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Towards automated appliance recognition using an EMF sensor in NILM platforms

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ABSTRACT

Non-Intrusive Load Monitoring (NILM) has been studied for a few decades now as a method of disaggregating information about appliance level power consumption in a building from aggregate measurements of voltage and/or current obtained at a centralized location in the electrical system. When such information is provided to the electricity consumer as feedback, they can then take the necessary steps to modify their behavior and conserve electricity. Research has shown potential for savings of up to 20% through this kind of feedback. The training phase required to allow the algorithms to recognize appliances in the home at the beginning of a NILM setup is a big hindrance to wide adoption of the technique. One of the recent advances in this research area includes the addition of an Electro-Magnetic Field (EMF) sensor that measures the electric and magnetic field nearby an appliance to detect its operational state. This information, when coupled with the aggregate power consumption data for the home, can help to train a NILM system, which is a significant step forward in automating the training phase. This paper explores the theory behind the operation of the EMF sensor and discusses the feasibility of automating the training and classification process using these devices. A case study is presented, where magnetic field measurements of eight appliances are analyzed to determine the viability of using these signals alone to determine the type of appliance that the EMF sensor has been placed next to. Various dimensionality reduction techniques are applied to the collected data, and the resulting feature vectors are used to train a variety of common machine learning classifiers. A vector subspace obtained using Independent Component Analysis (ICA), along with a k-NN classifier, was found to perform best among the different alternatives explored. Possible reasons behind the findings are discussed and areas for further exploration are proposed.

1. Introduction

Electricity constitutes approximately 41% of total annual energy consumption in the United States (US), 67% of which is produced from fossil fuels [1]. Many other countries around the world have a similar composition of their energy demand. Hence, the impending shortage of non-renewable resources does not bode well, both for the US and the world [2]. Many influencing factors have been identified by researchers as possible solutions to sustain the ever-increasing demand for energy, such as promoting energy efficiency, generating new technologies for energy production, limiting energy consumption and raising social awareness on the rational use of energy [3]. Some authors posit that the most significant energy savings may be realized by changing people's habits [4]. Darby, for instance, claims that immediate feedback about consumption patterns can reduce consumption to produce savings of up to 15% [5]. Some other studies report this number to be as high as 20% [6]. Although the small sample size and limited time scale of these studies demand more research before conclusions about the exact percentage of savings can be safely drawn, the effect of feedback on energy consumption habits should not be discarded. Thus, considerable research has been underway in efforts to provide meaningful feedback about electricity consumption to consumers.

1.1. Background

One form of meaningful feedback about electricity consumption could be the appliance-level breakdown of electrical energy usage in a building. Numerous studies have looked into savings generated in electricity consumption based on feedback mechanisms, and real time disaggregated (appliance-level) feedback has been found to generate the maximum savings [7]. Fig. 1, adapted from a meta-review of previous studies reported in [7], lays out the

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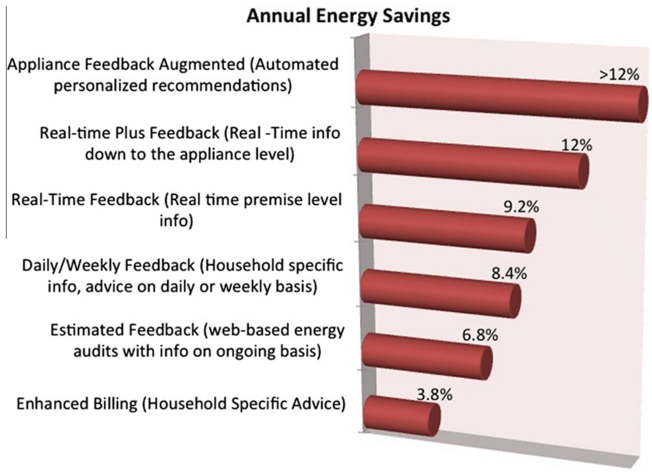

Fig. 1. Break-down of annual energy savings by type of feedback. This graph, adapted from [7], is based on the results of 36 studies that looked into potential energy savings based on different kinds of feedback provided to consumers.

potential savings from different kinds of feedback mechanisms. Again, the sample size and time scale of these studies render the actual numbers amenable to change, but the relative difference in effectiveness of one form of feedback over another should still hold true.

To achieve the highest savings according to this meta-review, connecting appliances directly to energy meters could be one way of providing disaggregated feedback. The technology for doing so is already available, but the cost of the hardware, operation and installation of these devices prove to be major drawbacks in this case [7]. A less invasive and perhaps more cost-effective approach would be one pioneered in the 1980s: Non-Intrusive Load Monitoring (NILM). NILM typically involves obtaining aggregate measurements of the power consumption of a home through an energy meter at the main electrical feed of the building, which is used be used to monitor changes in overall voltage and/or current that are produced when appliances being fed through that circuit change states [8]. Based on features of the signal changes (e.g., a change in magnitude, frequency content), the system identifies which appliance caused that change and uses this information to keep track of the power consumption and usage patterns of all appliances it can recognize.

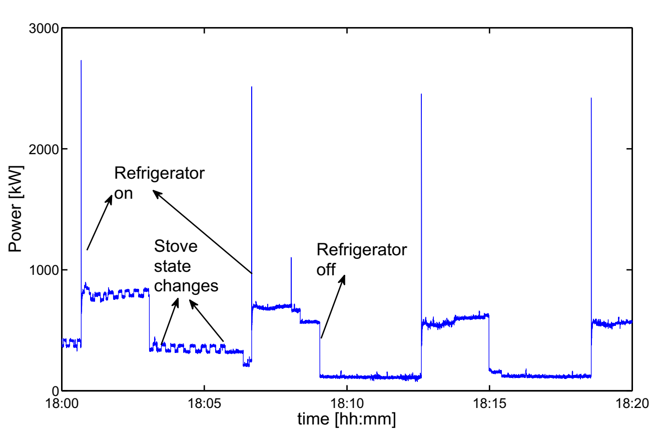

Fig. 2. Overall power consumption of a residential building during a 20 min interval. Some appliances change states quickly during operation (like the stove burner). By extracting appropriate features from these power signatures, appliance types can be classified.

Fig. 2 illustrates the initial idea proposed in [8], where step changes of power in the main power line are used to determine which appliance caused such change. Every time an appliance turns *on* within the house, there is a change on the overall power consumed by the building, which manifests as a step change – also known as power signature. Features based on these step changes, including the step change magnitude, the spike at the moment of change (also known as transient) [9,10], and other quantities describing higher frequency content on the voltage [11,12] and/or current signals [13], have been found to be characteristic to specific appliance types and may be used to distinguish one appliance from another. A good review of the features that have been used can be found in [14].

Although an intriguing concept in theory, the problem of identification and disaggregation can become very complex as the number of appliances in the house increases. As of date, no complete NILM solution suitable for all types of household appliances has been developed [15]. Roth and Zeifmann in [15] note that the available solutions are either unsuitable for some appliances or still at an early developmental stage and that no complete set of robust and widely accepted appliance features has been identified. One of the major challenges has to do with the fact that most of the proposed solutions require a training period (either during operation, or before the deployment of the system) during which the classification algorithms are given labeled examples of the signals for each appliance to be recognized. This process is typically performed under human supervision, and may involve asking the user to identify the appliance state transitions as they occur.

1.2. Sensor-aided NILM

To overcome some of the aforementioned limitations and challenges, numerous attempts have been made to develop solutions that either aid NILM or act as substitutes [15]. Some researchers, for example, have used a combination of several radio-enabled sensors (magnetic, acoustic, and light) that send information to a central "fusion-center" that calibrates the sensors automatically and estimates power consumption for each appliance that they have been placed near to [16]. Other authors cite the difficulty of using magnetic sensors as the reason for using an improved EMF sensor, which works with a more amplified magnetic field signal [17]. The sensor system presented in [17] is placed in the vicinity of an appliance (typically, within a couple of centimeters) from where it senses the electro-magnetic field around that appliance and processes the measurements locally to detect changes in its operating state. This information can then be synchronized with overall power consumption measurements for the building, to train the NILM algorithms and estimate the appliance power consumption of the appliance in question. A similar approach of using electro-magnetic field information to recognize appliances (portable and handheld – in this case) has been explored before, but not with the object of energy disaggregation in mind [18,19]. These approaches require the EMF sensor to be worn in the user's hand as opposed to being placed next to a device and is targeted mostly at recognizing portable devices for activity recognition. Some researchers have also tried using other multi-modal sensor fusion schemes to perform automated annotation with some success [20].

The results presented in the literature indicate that a system that fuses NILM with an indirect sensing platform and performs automated calibration, training and annotation presents many positive characteristics and may be a suitable path towards more widespread application of NILM techniques. With that motivation, this paper further explores the possibility of using an EMF sensor with the same wireless sensor-networking platform used in [17] to automatically train a NILM system. Specifically, this paper will