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OFFICE APPLIANCE CATEGORY CLASSIFICATION BASED ON NON-INTRUSIVE LOAD MONITORING

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ABSTRACT

Alongside the acceleration of building digitalization, making intelligent use of building energy consumption data attains more and more attention. As appliance-level energy consumption data is not generally available, the Non-Intrusive Load Monitoring (NILM) provides novel ways to disaggregate total energy consumption data into appliance-level while ensures privacy of customers. This work focuses on NILM algorithm that is applicable to common appliances and widespread smart metering infrastructure. The NILM energy consumption data of an office was collected with 1-min resolution and used for analysis. In the work, fuzzy c-means clustering NILM algorithm and inter-cluster entropy were used to classify and verify the categories of office appliances. The algorithm was proven to be able to disaggregate and classify office appliance energy consumption data with a satisfactory accuracy.

Keywords: non-intrusive load monitoring, smart building, energy disaggregation, fuzzy c-means clustering

NONMENCLATURE

Abbreviations	
NILM	Non-Intrusive Load Monitoring
FCM	Fuzzy C-Means
Symbols	
t	Index of time step
m	Index of appliances
n	Normalized value
C	Number of time steps
M	Number of appliances in the office room
N	Number of appliance-level normalized load feature vectors
X	Number of clusters
T	Vector transposition
i, i_a and i_f	Total, active and inactive current
p_a	Active power
u	Voltage
U_{rms}	Root mean square voltage
F	Load feature
F_{ref}	The maximum load feature
u_{kj}	The membership of appliance-level normalized load feature vector $F_{m,n,k}$ in *j*th cluster
h	Cluster fuzziness, $h \in [1, \infty]$
x_j	Center vector of *j*th cluster
S^j	The jth Cluster
S_j	Number of appliance-level normalized load feature vectors in jth cluster
Σ_x	Covariance matrix

1. INTRODUCTION

On the arrival of digital age, the smartness of buildings are greatly improved by the various smart applications. The data acquirement and processing become the very primary steps for intelligent energy management in order to achieve more efficient operations of buildings. The energy management usually requires detailed energy consumption data of specific appliances [1]. While smart appliances provide accesses to individual load monitoring, the appliance-level energy consumption data is not generally acquirable and often

(a) (b)

Fig 1 (a) Smart meter with clamps on the electric mains. (b) Communication module.

requires intrusive load monitoring based on dedicated sensors. The large quantity of data from ubiquitous sensing infrastructure could also cause daunting computational problems and slow down the communication network. Moreover, the customers are usually hesitate to adopt intrusive load monitoring because of concerns about privacy.

NILM, also called energy disaggregation, could separate office energy consumption data collected from a single point of measurement into appliance-level energy consumption data [2]. NILM requires far less sensing and metering than intrusive load monitoring, and thus be regarded as more economical approach than approach [3]. As energy consumption data is monitored at the main breaker level, the risk of privacy leak has been greatly reduced. The characteristics of the existing NILM approaches could be found in [4] and [5].

The aim of this work is conducting energy disaggregation and classification on office energy consumption. In this work, the time-domain energy consumption data of an office room was collected using NILM approach and the FCM-based NILM algorithm was applied to the data set for appliance category classification.

2. METHODOLOGY

2.1 Office energy consumption Data Collection

In this work, an office room of a campus building in Shandong University was selected. As shown in Fig 1, the smart meter is installed in the electric mains to measure the voltage, current and power of the entire office room, and the measured data are uploaded to the cloud by the communication module.

The office energy consumption data is monitored for 10 days. The data collection took place during April 2019. The resolution of the data set is 1 minute.

2.2 Appliance-level feature extraction

The active power and inactive current of the office room, which are referred to as load features in this paper, are used to derive appliance-level data. The inactive current could be calculated by equations 1-4.

$$i_f(t) = i(t) - i_a(t) \tag{1}$$

$$i_a(t) = \frac{P*u(t)}{U_{rms}^2} \tag{2}$$

$$P = \frac{1}{C}\int_0^C IPdt \tag{3}$$

$$IP = i(t) * u(t) \tag{4}$$

The load feature vector of appliance m is shown in equation 5. The load features of the total energy consumption of the office room could be expressed by the vector in equation 6, where the normalized time-domain data is used. With regarding to the 1-min time resolution data, it is reasonable to assume that the difference of vector between two time steps is caused by switch event of one appliance. Therefore, the appliance-level normalized load feature vectors $\mathrm{F} = \{\boldsymbol{F_{m,n}}(\boldsymbol{t_1}), \boldsymbol{F_{m,n}}(\boldsymbol{t_3}), \dots, \boldsymbol{F_{m,n}}(\boldsymbol{t_N})\}$ could be obtained through equation 7.

$$\boldsymbol{F_{m,n}}(\boldsymbol{t}) = [i_{f,m,n}(t), p_{a,m,n}(t)] \tag{5}$$

$$\begin{aligned}\boldsymbol{F_n}(\boldsymbol{t}) &= [i_{f,n}(t), p_{a,n}(t)] \\ &= \frac{\boldsymbol{F}(\boldsymbol{t})}{\boldsymbol{F_{ref}}} \\ &= \frac{[i_f(t), p_a(t)]}{\max\{\boldsymbol{F}(\boldsymbol{t}), t=1,\dots,C\}} \\ &= \sum_1^M \boldsymbol{F_{m,n}}(\boldsymbol{t})\end{aligned} \tag{6}$$

$$\begin{aligned}\boldsymbol{F_{m,n}}(\boldsymbol{t+1}) &= \left[i_{f,m,n}(t+1), p_{a,m,n}(t+1)\right] \\ &= \boldsymbol{F_n}(\boldsymbol{t+1}) - \boldsymbol{F_n}(\boldsymbol{t})\end{aligned} \tag{7}$$

2.3 FCM clustering based load classification

The FCM clustering algorithm is adopted to sort similar appliance load features into X clusters $\{S^1, S^2, \dots, S^X\}$. The FCM clustering algorithm is an iterative optimization that minimizes the cost function shown in equation 8-10 [6].

$$J = \sum_{j=1}^{X}\sum_{k=1}^{N} u_{kj}^h \left\|\boldsymbol{F_{m,n}}(\boldsymbol{t_k}) - \boldsymbol{x_j}\right\|^2 \tag{8}$$

$$\sum_{j=1}^{X} u_{kj} = 1, 1 \le j \le N \tag{9}$$

$$u_{kj} \ge 0, 1 \le k \le X, 1 \le j \le N \tag{10}$$

The inter-cluster entropy is used to determine the optimum number of clusters. The inter-cluster entropy is calculated by equation 11-12.

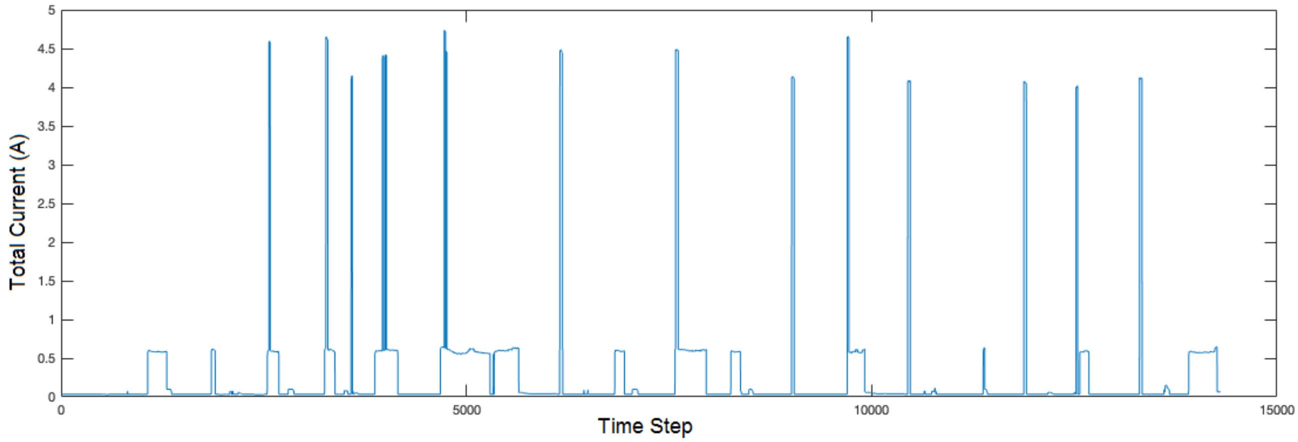

Fig 2 The current profile of the office room.

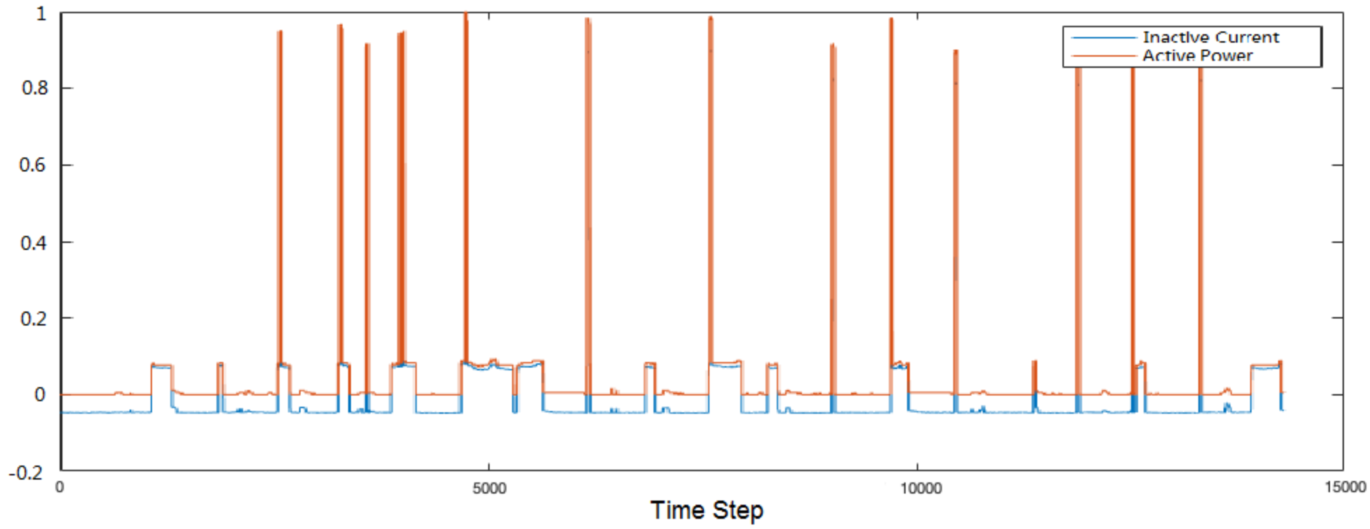

Fig 3 The normalized inactive current and active power profiles of the office room.

$$H(S^1,\dots,S^X) = -\log[(\sum_i^N \sum_k^N b\left(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k)\right) Gauss\left(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k), \boldsymbol{\Sigma}_x\right)) /\ 2\prod_{j=1}^X S_j] \tag{11}$$

$$Gauss\left(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k), \boldsymbol{\Sigma}_x\right) = \frac{1}{\sqrt{(2\pi)^N \det(\boldsymbol{\Sigma}_x)}} * \exp(-\frac{1}{2}(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k))\boldsymbol{\Sigma}_x^{-1}(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k))^T \tag{12}$$

where the $b\left(\boldsymbol{F}_{m,n}(\boldsymbol{t}_i) - \boldsymbol{F}_{m,n}(\boldsymbol{t}_k)\right)$ is equal to unity if $\boldsymbol{F}_{m,n}(\boldsymbol{t}_i)$ and $\boldsymbol{F}_{m,n}(\boldsymbol{t}_k)$ belong to different clusters, and zero otherwise.

3. RESULTS AND DISCUSSION

The 10-day current data of the office room is shown in Fig 2 (with 1-min resolution, totally 14400 values). The fluctuation of current profile is caused by switch events of appliances. The profiles of normalized inactive current and active power are shown in Fig 3.

Through the analysis of the collected data over 10 days, the appliance category classification was realized using the FCM clustering algorithm. The number of appliance categories are assumed to be unknown during

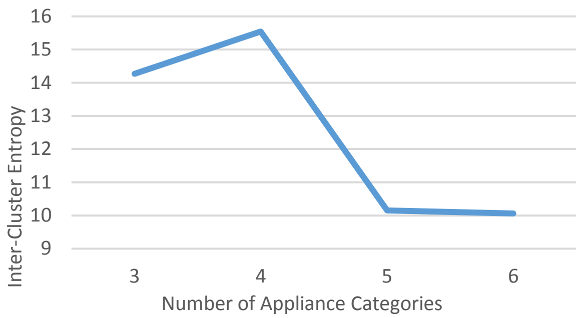

Fig 4 Inter-cluster entropy under different number of appliance categories

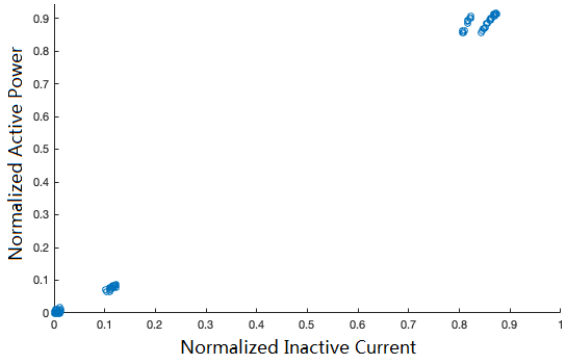

Fig 5 The FCM clustering results under 4 appliance categories.

the simulations. To determine the optimum number of appliance categories, the inter-cluster entropy was calculated under different number of appliance categories, which are shown in Fig. 4. It could be found that when the number is 5, the inter-cluster entropy is the highest. Therefore, the categories of the office appliances are 5. The classification results are shown in Fig 5.

Through a survey conducted in the selected office, it is found that there are four types of appliances including kettle, aquarium aerating device, light and personal computer. Therefore, the appliance category classification results were relatively satisfactory.

4. CONCLUSIONS

In this work, the FCM clustering based NILM analysis was conducted on office energy consumption. The work realized satisfactory classification of office appliances with 10-day NILM data. For further application, the method could be adopted in the construction of the smart grid and the ubiquitous power internet of things, and could be fulfilled by the prevailing smart metering infrastructure installed in the main breakers. Therefore, it is of significant potential in the smart building energy management in the future.

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