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Automatic recognition of electric loads analyzing the characteristic parameters of the consumed electric power through a Non-Intrusive Monitoring methodology

O.Hamid[a], M.Barbarosou[a,b], P.Papageorgas[a]*, K. Prekas[a] and C-T Salame[c,d]

[a]*Department of Electronic Engineering, Piraeus University of Applied Sciences, 12244 Egaleo-Athens, Greece*
[b]*Department of Aeronautical Sciences, Hellenic Air Force Academy, Dekeleia Air Base, 13671 Tatoi, Greece*
[c]*CNRSL, National Council for Scientific Research, Beirut, Lebanon*
[d]*CEER, Faculty of Sciences II, Lebanese University, B.P 90656 Jdeidet El Mten, Lebanon*

Abstract

Non-Intrusive Load Monitoring (NILM) consists in measuring the electricity consumption using a power consumption data acquisition system, typically placed in the main supply of the building. Relying on a single point of measure it is also called one-sensor metering in contrast to the common metering hardware that can be embedded in each appliance (electronic metering ore-metering) and in differentiation with the common utility smart meters. NILM is the process in which you are able to disaggregate a set of energy readings over a period of time to determine exactly what appliances have used the power and how much power each appliance has used during that time period. In this work a supervised classification method was employed for offline appliances classification, based on low frequency power consumption. The classification feature set consists of the true power, reactive power, and the step changing of the true power. Multiple classifiers were tested and evaluated, such as Decision Tree, Nearest Neighbor, Discriminant Analysis, and the multilayer Feed-forward Neural Network classifier. The methods were tested on the ACS-F2 appliance consumption signatures database.

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Keywords: Non-Intrusive Load Monitoring;Intrusive Load Monitoring; Appliance Load Monitoring; E-meters; Submetering

* Corresponding author. Tel.: +30-210-538-1405; fax: +30-210-538-1405.
E-mail address: ppapag@puas.gr

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Nomenclature

ALM	Appliance Load Monitoring
ILM	Intrusive Appliance Load Monitoring
NILM	Non-Intrusive Appliance Load Monitoring

1. Introduction

Nowadays appliances cover a large amount of residential and building energy consumption. In residential buildings lighting and appliances represent 30% of the electricity consumption [1]. To this end, Appliance Load Monitoring (ALM) [15] has become important for consumption and energy savings monitoring. Taking advantage on appliance monitoring information, may lead to the reduction of energy consumption. Furthermore, knowledge of the exact time an appliance is used can be employed in an energy-consumption optimization system. Such system could provide recommendations to households for potential savings, by deferring appliance use to a day period when electricity is either cheaper or has a lower carbon footprint realizing Virtual Power Plants.

ALM employs two major approaches. (i) In Intrusive Appliance Load Monitoring (ILM) each appliance is measured independently in a distributed way ([1]-[5]). This requires the installation of a low-end [6] sensor on each appliance. (ii) In Non-Intrusive Appliance Load Monitoring (NILM) an e-metering [5] device embedded in the building's central energy distribution panel is utilized, to measure electricity consumption of all monitored devices simultaneously ([2], [7]-[11]). Thus no additional sensors are required. However, since the aggregate appliance of all monitored devices is measured, the household's total electricity consumption needs to be disaggregated into its contributing appliances. ILM ([1], [4],[5], [7]) and NILM ([2],[7],[9], [11]) are alternatively referred to as distributed sensing and single point sensing methods respectively.

Although the ILM is more accurate in measuring appliance specific energy consumption, compared to the NILM, the practical disadvantages include high costs, multiple sensor configuration as well as installation complexity favoring the use of NILM especially for the case of large scale deployments. Consequently, established start-up companies along with academic researchers have focused their attention towards the improvement of NILM based approaches to make it a viable solution for a realistic environment [12].

NILM energy disaggregation has been performed through advanced machine learning techniques. Two major approaches have been adopted. The first employs training sets prior to disaggregation ([13]-[16). This approach however, requires the acquisition of datasets for machine-learning training. The second uses unsupervised disaggregation methods in which no prior knowledge of the appliances is required ([12], [17]-[19]). The appliances are classified into arbitrary classes, which are manually labeled after the disaggregation process. This approach however, requires knowledge of the number of household appliances.

In this study, supervised machine-learning classification was employed for offline appliances classification, based on low frequency power consumption measurements. Two cases were addressed. In the first case, the appliances were classified into eight classes based on their power signatures. In the second, three appliances that were operating simultaneously were disaggregated. The feature space for the classification process was the true power, reactive power, and the step changing of the true power. Multiple classifiers were tested and evaluated, such as the Decision Tree, Nearest Neighbor, Discriminant Analysis, and multilayer Feed-forward Neural Networks. All computations were implemented in the MATLAB environment. The methods were tested on the ACS-F2 [20] appliance consumption signatures database.

2. Appliances States, background Methodology for implementation of a NILM System

Appliances can be in different states according to their use or functioning. These types actually emphasize the need for a mix of different techniques for signal processing and feature extraction. Up to four states can be listed [12]: