Towards Low-Cost Energy Monitoring

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INTRODUCTION

Concern over decreasing energy resources, increasing energy demand, carbon dioxide (CO_2) emissions, and global climate change has motivated serious efforts to make more efficient use of energy resources. Buildings consume more than 40 percent of overall energy expenditure worldwide[1]. A significant portion of this energy is considered as wastage. Effective energy conservation in buildings is critical both to reducing the seemingly ever-increasing energy demand and to mitigating concerns over global climate change. However, as a first step towards energy conservation, greater transparency over the traditional invisibility of energy usage must be engendered. Appliance-level energy usage monitoring is considered is a pre-requisite for energy conservation in buildings (Hutton, 1986). Recent research efforts have produced solutions that range from low-cost to high-cost methodologies. Two major categories of such methodologies are often referred as: distributed monitoring or Intrusive Load Monitoring (ILM), and single point monitoring or Non-Intrusive Load Monitoring (NILM) (Froehlich, 2011).

Non-intrusive load monitoring is considered to be a low-cost and simple technique to acquire individual appliance power consumption information. Metering devices are installed at fuse boxes to obtain energy usage measurements for whole buildings; these measurements are then further analyzed using pattern recognition algorithms to disaggregate appliance specific information. Figure 1 highlights appliance specific information that is present in an aggregated measurement of a household. In the recent past, researchers have presented many variations of the NILM method. However, a common principle is to create appliance specific energy usage signatures by turning them on/off, measure aggregated power usage of the building, and then, based on these known signatures, analyze power changes within the measurements to disaggregate appliance specific information.

NILM techniques presented in literature are mostly based on two major appliance features: Steady State and Transient State. Steady-state analysis requires less expensive hardware in comparison with transient-state analysis. Despite an intensive amount of research in the area, NILM techniques still have limitations. These include: manual annotation of training data sets when using supervised machine learning, limitations when distinguishing appliances with similar load profiles and low-energy consuming appliances, and validity of performance evaluation metrics.

BACKGROUND

Hart (1992) proposed non-Intrusive Appliance Load Monitoring (NALM) later referred as Non-Intrusive Load Monitoring (NILM) or single-point sensing. According to Hart, NILM monitors aggregated energy load, and analyzes measurements to identify certain appliance signatures so as to obtain information on appliance activities within a monitored environment. For example, consider a simple case where a building contains a microwave oven that consumes 1200 watts when turned on at high state; then a sudden increase or decrease of 1200 watts in total load will indicate that the microwave is turned on or off. Similarly, other appliances with different characteristics or signatures can be identified from an aggregated load measurement. The very first step in NILM is to install a meter-

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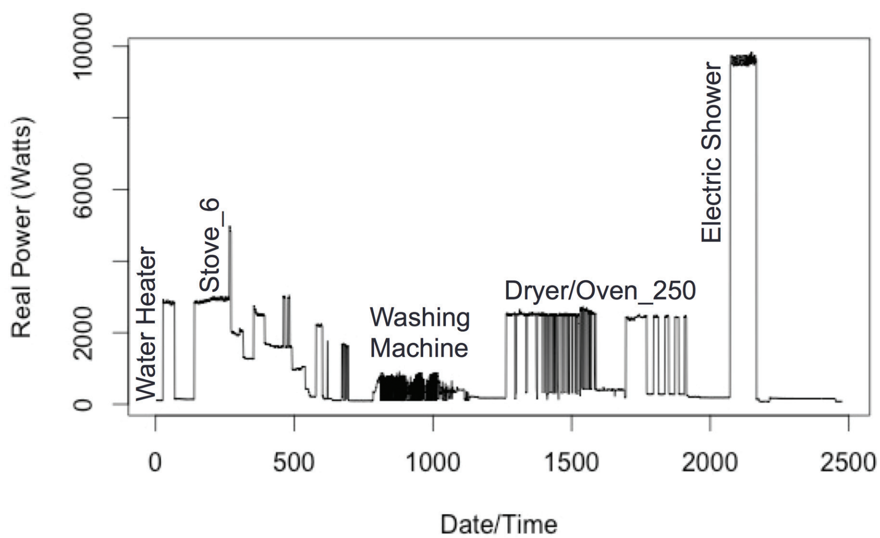
Figure 1. Power usage highlighting step changes corresponding to individual appliance events



ing device, which is often a smart meter, to measure energy consumption of a building in real-time. This information is then transferred to a PC via gateway. Appliance signatures are learned by turning each appliance on/off during the system-training phase and then the signatures are annotated appropriately. The next step is to observe a step change in total load and utilize appropriate machine learning algorithms to identify and classify appliances based upon learned signatures. Appliances having different load signatures are easy to identify but classifying those having similar signatures is a complex task.

In the recent past, single-sensor based monitoring has been the subject of much research due to its simplicity and low-cost. Based upon feature selection, NILM techniques may be further divided into following categories:

- Power Based Approach and
- Electrical Noise Based Approach

Power Based Approach

Power based NILM approach uses real power, reactive power or Volt-Ampere Reactive (VAR), and Root Mean Square (RMS) current and voltage measurements to construct appliance signatures. These features can make a NILM system simple when used alone with step change detection; however this technique has limitations when identifying low power consuming appliances. The microwave example highlighted earlier is a single power feature based technique. Using a combination of power features improves overall accuracy and increases the number of appliances that can be classified in comparison with single feature based technique. Using reactive power in combination with real power helps classification algorithms to differentiate loads that have similar real power consumption, since these appliances are most likely to have different reactive power levels. However, this approach requires sophisticated hardware (metering device) and complex appliance classification algorithms.

An example of a system that uses multiple power features together to classify appliances is Recognition of Electrical Appliances in Real-time (REAR) (Ruzzelli, 2010). REAR reports appliance classification accuracy of 95% with major energy consuming appliances. However, this accuracy drops down to 84% when low power consuming appliances were used. The authors have acknowledged REAR's limitation to classify multi-state appliances. To improve appliance classification, Marchiori (2011) presented a circuit level energy monitoring technique. This technique uses multiple metering devices installed on each circuit breaker box in a household. Higher accuracy is reported because of the low occurrence of appliances with similar power usage on each circuit. However, using multiple sensors increases installation complexity and makes the overall configurations more expensive.