Intelligent IoT for Non-Intrusive Appliance Load Monitoring Infrastructures in Smart Cities*

Alina Buzachis[1], Maria Fazio[1], Antonino Galletta[1] *AIxIA student member*, Antonio Celesti[1,2] and Massimo Villari[1]

(1) MIFT Department, University of Messina, Messina Italy
{abuzachis,mfazio,angalletta,acelesti,mvillari}@unime.it,
(2) On behalf of Gruppo Nazionale Per il Calcolo Scientifico (GNCS) - INdAM

Abstract. Increasing energy efficiency is a key topic in smart cities management. To this aim, Non-Intrusive Appliance Load Monitoring (NIALM) has a crucial role in smart infrastructures for reducing power consumption and, hence, improving energy saving. Combining Internet of Things (IoT) and Artificial intelligence (AI) can significantly support NIALM activities, promoting the development of next-generation Cognitive Smart Meters (CSMs). CSMs allow better tracking of power consumption and generation, and can be used to accomplish reliable transmission of monitored data through wireless communication infrastructures in a smart environment. In this paper, we present the development of a cost-effective NIALM infrastructure exploiting IoT features and AI solutions. Specifically, the proposed infrastructure involves IoT-based CSMs and an Edge-based Accumulator that collects CSMs transmitted data and extracts the features necessary to train an on-board Machine Learning (ML) model with limited computational requirements to minimize costs and latency. We performed initial evaluations of the proposed solution to demonstrate the goodness of the approach and of the used ML model.

Key words: Smart Meter, Load Monitoring, Load Characterization, NIALM, IoT, Machine Learning.

1.1 Introduction

The smart city is a relatively new concept that has been investigated and used by many more [1, 2, 3]. Increasing energy efficiency in the smart cities management has been a significant concern today [4]. The smart city is intended to deal with or mitigate, through the highest efficiency and resource optimization, the problems generated by rapid urbanization and population growth, such as energy supply, waste management [5], and mobility [6].

The electricity network is undergoing a significant change towards a more adaptive, intelligent, self-managing, collaborative, and information-driven grid. The Smart Grid

(SG), Smart Building (SB), Smart Factory (SF), Smart Hospital (SH) are the enabling concepts supporting this advancement within the smart cities.

To this end, Appliance Load Monitoring (ALM) [7] are becoming more and more important non only for managing and saving energy consumption but also for recognizing and identifying electric loads. That is, considering a smart city scenario with several ALMs, municipalities are able non only to check the status of public illumination and to verify lamps, but also to identify the theft of electricity.

The traditional ALM method uses electricity meters at different points of the electrical installation to measure all possible variables. ALM follows two main approaches. The first one, Intrusive Appliance Load Monitoring (IALM), where each device is measured independently in a distributed way. This requires the installation of a low-end sensor on each device. Secondly, Non-intrusive Appliance Load Monitoring (NIALM), where an electronic measuring device is used, incorporated in the central energy distribution panel of the building to measure the electricity consumption of all monitored devices simultaneously. Although IALM is more precise in measuring the specific energy consumption of the equipment, compared to NIALM, various drawbacks are present when applying this method such as the division of the load circuits, the cost of the electricity meters, the cost of installation, the available space for installing the hardware, among others.

Internet of Things (IoT) and Artificial Intelligence (AI) can support NIALM. Comprehensive sensing and processing abilities of Intelligent-IoT (IIoT) can improve NIALM abilities such as processing, warning, self-healing, disaster recovery, and reliability. Combining IIoT and NIALM can greatly promote the development of next-generation Cognitive Smart Terminals (CSTs), meters and sensors, information equipment, and communication devices. In this context, Cognitive Smart Meters (CSMs) allow better tracking of consumption and generation, and better energy management. They can be used to accomplish reliable data transmission in wireless communication infrastructures in different parts of NIALM within the buildings.

This paper shows the development of a cost-effective NIALM infrastructure in a smart city scenario. Specifically, the proposed infrastructure involves IoT-based CSMs and an Edge-based smart Accumulator that collects the CSMs transmitted data and extracts the features necessary to train an on-board ML model with limited computational requirements to minimize the infrastructure costs and latency. To do so, the data consumption of an electrical network is acquired, and electrical features are extracted. A ML model, based on their combination, is used to characterize appliance when they are plugged into the network. Our contributions in this article can be summarised as follows: firstly, we propose a cost-effective NIALM; secondly, we evaluate a multi-label classifier based on a ML model trained on an Edge device with limited computational capabilities. The experiments carried out show the goodness of the used ML model in terms of accuracy and log loss.

The rest of the paper is structured as follows. Some significant works that motivated our research are discussed in Section 1.2. The NIALM high-level architecture is described in Section 1.3. Section 1.4 presents the implementation of the proposed infrastructure. The results are presented and discussed in Section 1.5, finally Section 1.6 presents our conclusions and expected developments for this activity.

1.2 Related Literature

This section discusses the most relevant research efforts and related solutions in terms of signal processing/machine learning background, which have been proposed for supporting the NIALM.

Smart cities include technical development in the field of electricity generation, transmission and distribution, which is followed by SG, and different SEs as listed above. SMs are the key component for the entire smart city ecosystem. Data mining and analysis of energy data of electrical appliances in SEs, e.g., for the dynamic load management, is of fundamental importance for the energy management both from the consumer perspective by saving money and also in terms of energy redistribution and reduction of the carbon dioxide emission.

Therefore, researchers all over the world are proposing new tools and methodologies to provide further information about energy consumption [8, 9], as well as proposing innovative ways for energy-saving [10, 11]. Hart [12] initially introduced the NIALM method, considering active power levels and distributing them into individual appliance data. With such a type of cognition, the consumer profile can be mapped by using AI techniques [13]. After Harts seminal paper, numerous investigations have attempted to improve upon his results, and NIALM is now accepted as an important facet of smart city technology. The main differences between published NIALM methods are the models and features that they have used for appliance identification.

Classification methods such as Support Vector Machine (SVM) [14], k-Nearest Neighbor (k-NN) [15], and clustering methods such as k-means [16] are commonly applied models in NIALM. Active power, reactive power, current and voltage transients and harmonics, duty cycles, and/or combinations thereof are commonly used as features.

In recent years NIALM problem has been modeled as a multi-label classification problem. In [17], the temporal sliding window technique is employed to extract features from the aggregated power data. Binary relevance, classifier chains, and LP classifiers (SVM and decision tree as base classifiers) are trained using extracted features. The disadvantage of this method is that it does not consider any label dependency and fail to predict label combinations when some dependency exists.

The relative merits of supervised versus unsupervised learning (plus the possibility of semi-supervised learning); the feature sets to be employed; the performance measures used to compare different algorithms; all of these questions have previously been investigated for single-label classifiers as applied to NIALM. However, they have not been examined in-depth for multi-label NIALM approaches, and our work is intended to help fill this gap.

As well as, the main approaches emerged from the above-related works facing with automatic identification of electrical devices, consider in some cases the involvement of additional monitoring devices either distributed or centralized which results expensive in terms of costs for their installation and hardly scalable; while in others there is not used any additional devices, they are mainly focused on energy measurements, but this lacks in the categorization and formalization of the adopted features.

1.3 System Architecture

This Section illustrates the high-level architecture of a NIALM infrastructure in a smart city scenario.

Let us consider a general smart city scenario composed of a Smart Grid, as shown in Fig. 1.1, connecting different Smart Environments ($SE_i, i = 1,..,N$), in particular, Smart Factories, Smart Hospitals, Smart Buildings, Smart Transportations, and so on. Each SE has attached a Cognitive Smart Meter ($CSM_j, j = 1,..,M$). The CSMs are attached between the outlets and the appliance. These CSMs perform data acquisition and feature extraction of all the appliances connected to the outlets within the respective SE.

CSMs rely on the Accumulator (AC), which has a back-end to provide information for views using a user interface. Moreover, the AC collects and sorts all the features extracted from the CSMs of each SE's electric network and use ML techniques to characterize the plugged appliances. Hence, each AC ($AC_i, i = 1,..,L$) manages the dataflow coming from the CSMs of several SEs according to the SEs' complexity, position, and hardware capabilities necessary to manage the dataflow and perform the ML techniques necessary to characterize the plugged appliances. Through the user interface, the user can control the turning on or off of the connected appliance, allowing not only remote user access but also control, billing, energy consumption, and so on. This information can also be used for statistical purposes to ensure the energy consumption balance within the smart city, minimizing energy consumption and avoiding energy waste.

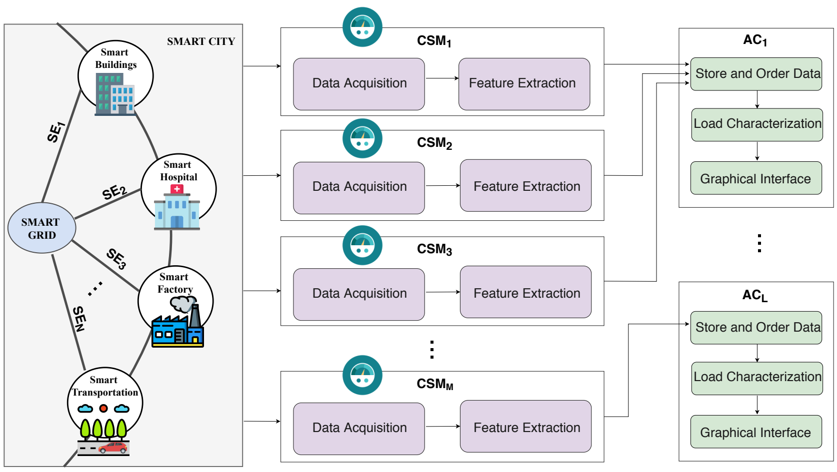


Fig. 1.1: A NIALM High-Level Architecture in a Smart Building

The same idea of the cost-effective NIALM infrastructure can be extended to other common utilities like gas and water. Similarly, in utilities of water and gas, the CSMs collect and forward measurements to the AC. In the smart cities, extensive data will flow from many sources, which will be carry out over many communication networks to be analyzed, and integrated for providing benefit to all in smart cities.

NIALM infrastructures are becoming a vital part of the water, electric, and gas utility distribution networks, enabling the measurement, configuration, and control of energy, gas, and water consumption through two-way scheduled and on-demand communication. NIALM infrastructures are composed of millions of endpoints, including smart meters, distribution automation elements, and, eventually, Home Area Network (HAN) devices. They are typically interconnected using some combination of wireless and power-line communications.

1.4 Implementation

In this Section, we discuss the hardware and software technologies that ground the NIALM infrastructure. As said in Section 1.3, the NIALM infrastructure is mainly composed of two components (i) Cognitive Smart Meter, and (ii) Accumulator. In the following, we will discuss their implementation.

1.4.1 Cognitive Smart Meter Prototype

Hardware The CSM is implemented using low-costs IoT devices such as ESP32 micro-controller, a YHDC SCT-013-000 Hall-effect current transducer, which allows non-invasive measurement of the electrical network, and an additional circuit as shown in Fig. 1.2. We chose to involve these devices due to their costs, specifications (e.g., $ESP32 \leftarrow 3.53\$$, YHDC SCT-013-000 Hall-effect current transducer $\leftarrow 3.70\$$) and ease of use. The transducer is used to interface to the electrical grid that in Italy supplies an alternating voltage of 220 V in an effective value at a frequency of 50 Hz. As shows in Fig. 1.2, the resistor R1 is used to obtain the voltage proportional to the current measured by the transducer. As well as, the remaining part of the circuit constitutes a single half-wave rectifier with capacitive filter formed by a Schottky diode D, and a 1 μF capacitor C in parallel to a 1 $M\Omega$ resistor R2. ESP32 also integrates an A/D converter, but we preferred to use an external one, MCP3008, that can guarantee a higher sampling frequency.

Software The ESP32 acquires the data from the electrical network and extracts the features through the Fast Fourier Transform (FFT) algorithm implemented in the C programming language. The result consists of the representation of a power spectrum in a frequency window ranging between 0 Hz and 4000 Hz, which is sufficient for our purpose. The data is then sent via the MQTT protocol to an MQTT broker running on the AC. Further details of the software are discussed in our previous work [18].

1.4.2 Accumulator Prototype

Hardware The AC is implemented on the Raspberry Pi 3 Model B that aims to collect and sort the received data. We choose to use a Raspberry Pi Model 3 Model B in order

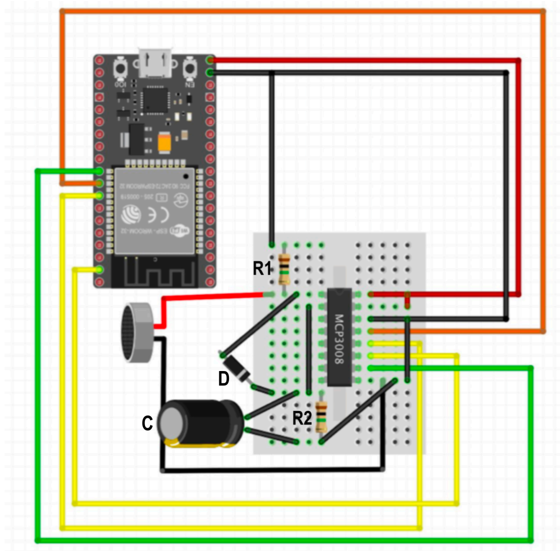


Fig. 1.2: Cost-Effective Smart Meter Diagram

to reduce costs (only 35$) and also thanks to its ease of use. Raspberry Pi acts as Edge node allowing to train an on-board ML model with limited computational requirements to minimize the infrastructure costs and communication latency.

Software The communication between the AC and the CSMs takes place by wireless connection to a hotspot. This service is provided by the AC itself and is made available through a Docker container. The AC collects and formats all the data coming from each smart meter's apartments within the smart building. To do so, a Node-RED flow has been implemented. As well as, to allow users accessing information about the CSM and plugged appliances, a Node-RED user interface is also implemented.

Neural Network Configuration We chose to use the Brain.js library, which can be used with Node.js and allows us to configure neural networks using the JavaScript programming language easily. Brain.js is a GPU accelerated library quick and easy to use and can also be used within a Node-RED flow with the appropriate official node.

The data for each appliance is collected in four steps:

1. during 10 seconds, signal samples are acquired without the appliance being plugged to the socket;
2. the appliance is plugged in and samples are collected for 10 seconds;
3. the appliance is switched on and it runs for a period of 15 seconds;
4. the appliance is switched off after, a 15 seconds sampling period occurs.

The system described above gives us for each measurement 512 amplitudes of the power spectrum and its relative frequencies in the range of our frequency window. For the implementation of the load characterization function, a supervised learning approach was chosen, particularly, a feed-forward neural network. This approach is the easiest one and fits well with the constraints capabilities of the Raspberry Pi.

The appliances chosen for the experiments were: (i) computer, (ii) monitor, and (iii) lamp. The labels depend on the number of appliances that are considered, in our case we have an array of three elements of the three appliances seen above, each position corresponds to an appliance that can be turned on, then marked with '1' or turned off and marked with '0'. For example, when the lamp turned on, the corresponding label will be $[0,0,1]$. Thus, we have 2^n combinations where n is equal to the number of the appliance to be characterized; in our case are n=3, and all the possible combinations are 8. The input layer, therefore, has 512 input neurons corresponding to the 512 features of the measurement, the hidden layer presents 256 neurons, and finally, the output layer has a number of neurons equal to the number of loads to be characterized. The dataset is made up of one hundred records for every possible combination between the various devices and to work with Brain.js, each measurement must be structured as follows:

$$\{input : [amp_1, amp_2, amp_3, ..., amp_{512}], output : [label_n]\}$$

1.5 Evaluations and Findings

The purpose of this analysis is to verify the correctness of the implemented ML model in terms of loads' characterization. The data used to evaluate the performance of the ML model come from three appliances: (i) computer, (ii) monitor, and (iii) lamp. Given that the ML model is trained on a device with limited computational capabilities, our objective is to minimize the number of records for each appliance in order to lightweight the training in terms of computational requirements and time.

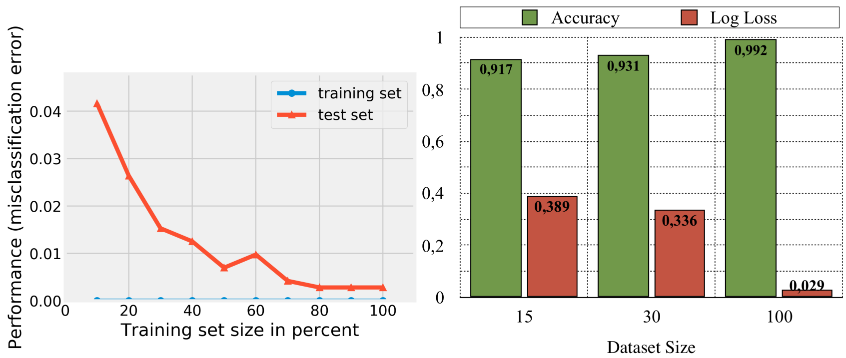
For instance, each appliance was evaluated by varying its number of records in the dataset in the following cases: (a) 15 records per case, for a total of 120 total records, (b) 30 records per case, for a total of 240 total records, (c) 100 records per case, for a total of 800 total records, (d) 300 records per case, for a total of 2400 total records.

The first three values (15, 30, and 100) of total records in the dataset have been used to carry out more in-depth assessments of the performance of the neural network to characterize electrical loads (see Fig. 1.3b), while the last case, since the system can not acquire it in an acceptable time, will be used only for evaluating the quality of the model used when the size of the dataset varies (see Fig. 1.3a).

The neural network, necessary to characterize the electrical loads, was trained on a Raspberry Pi 3 Model B. We calculated the following metrics, such as learning curve, accuracy, log loss, and confusion matrix. We have also considered the Classification Report with the following metrics, such as precision, recall, and F1-score.

Fig. 1.3a illustrates the corresponding learning curve. It can be pointed out that the goodness of the highlighted model allows excellent performance to be achieved in terms of accuracy using less than 50% of the maximum dataset size (2400 records). As well as, Fig. 1.3b shows the accuracy and log loss trends. We notice the accuracy reaches a high value even with few records, with 15 records the accuracy reaches 0.917.

The accuracy values provide only global information: high accuracy is not necessarily related to a precise identification of true positives. We try to increase the number of data in the data set to reduce the value of the log loss.



(a) Learning Curve

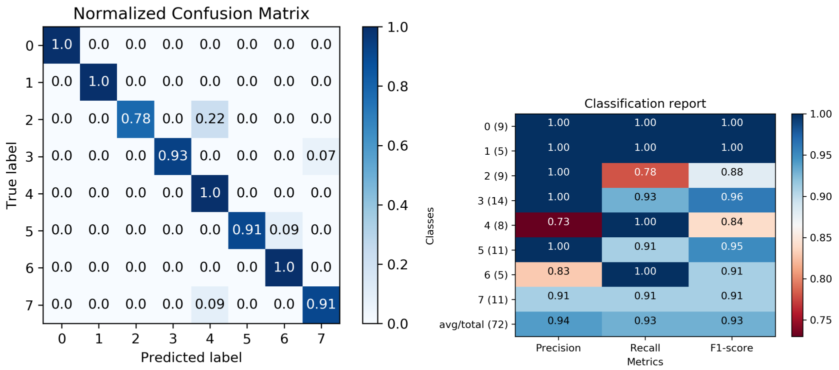
(b) Accuracy and Log Loss Trends

Fig. 1.3: Neural Network Metrics

By increasing the dataset size up to 30 records, we notice an improvement for both accuracy and log loss. Specifically, the accuracy is 0.992, while the log loss is 0.336. By further increasing the dataset size up to 100 records, as we expected, both accuracy and log loss are improved.

Given that our goal is to minimize the number of records in order to lightweight the training in terms of computational requirements and time, the performances obtained with the case with 30 is the optimal for our purposes.

Fig. 1.4a reveals the confusion matrix in this case. At first sight, it can be seen that we have a low classification error between the labels. The trend of the metrics shown in Fig. 1.4b proves that the error is distributed among several classes, but in minimal form, in fact, the average precision, recall, and F1-score values are satisfactory.



(a) Confusion Matrix (b) Classification Report Parameters

Fig. 1.4: Confusion Matrix and Classification Report obtained using a dataset of 240 records

1.6 Conclusion and Future Work

In this paper, we presented how the combination between IIoT and AI can support NIALM in a smart city scenario. Specifically, we presented the development of a cost-effective NIALM infrastructure.

The central dominant goal of a NIALM infrastructure-based on CSMs is to recognize appliances connected to the grid, while providing much more information to consumers allowing them to make better decisions concerning saving electricity, as well as implementing energy management systems for automatic generation/consumption regulation within the smart city. To conclude, a smart city uses digital technology to improve the overall productivity, optimize the usage of resources like: electricity, gas, and water. The same idea of the cost-effective NIALM infrastructure can be extended to other common utilities like gas and water.

In our on-going work, we are planning to involve devices with better performances to guarantee a higher quality of the acquired data. This solution would make the measurements performed even more accurate and thus improve the performance of the implemented loads' characterization model. Then, we are planning to use semi-supervised learning techniques to avoid the need for labeled data.

ACKNOWLEDGMENT

We would like to express our gratitude to Adriele Magistro, student at the University of Messina, for his valuable support.
This work has been supported by the MESm@rt project.

References

1. Calvillo, C., Snchez-Miralles, A., Villar, J.: Energy management and planning in smart cities. Renewable and Sustainable Energy Reviews **55** (2016) 273–287

2. Ghosh, S.: Smart homes: Architectural and engineering design imperatives for smart city building codes. In: 2018 Technologies for Smart-City Energy Security and Power (ICSESP). (2018) 1–4
3. Molina, B., Palau, C.E., Fortino, G., Guerrieri, A., Savaglio, C.: Empowering smart cities through interoperable sensor network enablers. In: 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC). (2014) 7–12
4. Cui, S., Wang, Y., Xiao, J.: Peer-to-peer energy sharing among smart energy buildings by distributed transaction. IEEE Transactions on Smart Grid (2019) 1–1
5. Prisyach, E.Y., Shvetsova, O.A.: Elements of innovative scenarios development of waste management system in russia. In: 2018 IEEE International Conference"Management of Municipal Waste as an Important Factor of Sustainable Urban Development" (WASTE). (2018) 63–65
6. Celesti, A., Galletta, A., Carnevale, L., Fazio, M., ay-Ekuakille, A., Villari, M.: An iot cloud system for traffic monitoring and vehicular accidents prevention based on mobile sensor data processing. IEEE Sensors Journal **18** (2018) 4795–4802
7. Figueiredo, M., De Almeida, A., Ribeiro, B.: Extracting features from an electrical signal of a non-intrusive load monitoring system. (2010) 210–217
8. Fagiani, M., Bonfigli, R., Principi, E., Squartini, S., Mandolini, L.: A non-intrusive load monitoring algorithm based on non-uniform sampling of power data and deep neural networks. Energies **12** (2019) 1371
9. Souza, W., Garcia, F., Marafao, F., Silva, L., Simoes, M.: Load disaggregation using microscopic power features and pattern recognition. Energies **12** (2019) 2641
10. Geelen, D., Mugge, R., Silvester, S., Bulters, A.: The use of apps to promote energy saving: a study of smart meterrelated feedback in the netherlands. Energy Efficiency (2019)
11. Chui, K., Lytras, M., Visvizi, A.: Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. Energies **11** (2018) 2869
12. Hart, G.W.: Nonintrusive appliance load monitoring. Proceedings of the IEEE **80** (1992) 1870–1891
13. Makonin, S., Popowich, F., Gill, B.: The cognitive power meter: Looking beyond the smart meter. (2013) 1–5
14. Depuru, S.S.S.R., Wang, L., Devabhaktuni, V.: Support vector machine based data classification for detection of electricity theft. (2011)
15. Cuado, J., Linsangan, N.: A supervised learning approach to appliance classification based on power consumption traces analysis. IOP Conference Series: Materials Science and Engineering **517** (2019) 012011
16. Hernndez, L., Baladrn, C., Aguiar, J., Carro, B.: Classification and clustering of electricity demand patterns in industrial parks. Energies **2012** (2012)
17. Basu, K., Debusschere, V., Bacha, S., Maulik, U., Bondyopadhyay, S.: Nonintrusive load monitoring: A temporal multilabel classification approach. IEEE Transactions on Industrial Informatics **11** (2015) 262–270
18. Buzachis, A., Galletta, A., Celesti, A., Fazio, M., Villari, M.: Development of a smart metering microservice based on fast fourier transform (fft) for edge/internet of things environments. In: 2019 IEEE 3rd International Conference on Fog and Edge Computing (ICFEC). (2019) 1–6