Training Schemes in Non-Intrusive Load Monitoring

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ABSTRACT

Non-Intrusive Load Monitoring (NILM) is a technique to manage energy consumption by the determination of the operating schedule of individual appliances from aggregate voltage/current measurements. NILM technique for gathering appliance load information does not require intrusive sensor placement on individual appliances. Machine learning methods have been proposed for NILM yielding promising results. Training is one of the key phases in machine learning approach for NILM. In this paper, we address the training schemes in NILM, including manual training, sensor assisted training, and cloud based training. We analyze their advantages and disadvantages as well as the challenges. It opens discussions on the efficient and effective training schemes for NILM.

Keywords

Non-intrusive load monitoring, machine learning, training

1. INTRODUCTION

Non-intrusive load monitoring (NILM) is of growing interest and rapid evolution in power and energy research and sustainable development. NILM is a process for analyzing changes in the voltage and current going into a building and deducing what appliances are used in the building as well as their individual energy consumption. NILM is considered a low cost alternative to attaching individual monitors on each appliance. It typically is a *single point sensing* technique. NILM can potentially enable itemized energy bill, manage the power usage and reduce the cost (e.g., by turning off the unnecessary devices), detect or diagnose the devices draining too much energy so as for replacement with more energy efficient ones [1-12].

Machine learning methods have been proposed for NILM yielding encouraging results. Training is one of the key phases in machine learning approach for NILM. Training process in this paper is defined as the process through which the *characteristic signatures* of the different appliances' state transitions are learned.

The training can have both offline training and online training. The majority of research to date has an offline training strategy, where the system is trained before installation or during an initial post-installation period. For online training, it can be more interactive and continuous process in which the signatures of the appliances can be learned or updated after the system installation. Different training schemes can be for offline and online training.

Often times the training process requires a manual training, including manual turning on and off of each appliance in the residence, and manual labeling of the events and timing. Thereafter, each signature is observed, classified then named in the database [5-6,10]. The manual training typically can be for the offline training, but not very friendly for online training.

To help the online training, sensor assisted training schemes are proposed [1,11]. A sensor placed close to an appliance can sense the states of the appliance, and transmit the states with the time stamps to a gateway by using wireless communication. The gateway then sorts out the events and records or updates the signatures in the database.

A cloud based training can be automatic. It can set itself up as it measures the load, using prior information (e.g., gathered in laboratory or by opinion poll, etc.) about the characteristics of possible appliances [6,9]. The cloud can have the big database of various signatures pre-studied, and each user's system can capture the signatures for its appliances after the training process. The cloud based training can be for offline and online training.

All these training schemes have their challenges. In this work, we analyze their challenges via their advantages and disadvantages. It opens discussions on the efficient and effective training schemes.

2. TRAINING SCHEMES

Here we discuss in detail about the training schemes of manual training, sensor assisted training, and cloud based training.

2.1 Manual training

Manual training builds up the local data base typically via human manually turning on and off the appliances, manually labeling the events and time stamps, and tagging the events in software. Figure 1 shows an example. In the figure, the manually tagged events and time stamps are input to the gateway. The NILM sensor which is the single point sensor for NILM, senses or measures the voltage and current, and inputs to the gateway. The gateway then can establish the local database in the building, by observing, classifying and marking the signatures of appliances.

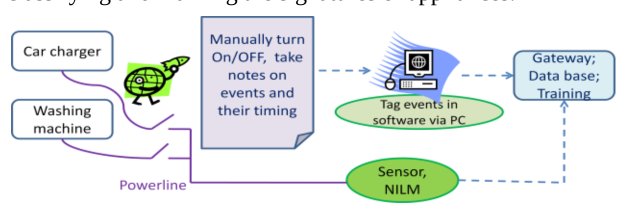

Figure 1 An example of manual training

The manual training can be conducted in home. It is typically operationally expensive and not tenable for a commercial solution. It requires cooperation from the home-owner or end-user to perform the manual training. It is mostly useful for offline training, which is the training before installation or during an initial post-installation phase. It can also be used from time to time for re-train the system for updated signatures, or when there are new appliances added to the system. However, it may not be very useful for very interactive or continuous training purposes.

Manual training has the following difficulties and challenges. It requires a lot of involvement of human. It may lead to errors such as labeling errors. It is difficult to capture the multiple internal states for appliances such as dishwashers or washing machines.

2.2 Sensor assisted training

For sensor assisted training, in addition to the single point NILM sensor, it requires individual sensors close to each of the appliances to monitor the states of the appliances, and send the sensed results (e.g., including the appliance state changes and time stamps, etc.) to the gateway, via wireless communications such as IEEE 802.15.4. The gateway then can capture these labels and use them for training purposes. Figure 2 shows an example. In the figure, proximity sensors sense individual appliance's states and send the state change events to the gateway.

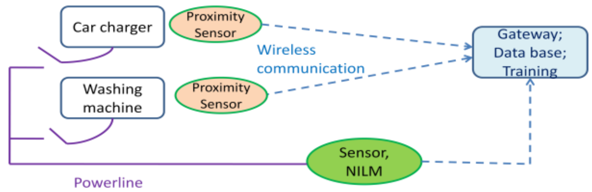

Figure 2 An example of sensor assisted training, by using sensors close to the appliances

NILM methods need to be continuously trained as events change over time. One of the main purposes for sensor assisted training is to provide automatic labeling, especially to enable online training, in which the signatures of the appliances can be learned or updated after the system installation.

One example of the proximity sensor is an event detector called the Wire Spy in [1] to automatically label on/off cycles for a single appliance. It clamps onto the appliance's power cable such that it is not necessary to even unplug the appliance. Another example is by using electromagnetic field (EMF) sensors [11]. EMF sensor is installed close to an individual device, and senses its ON/OFF events, then inputs to the training database, e.g., via a gateway. When an event is detected, a notification is sent from the proximity sensor to the main data acquisition computer. The notification contains a sheared appliance ID (input by the user) as well as the pre-and post-event signal averages.

The usage of sensor assisted training requires one-time end-user input with respect to pairing the sensor with the particular device which it is monitoring. One of the challenges of this scheme is that the proximity sensor may not be very accurate to sense the event of appliance state changes, due to cross talk, interference, etc. It needs to make it monitor appliances with multiple states in the future accurately. Another challenge is the controversial aspect that the usage of many proximity sensors may defeat the purpose of single point sensing of NILM.

2.3 Cloud based training

For the cloud based training, a big database is assumed to be established in the cloud, where the cloud can be in a network such as Internet. The big database contains various characteristic signatures of the different appliances' state transitions, including appliances of different makers, models, years, etc. In cloud based training, an automatic training setup can set itself up as it measures the load, using prior information (e.g., gathered in laboratory or by opinion poll, etc.) about the characteristics of possible appliances. A local end-user database can be established only related to the end-user. Figure 3 illustrates an example.

One way is that the NILM system monitors the measurements and finds out which could be the possible appliances that the end-user has used in which time frames. Then the NILM system sends the end-user polling questionnaire, asking the users for confirmation. Another possible way is that the end-user inputs the appliances' information, such as maker, model, year, etc., then the local NILM database can get the possible signatures for the end-user.

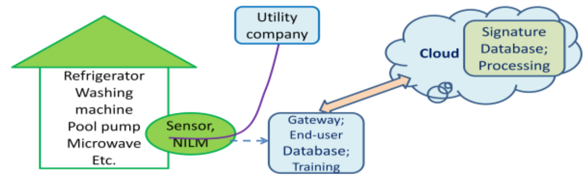

Figure 3 An example of cloud based training

Cloud based training provides active deployments of NILM source the events and classifications in the cloud. It can be used for offline training (before installation or initial post-installation) and online training (after installation). As more deployments are added the cloud based database becomes more comprehensive and confidence levels with respect to event matching and signature classification improvement. It may require cooperation from the home-owner/end-user in the near-term, but has the potential to not require such cooperation in the longer term as the appliance signature databases get populated and become comprehensive over time. Stored data could be the extracted features if there is generic agreement on what these should be; if not the raw captured events (suitable tagged) could also be used.

One of the challenges of cloud based training is that it requires gathered a data base of the signatures of each residential appliance in various states and it remains difficult.

3. COMPARISON

To sum up the features of different training schemes, the comparison of different schemes is listed in Table 1.

	Manual training	Sensor assisted training	Cloud based training
ON/OFF states	Yes	Yes	Yes
Internal states	Very limited	Yes or Limited	Yes
User interaction	Manual labeling	Input of pairing the sensor with the appliance it monitors	Answer the polling. Or input appliances' information
Database	Local, small	Local, small	Large database in the cloud. Local database can be established based on the cloud.
Online or offline	Mostly offline	Mostly online	Online & offline
Challenges	Capturing internal multiple states. Much Involvement of human.	Tradeoff of the local sensor complexity and accuracy. Not aligned with the purpose of single point sensing.	Database establishment in the cloud.

Table 1 Comparison of different training schemes

4. CONCLUSION

We analyze different training schemes in NILM via their operations. Efficient and effective training schemes in NILM need yet to be developed. Combinations of schemes can be used. Cloud based scheme is promising with many merits if overcoming the efforts to establish the signature database in the cloud.

5. ACKNOWLEDGMENTS

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