Non-Intrusive Load Monitoring in Commercial Buildings: Recent Developments and Challenges

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***Abstract* — Non-Intrusive Load Monitoring (NILM) in buildings is a very important topic widely researched since late 80s. It was developed with many productive contributions from many researchers, particularly in the residential buildings. To address the lack of detailed discussion in relation to NILM in the commercial building sector, this paper is focused on recent developments of the related technologies as well as highlighting future challenges.**

Keywords - Energy Disaggregation, commercial buildings, Non-Intrusive Load Monitoring

I. INTRODUCTION

Commercial buildings contribute to 48% of the electrical energy consumption of Malaysia in 2012[1]. Despite many energy conservation measures implemented, observed energy consumption of commercial buildings usually exceeds by at least 30% of the designed value[2]. In such cases, occupant behaviour can be identified as a key factor in building energy consumption. Unlike in the residential buildings, commercial building occupants are less motivated to conserve energy since they are not directly responsible for the payment of their utility bills. Therefore, it is required to motivate and influence the occupants to conserve energy by taking practical approaches such as by introducing a feedback/ reward/penalty mechanism[3].

However, the success of any such energy management approaches will depend on the accuracy and sensitivity that focus to the level of appliances and occupants. Compared to the conventional methods [4], Non-Intrusive Load Monitoring (NILM) methods have been popular in the last 3 decades [5]–[7] but its application in commercial buildings is still challenging due to its practical constraints. Therefore, this paper discusses the current challenges in applying NILM in the commercial building sector by reviewing the suggested solutions published in recent literature.

II. NILM FRAMEWORK

The concept of NILM was presented in 1989 by George.W. Hart. [8] Since then, it has been developed by a number of researchers to suit different built environments and appliances. However, the basic framework remains the same and it is shown in Fig. 1.

As shown in Fig. 1, the aggregate power consumption and other features (current, power factor, harmonics) of a building is monitored at its mains. Detected changes in those features are analyzed to identify the switching events of different appliances of the building. Accordingly, the individual energy consumption is disaggregated from the total.

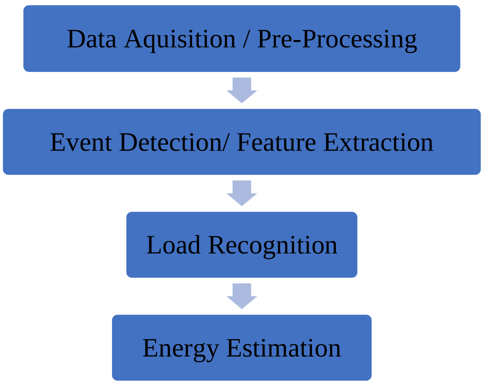

Fig. 1. General framework of NILM [7]

Data acquisition can be either low resolution or high resolution [6] depending on the algorithm. More features like start up transients, power/current harmonics can be extracted in high resolution data acquisition systems [7]. For load recognition, supervised and unsupervised algorithms are used [6], [7]. In supervised algorithms we need to train the algorithm with a known database of load signatures.

In contrast to the conventional methods where it is necessary to install energy meters at all sub circuits, the significance of NILM is its ability to disaggregate the energy consumption to the level of subcircuits while having metered only at the main breaker of the installation. Such detailed information on energy use of a building obtained at a relatively low cost is useful in implementing energy conservation measures on specific categories of appliances [5].

III. CASE STUDY

In order to provide a clear understanding of the NILM process, a simple case study in the Universiti Teknologi Malaysia is presented in this section. A postgraduate research lab was selected for the study and its load curve (excluding lighting and HVAC) during a weekday in the month of August 2020 is shown in Fig. 2 . The research lab consists of a cubicle for the lab in charge and 10-15 workstations for research students but only five research students are currently occupying and attending the lab on a regular basis. In addition to the computers used by the lab in charge and students, there is a common PC, printer (3 in 1), mini refrigerator and a network switch. In addition to the regularly used equipment, the power meter itself consumed power from one workstation.

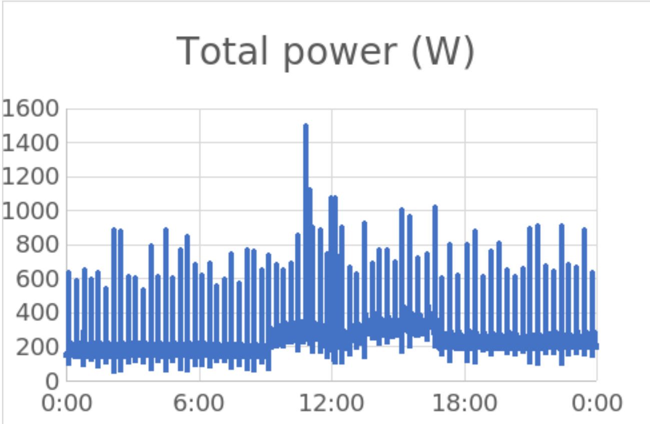

Fig. 2 – Daily load curve of the research lab selected for the case study

First of all, a median filter was applied on the load curve to remove impulsive noises. Then all positive and negative power changes were plotted as shown in Fig. 3. Two clear clusters; P+ and P- were identified from the plotted data so that 50<p<70 for p ϵ P+ and -60<p<-40 for p ϵ P-. From the power measurements done on individual appliances, two clusters were identified as the switching on and switching off events of the compressor in mini refrigerator

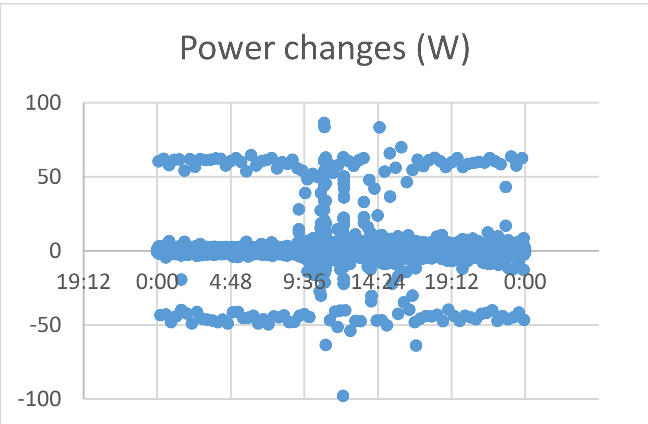

Fig. 3 - Detected power changes

Accordingly, 68 positive power changes and 62 negative power changes were identified for P+ and P- clusters. However, the actual power consumption of the refrigerator was also measured for validation purposes and it was found that the actual number of switching events was 71. Therefore, the estimation accuracy for the switching on and off events of refrigerator were 95.77% and 87.32% respectively

IV. Identified Challenges & Developments

NILM has shown significant success in the residential building sector [9][6][10] but its application in commercial buildings is challenging mainly due to the availability of large numbers of similar devices and high event density [9]. Presence of complex and variable power devices is also another barrier to disaggregate commercial building energy consumption [6], [7]. There are a significant number of published articles [9], [11]–[19] on the application of NILM in commercial buildings and the identified key aspects are discussed in the following subsections.

A. HVAC load disaggregation

Energy consumed through heating, ventilation and air conditioning (HVAC) systems accounts for a substantial portion of energy usage in commercial buildings. Because of the complexity and power variation, disaggregation of HVAC load is quite complex when compared to other loads. Norfold and Leeb [9] managed to identify start-up and shut down events of space-conditioning equipment in a laboratory building based on steady state power changes. In central air-conditioning systems, the main equipment such as chillers, pumps, cooling towers are sometimes metered separately but the end-use equipment are mixed up with lighting and other loads. In order to filter out the energy of end-use equipment, Ying et al. [16] proposed a method based on the Fourier Series Model (FSM). The basic mechanism of the FSM-based method is to separate the HVAC and other loads taking into consideration the dependency on the weather data. While most of the other methods required high resolution power measurements, Liang et al. [17] presented a sequential energy disaggregation algorithm which could extract HVAC energy consumption from low resolution (30 min) data using Day Type Classification (DTC) and Average Value Subtraction (AVS). However, none of the above approaches clearly address the issue of identifying power variation in central air-conditioning systems due to different thermostat settings.

B. Individual disaggregation methods for Non-HVAC loads

Since a common method is unlikely to disaggregate all types of loads effectively, certain authors have proposed separate methods for each type. Jazizadeh and Becerik-Gerber [12] proposed a unique methodology to extract lighting energy by linking power measurement with the data acquired through light sensors. For the disaggregation of power electronic loads, Renaux et al.[18] suggested an algorithm based on the derivative of half cycle active power. A hybrid approach incorporating supervised self-organizing map and Bayesian identifier was proposed by Du et al.[13] for identification of plugged-in loads utilizing statistical information. Wave-form based estimator was proposed for the extraction of variable power loads by Wichakool et al.[15]. All the above approaches have shown significant success in the experimented scale, but it does not ensure the same performance when more than three different types of loads are mixed with or in case of multiple numbers of the same appliance.

C. Association with occupancy data

Instead of relying entirely on aggregate power, some researchers have associated occupancy data in disaggregating the energy use of personal loads. Kavulya and Becrik-Gerber [11] associated visual observations to extract energy consumption and potential savings of computers and printers. Instead of visual observation which is not viable in continuous load monitoring, Thakur et al.[14] utilized the data acquired from location and audio sensors in their ‘Wattshare’ algorithm for energy apportionment among individuals living in a shared space of a commercial building. Chen and Ahn[20] suggested the utilization of Wi-fi connectivity of the occupants to extract their energy use events and based on the same concept Rafsanjani et al. [21] developed an algorithm to extract individuals’ energy consumption using Density Based Spatial Clustering Algorithm with Noise (DBSCAN) and Quadratic

Discriminant Analysis (QDA). They have further improved their method by associating the distance to the load consuming point which was detected by an energy node locator[22]. Results of the above researches clearly indicated that the NILM performance can be improved by associating the occupancy data. Such approaches also demonstrate the ability of disaggregating total energy to the level of occupants rather than appliances.

V. CONCLUSION

NILM applications utilized in commercial buildings focus mainly on energy disaggregation at the appliance level. Such information is useful but not sufficient to manage individual occupants' energy usage. As a solution, there is a limited number of studies conducted on occupant energy monitoring in association with occupancy data.

Association of occupancy data in NILM is observed as an emerging research topic. However, the types of occupancy data used must be relevant to energy consumption and the methods of acquisition are to be practical and cost effective. As such, there is an opportunity to explore other occupancy data types which can easily be obtained but have not yet been associated in NILM. Disaggregation of energy to the occupant level can also be researched using such methods.

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