power signal on time windows of a few minutes or even hours. Although in most algorithms, an event detection step is followed by device identification, in this work, event detection and classification of the related device are performed by the same and unique process.

The operational characteristics of the proposed system have been verified by extensive measurements. The results obtained from field applications are also reported. Finally, the possibility of using the system for the identification of multi-state appliances will be shown and discussed.

II. FORMULATION OF THE NILM PROBLEM

The goal is to break down the building data of the entire house into its main components. The simplest formulation of the problem can be written as follows:

$$\boldsymbol{P(t)} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{p_i(t)} \qquad (1)$$

where $P(t)$ is the aggregate power signal, $p_i(t)$ is the power consumption of individual appliances contributing to the aggregated measurement and N is the total number of appliances powered within the monitored environment.

Since the effects of changes in power consumption are reflected on current draw, the problem can alternatively be formulated as follows:

$$\boldsymbol{I(t)} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{i_i(t)} \qquad (2)$$

Similarly, $I(t)$ is the total instantaneous current signal and $i_i(t)$ is the instantaneous absorbed current of the individual appliances contributing to the aggregate measurement.

The task of the NILM algorithms is to perform decomposition of $P(t)$, or $I(t)$, into appliance specific signals in order to achieve disaggregated energy sensing. Electrical loads exhibit a unique energy consumption pattern often termed as “load or appliance signatures”, that enables the disaggregation algorithms to discern and recognize appliance operations from the aggregated load measurements. Appliance identification is highly dependent on load signatures, which are further characterized by the appliance category.

The concept of electrical load disaggregation was introduced nearly three decades ago by Hart [2], who proposed the following classification of appliances according to their consumption patterns:

- Type I) Devices with only two operating states (ON / OFF); e.g. table lamp, toaster, etc.
- Type II) Multistate devices, also called finite state machines (FSM); e.g. washing machines, frost-free refrigerators, heat pumps, etc.
- Type III) Continuously variable devices (CVD) due to their variable power absorption characteristics. The electric drill is an example of CVD without repeatability in its power absorption characteristics.
- Type IV) Devices that remain active for weeks or days by consuming energy at a constant rate, called "permanent consumer devices", such as smoke detectors, telephone sets, cable TV receivers [11].

Although Type I appliance operations are the easiest to manage, the same cannot be said for Type II appliances. These in fact have different characteristics depending on the state in which they are found, being able to present both a predictable succession of states as in the case of washing machines or dishwashers, and unpredictable as in the case of hair dryers or microwave ovens. The characteristics of the loads can be analyzed by observing the trend over time, or by performing an analysis in the frequency domain. The type of information that can be extracted from voltage and current strongly depends on the sampling frequency. Surely the absorbed active power is a fundamental parameter for the discrimination of the different loads, but sometimes also the absorbed reactive power and the power factor can provide substantial information [12], therefore the power measurement must be performed adequately [13]. Often the step power variations are measured using a low sampling frequency, but observing their repetition over a long time span. Analysis of the characteristics based on harmonics and transients requires higher sampling rates, but can be conducted instantaneously. The load features are also classified in steady-state and transient state characteristics, based on the state of the measured waveform they represent. In the literature it is possible to find numerous works that use different features: Characteristics based on P, Q, I and V at low frequency [12], Short Time Fourier Transform [14], V-I trajectories [15] or unconventional features [16], [17]. In the following section, an algorithm will be shown that allows to identify and classify the events that occur on the instantaneous current signal, in order to keep track of all the operations taking place within the monitored environment through a single measurement point.

III. THE PROPOSED CNN BASED SYSTEM

The load signature proposed in this paper is based on transient characteristics; more precisely, they are analyzed by means of the spectrogram of the derived rms current signal. By deriving the rms current, the steady states are filtered and all the transient information is maintained. In this way it is possible to classify an event regardless of the load conditions in which this occurs.

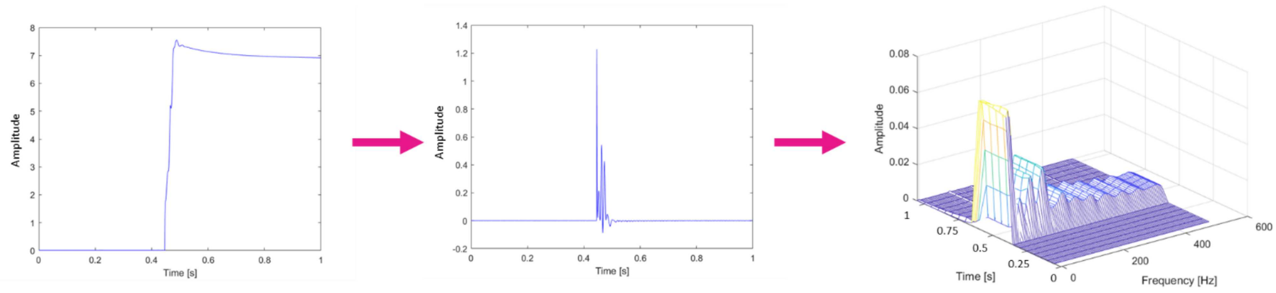

Fig. 1. Pre-processing of the CNN input: trend over time of rms current $I_{rms(n)}$ (left), its derivative $I'_{rms(n)}$ and its STFT (right).

First, the current effective (rms) value has been calculated, by processing the acquired raw current with a sliding window technique, as follows:

$$I_{\text{rms}\,(k)} = \sqrt{\frac{1}{N}\sum_{n=k}^{k+(N-1)} i_{(n)}^{2}} \tag{3}$$

where k is the k-th measured current sample, N is the number of samples per cycle, $i_{(n)}$ is the sampled signal and n is the summation index.

This signal has been then derived, obtaining an impulsive signal, which pulses represent the transient states of the rms current, as shown in the example of Fig.1. The position of the pulse, in the derived signal, identifies the instant in which a certain event occurred.

This impulsive signal has been successively processed by the STFT, through the known transformation [18], [19]:

$$STFT_{(m,\omega)} = \sum_{n=-\infty}^{\infty} I'_{rms\,(n)}\, w_{(n-m)}\, e^{-j\omega n} \tag{4}$$

in order to be able to distinguish each specific event on the basis of its spectral content, and locate it in a precise instant of time. In this formula: w is a window function and $\mathrm{I}'_{\mathrm{rms(n)}}$ is the sampled signal to be transformed, the derivative of the rms value of the current.

The absorbed current is processed cyclically at 1 second acquisition intervals, following the described procedure. Each acquisition slot is processed (to calculate rms and the derivative) by adopting an overlap of 500 ms, in order to ensure correct analysis, also for transient events that can be fragmented into two successive slots.

The STFT is implemented considering processing windows of 10 cycles (200 ms), with an overlap of 4/5 of the processing window.

To keep track of the type of event (switching ON or OFF), since often the spectrograms of a device are identical for both cases, the spectrogram (4) is multiplied by the sign of the cumulative sum, evaluated on the rms current signal as follows:

$$S_N = \sum_{n=1}^{N}\left(I_{rms\,(n)} - I_{rms\,(n-1)}\right) \tag{5}$$

where $\mathrm{I}_{\mathrm{rms(n)}}$ is the rms value of the current (3), N is the number of samples and S_N is the value of the cumulative sum, obtaining the final signal $S_{(i,j)}$, a 101x26 matrix:

$$\boldsymbol{S(i,j) = STFT_{(m,n)} \cdot sgn(S_N) =}$$
$$\boldsymbol{= \sum_{n=-\infty}^{\infty} I'_{rms\,(n)} w_{(n-m)} e^{-i\omega n} \cdot sgn\left(\sum_{n=1}^{N}\left(I_{rms\,(n)} - I_{rms\,(n-1)}\right)\right)} \tag{6}$$

The spectrograms obtained by processing the currents absorbed by the different loads have been used as input of an ANN. We have adopted a particular type of ANN, the CNN [20], for its aptitude to process complex inputs, such as multidimensional arrays. More specifically, the CNNs are designed to exploit the intrinsic properties of some two-dimensional data structures, in which there is a correlation between spatially close elements (local connectivity).

The network provides a response every 500 ms, indicating the presence or absence of events in the signal, and the type of device involved.

We designed a CNN suitable to process the current spectrograms. The proposed system, shown in Fig.2, includes different layers: an input level for the signal loading; three group of: convolution, Relu and Max pooling layers, to extract features from the input; a group of: flatten, fully connected and softmax layers, that uses data from convolution layers to generate the output.

The setting of the classification problem requires the definition of 2 different classes for each appliance associated with its on and off transients, and an additional class relating to the case in which none of the events occurred.

IV. Performance Evaluation

The measurement system, created in order to test the proposed algorithm, includes an Agilent U2542A data acquisition module, with a resolution of 16 bits, whose sampling frequency has been set at 10 kHz. The current signal necessary for the identification of the various household appliances connected to the system was acquired by means of a current transducer TA SCT-013. The DL algorithm, which as already explained consists of a CNN, was implemented in Anaconda's open source Python 3.7 [21], on a desktop computer, based on the Windows 10x64 operating system.

Additionally, in order to provide guidance on the accuracy of the measurement system, the measurement channel was calibrated using the Fluke 6100A Electrical Power Standard. Specifically, we generated a reference current, which was applied to the CT SCT-013 current transducer. The current was acquired through the Agilent U2542A acquisition system and the data was processed in order to obtain the rms value and test the entire signal acquisition and processing process.

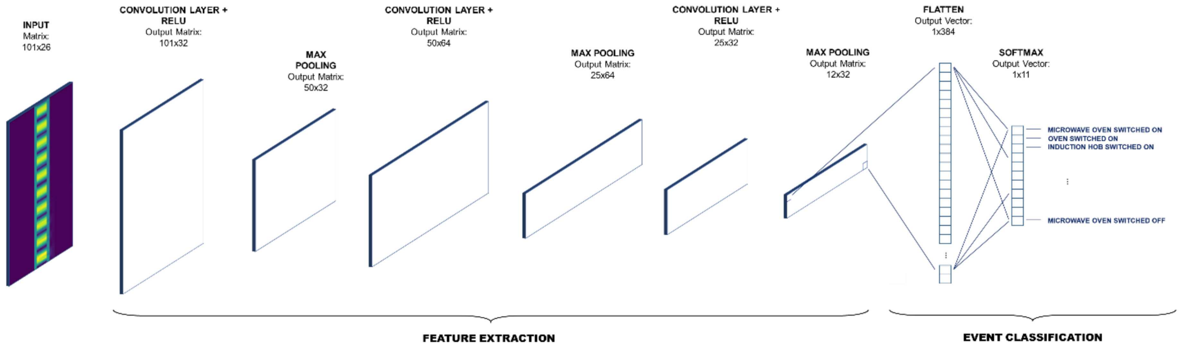

Fig. 2. Structure of the proposed CNN.

We calibrated the system with 10 different currents ranging from 2A to 20A. The maximum uncertainty was 1.3%.

In order to evaluate the performance of the measuring system in the most real conditions possible, a test system was designed that allows the generation of electrical loads of domestic users, located in an area of the Electrical Engineering Laboratory of the University of L'Aquila (I). This system was designed as part of the research project "Non-intrusive infrastructure for monitoring loads in residential users", and provides the possibility of reproducing the real problems of conditioning and measurment of the signals, like a residential building.

In previous works [22], the main tests were conducted on signals acquired directly from a real system, as this provides greater flexibility as regards both the sampling frequency and the generation of multiple events. Other tests were conducted using the BLUED (Building-Level fUlly-labeled dataset for Electricity Disaggregation), which is a residential electricity-usage public dataset. This dataset includes voltage and current measurements for a single-family house in the United States, sampled at 12 kHz for an entire week [23].

In both cases, encouraging results were obtained. To allow a comparison with the algorithms developed by other researchers, especially those who tested their algorithm on BLUED as we did, precision, recall, F1-Score and accuracy during classification were evaluated [24]. These parameters were obtained using the number of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) as follows:

$$precision = \frac{TP}{TP + FP} \tag{7}$$

$$recall = \frac{TP}{TP + FN} \tag{8}$$

$$F1 - score = \frac{2\,x\ precision\ x\ recall}{precision + recall} \tag{9}$$

$$Acc\% = \frac{Correct\ matches}{Total\ possible\ matches} 100 \tag{10}$$

In addition, the False Positive Rate (FPR) and the False Positive Percentage (FPP) were calculated:

$$FPR = \frac{FP}{FP + TN} \tag{11}$$

$$FPP = \frac{FP}{TP + FN} \tag{12}$$

For an evaluation of the algorithm's performance, Table I shows the scores achieved on both our data and the public dataset.

TABLE I. SCORES ACHIEVED.

	Acquired signal	BLUED dataset
precision	0.981	0.998
recall	0.981	0.998
F1-score	0.004	0.001
FPR	0.019	0.001
FPP	0.989	0.998
Acc%	98%	87.9%

The scores relating to the acquired signal were obtained by emulating situations of insertion and disconnection of electrical loads in order to reproduce the conditions that can occur within a civil user, for a total of 519 events relating to transients of 5 different appliances.

The scores relating to the BLUED dataset were obtained by processing 11918 windows obtained from the available measurements, in which 34 appliances were alternated.

TABLE II. CLASS DEFINITION.

Class	Event
0	Microwave oven switched off
1	Oven switched off
2	Induction hob switched off
3	Toaster switched off
4	Light switched off
5	*No events detected*
6	Light switched on
7	Toaster switched on
8	Induction hob switched on
9	Oven switched on
10	Microwave oven switched on

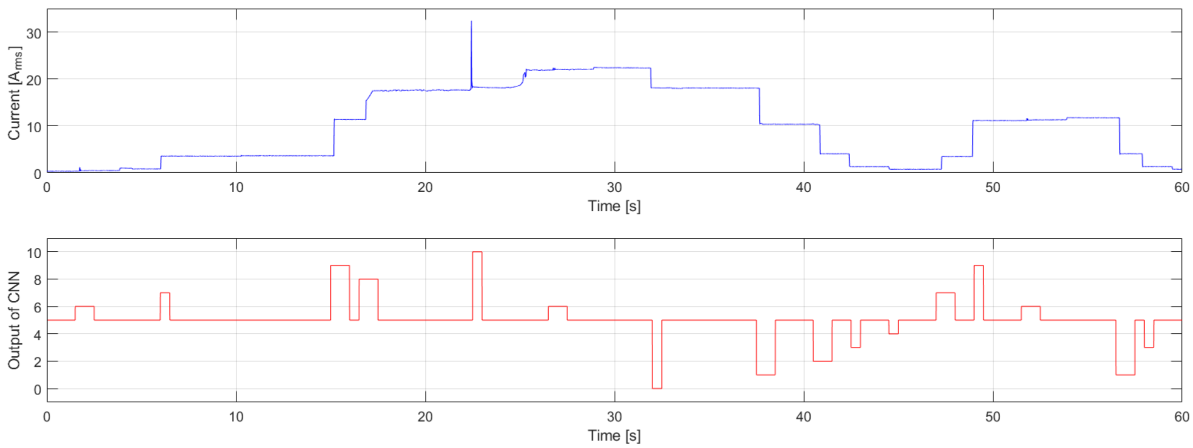

Fig.3. Sequence of events: variation of the rms current (above) and detected events (below).

The problem's setting required the definition of two different classes associated for each device's ON and OFF transients and an additional class (number 5 in Table II), which is related to the "no event occurred" case. Therefore 11 classes were defined in the tests with the acquired signal. The definition of classes is shown in Table II.

An example of the acquired signal representing the current variation for a 1-minute window is presented in Fig. 3.

V. Performance in the Multi-State Appliances Identification

The system has already proved capable of correctly identifying and classifying the on and off transients of ON / OFF appliances (Type I). In this work we verified its ability to operate in the presence of multi-state appliances, showing different possibilities for managing the problem. For this purpose, several measurements were made on a hair dryer in order to train the algorithm to recognize transitions from one state to another. Its operation can be represented by the finite state machine (FSM) model shown in Fig. 4.

The circles indicate the states, here identified by a name, and the rms current absorbed level. The arcs indicate the allowed state transitions, and are labeled with the signature which is observed to accompany the state transition. The algorithm was then trained to recognize the transitions from one state to another, each of which is associated with a CNN output according to the values shown in Table III.

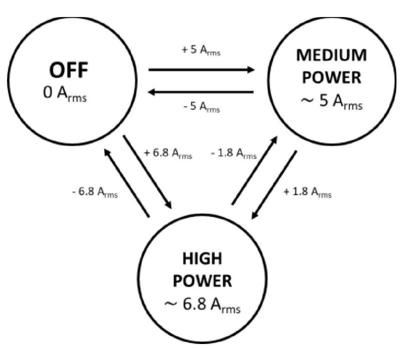

Fig. 4. Finite-state appliance models for the hairdryer.

TABLE III. Class Definition.

Class	Event
0	Hairdryer switched from "High Power" to "Off"
1	Hairdryer switched from "Medium Power" to "Off"
2	Hairdryer switched from "High Power" to "Medium Power"
3	*No events detected*
4	Hairdryer switched from "Medium Power" to "High Power"
5	Hairdryer switched from "Off" to "Medium Power"
6	Hairdryer switched from "Off" to "High Power"

The capacity of the system was verified by subjecting the system to a series of events, also carried out in rapid succession.

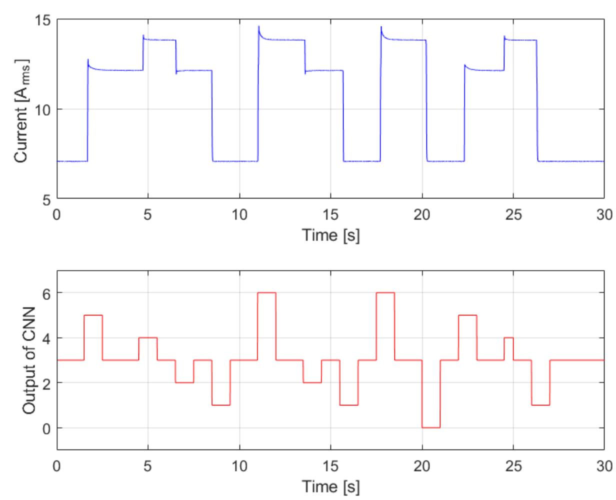

Fig. 5. Sequence of events: trend of the rms current (above) and detected events (below).

The proposed system has proven to be able to correctly identify the insertion of loads even by performing maneuvers at very short time intervals, up to about 500 ms. The Fig.5 shows an example of the acquired signal, relative to the trend of the current in a 30-seconds window.

VI. Conclusions and Final Remarks

A typical NILM system involves three main processes: signal acquisition (current and/or voltage), event detection and their classification [25]. Contrary to other NILM systems that base the load classification on the analysis of quantities also related to voltage (e.g. analysis in the P-Q or V-I plane [15]), the proposed system has the advantage of operating by measuring only the current absorbed by the house. In addition to the lower complexity of the processing system, there is the advantage of realizing a galvanically isolated measuring system, at low cost, using a clamp current transducer. With this algorithm, the detection of an event and the classification of the related device are carried out by the same and unique process. The system has been implemented in Python's open-source development environment, also to reduce system costs. Online system configuration (training) took about 7 minutes. The processing times were measured, obtaining times of the order of 105 ms for the processing of 1 s of acquired data (10Ksamples).

The proposed NILM algorithm allows the system to recognize a device, regardless of whether it operates singularly or in combination with other loads. The first results obtained after a large number of measurements appeared to be satisfactory, with error rates of approximately 2% for event classification.

The results obtained by processing the data available on the public BLUED dataset appeared very encouraging. The value obtained for the F1-score was 99.8%, which is higher than that obtained with other systems using the same dataset such as those proposed in [26] (91.5%) and [27] (93.2%).

Furthermore, this work shows the potential of the system in handling multi-state appliances, analyzing the different spectrograms that occur at the input to the artificial neural network when the appliance switches from one state to another.

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