An Extensible Approach for Non-Intrusive Load Disaggregation With Smart Meter Data

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***Abstract*—Appliance-level load models are expected to be crucial to future smart grid applications. Unlike direct appliance monitoring approaches, it is more flexible and convenient to mine smart meter data to generate load models at device level nonintrusively and generalise to all households with smart meter ownership. This paper proposes a comprehensive and extensible framework to solve the load disaggregation problem for residential households. Our approach examines both the modelling of home appliances as hidden Markov models and the solving of non-intrusive load monitoring based on segmented integer quadratic constraint programming to disaggregate a household power profile into the appliance level. Structure of our approach to be implemented with current smart meter infrastructure is given and simulations are performed based on public datasets. All data are down-sampled to the rate that is consistent with the Australia smart meter infrastructure minimum functionality. The results demonstrate that our approach is able to work with existing smart meters to generate device level load model for other smart grid research and applications.**

***Index Terms*—Load disaggregation, hidden Markov model, clustering, integer quadratic constraint programming, smart meter.**

I. Introduction

APPLIANCE-LEVEL models are crucial for many smart grid technologies such as demand response (DR), energy storage (ES) and integration of more renewables. However, many recent researches are still based on the clustering of the user's aggregated load profile [1], [2], which may not fully utilise the diversity between users. Specifically, for the residential electricity customers, different types of the household electric appliances can potentially participate in the DR programs at different levels. For example, the operations of air-conditioning, swimming pool pumps and water heaters provide virtual power reserves which can be released in the event of contingency by interrupting and deferring the loads, while the loads of electric stoves and microwaves are more reluctant to participate in load reduction [3]. Moreover, if socially average consumption of a type of appliances is made aware to the electricity customers, it would be specific to recommend those energy saving models of appliances to those who are using inefficient devices. This paper focuses on extracting the appliance-level power consumptions by only relying on data accessible from ordinary smart meters. The quasi-real-time appliance-level insight is hoped to be able to assist utilities and energy aggregators to design more efficient DR program to coordinate more renewable energy integration in the future smart grid, and enable public awareness of energy efficiency.

Instead of intrusively sub-metering all appliances of interest, Hart [4] innovatively initiated the field of NILM in 1992. Since then, there had not been much research focusing on this topic until the wide deployment of the accessible data acquisition facilities in recent years. The early approaches aim to label a state-changing event by identifying distinct electrical features of individual appliances. Such features are usually known as 'power signatures' in the field of NILM. The most common signatures are real and reactive power [4]. Electric harmonic is another popular signature and effective for certain types of appliances [5], [6]. Transient pattern at start-up is also a unique and effective discriminant [7]. The V-I trajectory analysis from voltage and current wave-shapes also provides a comparable result for energy disaggregation [8]. Such approaches, also known as event-based methods, rely heavily on the load power samples measured with high frequency. For example, it was suggested that the sampling frequency should be at least 8000 Hz if harmonics are to be used as a power signature for load disaggregation [9]. Unfortunately, such a high sampling rate is not the standard feature for currently available smart meters. The extra cost for the inevitable additional customised hardware and installation to each household limits the practical applications of the event-based approaches.

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More recently, approaches that work with lower sampling frequency have drawn increasing attention. It has been demonstrated that the latest event-based approach can disaggregate load based on empirical distribution of power step changes measured at 1Hz frequency [10]. However, the method in [10] only works with type I appliances, which are appliances with only ON/OFF states [11]. Instead of labelling step changing events, non-event based approaches try to infer the combination of active appliances which best explains a sequence of step changes, which can normally work with data sampled at 1Hz or even lower regardless how many states an appliance intrinsically has [11]. This sampling frequency is very closed to real-life scenarios: smart meters are required to update the reading of power consumption every 5 seconds according to Australian National Smart Metering Program's minimum functionality specification [12].

For non-event based approaches, a sparse coding algorithm was demonstrated to address the energy disaggregation problem with hourly data over two years from more than ten thousands households [13]. Although it was a good example of a non-event based approaches and showed that the maximum of about 55% of energy can be accurately assigned from hourly-sampled data, the massive deployment of sensors for appliance sub-metering appears to make this approach impractical and hard to reproduce. Recent work proposed to formulate new meta-features from aggregated power measurement sampled at 10-minute interval, and used such features to train classical multi-label classifiers such as Decision Tree Learner, Support Vector Machine and k-Nearest Neighbour [14]. It was demonstrated that the operation of high energy appliances could be identified with a good level of accuracy. However, the training process for every household, low tolerance to appliance number, and low effectiveness to non-repeated appliances may limit its adaptability in general households. The NILM problem was formulated as a factorial hidden Markov model (FHMM) and other variants of FHMM in [9], where each appliance is represented as a hidden Markov model (HMM). Although they showed that the variant of conditional factorial hidden semi-Markov model (CFHSMM) achieved the best results about 75.1% of accuracy over 5 appliances, the extra training data for the extended model, the two-state (ON/OFF) assumption and adoption of using evolutionary algorithm to solve the NILM problem limit the practicality of their work. Guo *et al.* [15] extended the HMM with the explicit duration and differential observations to model the single appliance. However, how their model can be utilised to solve NILM problem was not reported. Kolter and Jaakkola [16] proposed an approximation method using quadratic programming relaxation to solve the FHMM problem. Their method also utilised the differential observations [16]. However, the computational cost is apparently too high for the real-time application due to their massive variable matrix [17]. Makonin *et al.* [18] addresses the NILM problem by modelling a single household with a gigantic but sparse super-state HMM, which can encode the correlation between appliance activations within a household. To the best of the authors' knowledge, they have achieved the best disaggregation results by far, and outperformed the state-of-the-art [16] with a huge margin. However, the major limitation of the method in [18] is the extensibility of the super-state HMM model. It relies heavily on the synchronized sub-metered data for each of the circuits/appliances of interest, which makes the model less extensible and intrusive to apply in a new household. Sub-meters should be installed and run for several weeks in advance to build the model which encodes sufficient appliance dependency for further disaggregation.

In this paper, we propose an alternative non-event based NILM framework, based on the temporal graphical model. The method can be developed to seamlessly work with the currently available smart meter infrastructure (SMI), without utilising any extra customised hardware. The major contributions of this paper are 3-fold:

(1) Instead of training individual appliances based on days or weeks of sub-metered observation, we propose an iterative *k*-means method to fit a HMM with only one typical duty cycle of an appliance. Our learning algorithm eliminates the need for specifying the number of states as the prior for the model. The characteristic of using only one duty cycle makes our approach more extensible to new households. By maintaining a central appliance database, utilities can re-use the models by surveying new households to determine the right model for new load disaggregation problems without intrusively setting up sub-meters for individual appliances;

(2) Unlike [19] which builds the NILM solver by using the integer programming on high frequency data to minimise the Euclidean distance, we propose a segmented integer quadratic constraint programming (SIQCP) based algorithm to efficiently solve the NILM problem based on probabilistic modelling and low frequency data to maximise the likelihood; and

(3) We give a potential extensible architecture to integrate the NILM framework with the existing smart meter infrastructure.

The structure of this paper is given below. Section II introduces the proposed model fitting algorithm. Section III introduces the proposed solving algorithm. A NILM architecture is proposed in Section IV. Simulations and their result discussions are presented in Section IV. Section VI concludes this paper and explores some future opportunities.

II. Modelling Methodology for Individual Appliance

A. Model Representation for Individual Appliance

The basic HMM is ideal for modelling individual appliances. Suppose that an appliance state variable $\boldsymbol{Z} = \{1, 2, \ldots, K\}$ with K operating states, its operating cycle can be considered as series of state transitions among K states. For the period of observation with T time steps, a sequence of appliance operating states is represented as $\boldsymbol{z} = \{z_1, z_2, \ldots, z_T\}$. Note that at each time step, an operating state emits an observation of power consumption, so there is also a sequence of corresponding observation $\boldsymbol{x} = \{x_1, x_2, \ldots, x_T\}$. Usually, the operating state is not directly measured. Therefore, $\boldsymbol{z}$ are the hidden states while $\boldsymbol{x}$ are

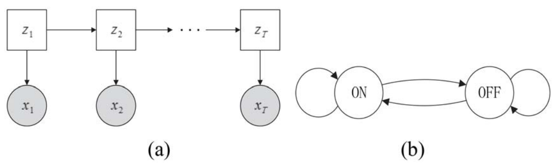

Fig. 1. (a) Graphical illustration of HMM; (b) Two-state appliance model.

the emissions of an HMM. The schematic representation of a HMM for single appliance is shown as Fig. 1.

In our model, unobserved hidden states are discrete variables, which are represented as blank and square blocks in Fig. 1, while observed continuous emission variables are represented as shaded circles. In the case where K is assumed to be 2 [11], [20], the hidden state Z alternates between ON and OFF as illustrated in Fig. 1(b).

Formally, a complete HMM is formulated by three sets of parameters:

1) Prior probability vector of initial state $\boldsymbol{\pi} \in \mathbb{R}^K$, which represents the probability with which the appliance is at state i at the first time step:

$$\pi_i = p(z_1 = i) \tag{1}$$

2) Transition matrix $\boldsymbol{A} \in \mathbb{R}^{K \times K}$, whose element $A_{i,j}$ represents the probability with which an appliance will transit state from i at $t-1$ to j at t:

$$A_{i,j} = p\big(z_t = j \big| z_{t-1} = i\big) \tag{2}$$

3) Emission vector $\boldsymbol{e} = \{e_1, e_2, \ldots, e_K\}$,

$$e_i \sim \mathcal{N}(\mu_i,\ \sigma_i) \tag{3}$$

where e_i means the emission distribution of the ith hidden state. The Gaussian distribution could be applied to model the emission distribution.

B. Determining Number of Hidden States With Iterative k-Means (IK) Algorithm

In many existing works [10], [11], an individual appliance is usually modelled as a HMM with two latent states: ON and OFF. Although this representation is reasonable for many appliances such as a water heater and air-conditioning, many appliances exhibit more complex behaviour during their operational cycles. For example, a dish washer can have three functional states: wash, rinse and dry, as shown in Fig. 2(a). Each state shows a fairly distinct time series power trace [3]. In this case, two hidden states become limited to represent its power profile.

It would be more practical to fit HMM for multi-state appliances without specifying the number of states in advance. The EM algorithm is one of the most widely used solutions to learn parameters for an HMM, but it requires the number of hidden states to be predetermined or selected based on some criteria. This may be the reason that many researchers are forced to model an appliance as a two-state machine. If the number of the dishwasher operating states is set to 2, then its profile is simplified to Fig. 2(b). From histogram analysis, 4 distinct clusters in a dishwasher's profile are obvious as in

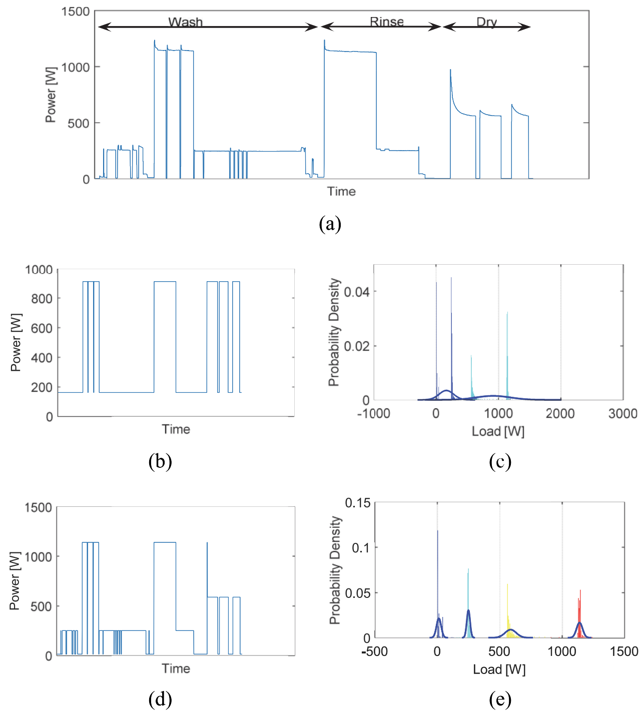

Fig. 2. (a) Original dishwasher profile; (b) PWC profile by traditional k-means and 2-state assumption; (c) HMM emissions with 2-state assumption; (d) PWC profile by Algorithm 1; (e) HMM learned with Algorithm 1.

Algorithm 1 Iterative k-Means (IK) With σ Threshold

Inputs: $\boldsymbol{x}$, σ_{th}, K_{max}
Outputs: $\boldsymbol{C}_1, \ldots, \boldsymbol{C}_K$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$
Set $K = 2$
While $\max(\boldsymbol{\sigma}) > \sigma_{th}$ && $K \leq K_{max}$
  Apply Algorithm 2 to initialise new centroids $\boldsymbol{\mu_{init}} = \{\mu_1, \mu_2, \ldots, \mu_K\}$
  Update $\boldsymbol{C}$ with traditional k-means using $\boldsymbol{\mu_{init}}$
  Calculate $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ from $\boldsymbol{C}$
  Update $K = K + 1$
End
Return $\boldsymbol{C_1}, \ldots, \boldsymbol{C_{N_c}}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$

Fig. 2(c), but the pre-set number of states forces the EM algorithm to cluster the profile into 2 levels. It is clear that the simplified piece-wise constant (PWC) profile under a 2-state assumption does not represent the dishwasher adequately and the HMM emission exhibits a large value in standard deviation parameters.

In this work, we propose a specialised k-means based algorithm to generate a HMM with most appropriate number of hidden states, while maintaining the standard deviation of each cluster within a desired standard deviation threshold σ_{th}. Our method does not need to specify the number of clusters at the beginning. Instead, the maximum number of clusters, K_{max}, is specified to prevent an appliance being modelled with too many states. Since there are at least two states for any appliances (ON and OFF), it is reasonable to start the iteration process of the proposed method with $K = 2$. The pseudo codes of the proposed algorithm are shown as Algorithm 1.

By applying Algorithm 1, the original dishwasher power trace can be reduced to a piece-wise constant time series profile as shown in Fig. 2(d). The HMM emission of the appliance is shown in Fig. 2(e), where each colour represents an operating state grouped by our algorithm.

It is worth pointing out that in traditional k-means, the initial centroids of clusters are randomly selected from the given data set $\boldsymbol{x}$. The complexity of solving the NILM problem grows exponentially as the number hidden states increases. Random initialisation normally does not naturally guarantee to find the minimum possible number of clusters while satisfying the standard deviation threshold. Therefore, a specialised initialisation Algorithm 2 is designed to reduce the number of states to mitigate the complexity of the subsequent NILM problem, while preserving sufficient gaps between consumption levels of different states. This initialisation algorithm is especially advantageous when the power trace of an appliance does not show dominant levels of consumption explicitly as the washing machine load profile shown in Fig. 3(a) [3].

The Algorithm 2 firstly selects initial centroids evenly given the appliance power profile $\boldsymbol{x}$ by:

$$\widetilde{\mu}_i = \widetilde{\mu}_1 + i \times d \quad i \in \{2, 3, \ldots, K\} \tag{4}$$

where $d = r/K$ and $\widetilde{\mu}_1 = 0$ since it is appropriate to assume each appliance has an OFF state.

The initial centroids are then evaluated by the frequency of the statistical ranges, which are also known as 'bins' for histograms. If any one of the initial centroids is sufficiently close to a frequently dense bin centre, then the particular initial centroid is replaced by that bin centre. This process is given as,

$$\begin{aligned} b_i &= (i-1)\frac{r}{N_b} + \frac{r}{2N_b}, i = 1, \ldots, N_b \\ \mathbf{1}_{B_i}(x) &:= \begin{cases} 1 & if \quad x \in \left[b_i - \dfrac{r}{2N_b}, b_i + \dfrac{r}{2N_b}\right] \\ 0 & if \quad x \notin \left[b_i - \dfrac{r}{2N_b}, b_i + \dfrac{r}{2N_b}\right] \end{cases} \\ c_i &= \sum_{t \in 1:T} \mathbf{1}_{B_i}(x_t) \end{aligned} \tag{5}$$

where N_b is the number of bins across the range of $\boldsymbol{x}$; b_i is the bin centre of ith bin, c_i is the count of data points that fall into the ith bin. Then, we can recursively find K bins with the highest occurrence frequency: $\boldsymbol{b_{top}} = \{b_{top}^{(i)} | i = 1, 2, \ldots, K\}$. Based on this, the initial centroids can be placed closer to the dominant power levels by:

$$\widetilde{\mu}_i = b_{top}^{(i)} \quad if \quad \left| b_{top}^{(i)} - \widetilde{\mu}_i \right| \leq \alpha \frac{r}{K_{max}} \tag{6}$$

where α is a constant parameter to control the frequency of the replacement. In this work, α is set to 0.8, N_b is set to 100.

Fig. 3(b)–(e) compare the results for different initialisation of finding suitable operating states for appliances. (b) and (c) show that the power profile of washing machine is grouped to 10 distinct levels by random initialisation; (d) and (e) demonstrate another solution of grouping operating states into only 5 states using Algorithm 2 for initialisation. It is illustrated that the 5-state PWC profile is fairly sufficient to capture washing machine's operating changes, and the emission distribution for each state satisfies the standard deviation requirement so that these distributions are not heavily overlapped.

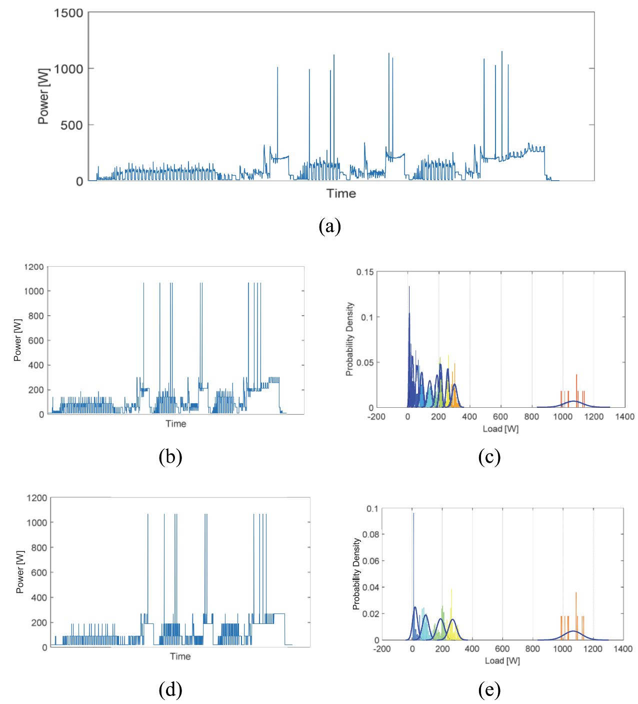

Fig. 3. (a) Original Washing Machine Profile; (b) PWC Profile with Algorithm 1 only; (c) HMM with Algorithm 1 only; (d) PWC profile with both Algorithms 1 and 2; (e) HMM learned with both Algorithms 1 and 2.

Algorithm 2 Even Initialisation

Inputs: $\boldsymbol{x}$, N_b
Output: $\boldsymbol{\mu_{init}}$
Calculate equation (4)
Update μ_i with (5), (6)
Return: $\boldsymbol{\mu_{init}}$

C. Fitting HMM for Individual Appliance

With the simplified PWC profiles, HMM parameters for individual appliances can be easily fitted by counting data points against the original profiles. The general idea is to learn parameters of prior probability $\boldsymbol{\pi}$ and transition matrix $\boldsymbol{A}$ from the sufficient statistics derived from the PWC profile, and the emission parameter $\boldsymbol{e}$ which is governed by another two parameters μ and σ, can be learned by fitting corresponding hidden states using the maximum likelihood estimation (MLE).

Suppose that the power trace of an appliance is reduced to K dominant levels. Let $M[\boldsymbol{C_i}]$ denote the counts of $\{x_t | x_t \in \boldsymbol{x}\}$ that are assigned to $\boldsymbol{C_i}$, and let,

$$\mathbf{1}_{\boldsymbol{C_i}}(x) := \begin{cases} 1 & if \quad x \in \boldsymbol{C_i} \\ 0 & if \quad x \notin \boldsymbol{C_i} \end{cases} \tag{7}$$

$$M[\boldsymbol{C_i}] = \sum_{t \in 1:T} \mathbf{1}_{\boldsymbol{C_I}}(x_t) \tag{8}$$

Then we have

$$\pi_i = \frac{M[C_i]}{T} \tag{9}$$

TABLE I
EXAMPLE OF LEARNED PARAMETERS FROM DISHWASHER'S POWER PROFILE

	State 1	State 2	State 3	State 4
π	0.43	0.31	0.11	0.15
μ	4.6W	248.6W	587.8W	1141.0W
σ	12.6W	13.9W	44.7W	23.8W

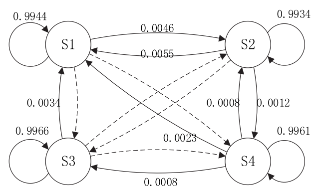

Fig. 4. HMM transition parameters learned from dishwasher profile.

Similarly, we construct an auxiliary function $\mathbf{1}_{A_{i,j}}(x_t)$ and $M[A_{i,j}]$,

$$\mathbf{1}_{A_{i,j}}(x_t) := \begin{cases} 1 & if\ \mathbf{1}_{C_j}(x_t) = 1 \& \mathbf{1}_{C_i}(x_{t-1}) = 1 \\ 0 & otherwise \end{cases} \tag{10}$$

$$M\big[A_{i,j}\big] = \sum_{t \in 2:T} \mathbf{1}_{A_{i,j}}(x_t) \tag{11}$$

Then each element of the transition matrix $\boldsymbol{A}$ can be written as:

$$A_{i,j} = \frac{M\big[A_{i,j}\big]}{T-1} \tag{12}$$

For the emission parameters, μ and σ can be simply calculated from the results of Algorithm 1:

$$\mu_i = \frac{1}{M[\boldsymbol{C}_i]} \sum_{x \in \boldsymbol{C}_i} x \tag{13}$$

$$\sigma_i = sqrt\left(\frac{1}{M[\boldsymbol{C}_i]} \sum_{x \in \boldsymbol{C}_i} (x - \mu_i)^2\right) \tag{14}$$

Given the operational power trace of a dishwasher shown in Fig. 2, the parameters for the dishwasher are learned and shown as in Table I.

As for the transition matrix, it is worth noting that normally it is a sparse matrix. The transition probability and paths are given in Fig. 4, where the solid line represents possible transitions and the dashed line represents the possibility of the transition between two states with the value of zero.

III. PROBABILISTIC APPROACH TO SOLVE NILM

A. Modelling NILM as FHMM

Assuming there are N appliances in a household, the NILM problem can be formulated as a factorial HMM (FHMM) model [21] by combining all individual HMM models for appliances. The schematic is shown as Fig. 5, where the superscript indicates the nth appliance.

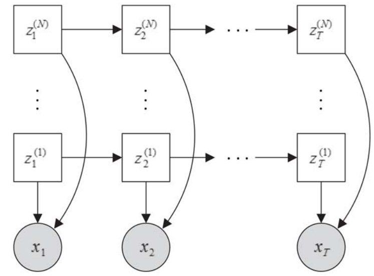

Fig. 5. Graphical structure of factorial HMM.

The joint likelihood of only one appliance of an observation sequence and a hidden state sequence given a HMM model can be calculated by,

$$p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}) = p\big(z_1\big|\pi\big) \times \prod_{t=2}^{T} p\big(z_t\big|z_{t-1}, \boldsymbol{A}\big) \times \prod_{t=1}^{T} p\big(x_t\big|z_t, \boldsymbol{e}\big) \tag{15}$$

where $\boldsymbol{\theta}$ is the set of all parameters for a complete HMM:$\boldsymbol{\theta} = \{\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{e}\}$. Similarly, the joint log-likelihood of a FHMM consisting of N appliances can be written as:

$$\begin{aligned} \mathcal{L}\Big(\boldsymbol{x}, \boldsymbol{z}^{(1:N)}|\boldsymbol{\theta}^{(1:N)}\Big) = & \sum_{n=1}^{N} \log p\Big(z_1^{(n)}\big|\boldsymbol{\pi}^{(n)}\Big) \\ & + \sum_{t=2}^{T}\sum_{n=1}^{N} \log p\Big(z_t^{(n)}\big|z_{t-1}^{(n)}, \boldsymbol{A}^{(n)}\Big) \\ & + \sum_{t=1}^{T} \log p\Big(x_t\big|z_t^{(1:N)}, \boldsymbol{e}^{(1:N)}\Big) \end{aligned} \tag{16}$$

where $\boldsymbol{\theta}^{(1:N)} = \{\boldsymbol{\pi}^{(1:N)}, \boldsymbol{A}^{(1:N)}, \boldsymbol{e}^{(1:N)}\}$, $\boldsymbol{x}$ is the observed sequence of aggregated power, and $\boldsymbol{\theta}^{(1:N)}$ is the set of HMM parameters for N appliances included in the NILM problem in Eq. (16). The NILM problem then becomes solving Eq. (16) to infer N most possible sequences of operating states $\boldsymbol{z}^{(1:N)}$ for all appliances, which can be formulated as follow:

$$z^{(1:N)} = \underset{z^{(1:N)}}{\mathbf{argmax}}\, \mathcal{L}\Big(\boldsymbol{x},\ z^{(1:N)}\big|\boldsymbol{\theta}^{(1:N)}\Big) \tag{17}$$

Usually exact inference for such a FHMM problem is intractable because the problem complexity is $O(TK^{2N})$. Approximate inference techniques such as variational and sampling methods [22], [23] can be used but they are also very time consuming and do not facilitate real-time implementation.

B. Approximate Solver for NILM—Segment-Wise Integer Quadratic Constraint Programming (SIQCP)

Instead of using the established methods, a specialised approximate solver is proposed in this paper featuring identification of appliances with higher demand response potential by solving NILM within the interval between two moments when smart meter transmits its remote reading to the utility. Approximation to the local optimal is formulated in three steps.

Firstly, parameter π can be interpreted as the probability that the starting point of a sequence is at the ith state if the starting point is chosen arbitrarily within the given length of an appliance's power profile. The length of NILM problem has very little probability to be the same as the appliance's length of active operation. Thus, initial probability parameter π learned individually would not be able to represent the true probability for an appliance's initial state in the NILM problem. Therefore, we assume that the initial states are all uniformly distributed on the length of NILM problem so that the first term of Eq. (16) can be discarded.

Secondly, it is worth noting that operational states of all appliances are modelled as a Gaussian distribution, so the observation x_t^* at $t = t^*$ is also normally distributed. Therefore, the third term of Equation (16) can be written as:

$$x_{t^*}|t = t^* \sim \mathcal{N}\left(\sum_{n=1}^{N}\mu_{z_{t^*}}^{(n)}, \sum_{n=1}^{N}\left(\sigma_{z_{t^*}}^{(n)}\right)^2\right) \tag{18}$$

where $\mu_{z_{t^*}}^{(n)}$ and $\sigma_{z_{t^*}}^{(n)}$ denote the mean and standard deviation of the nth appliance's operating state at time $t = t^*$. Eq. (19) can be interpreted as the observation likelihood given the combined parameters of all appliances. According to the properties of a normal distribution, the maximum value of the third term in (16) is guaranteed to be larger when standard deviation is actually smaller. Recall that in our HMM model learning section, a threshold of standard deviation σ_{th} is applied to all appliances. Hence, we can simply set all $\sigma_{z_{t^*}}^{(n)} = \sigma_{th}$ without affecting the result of Eq. (17). The third term of Eq. (16) at $t = t^*$ can then be replaced by calculating Gaussian probability density function as the following:

$$\log\frac{1}{\left(\sigma_{th}\sqrt{2\pi}\right)} - \frac{1}{\left(2\sigma_{th}{}^2\right)}\left\|x_{t^*} - \sum_{n=1}^{N}\mu_{z_{t^*}}^{(n)}\right\|^2 \tag{19}$$

To simplify Equation (19), we introduce another auxiliary function $\boldsymbol{Q}_t^{(n)} \in \mathbb{R}^{N_c^{(n)}}$ for the nth appliance:

$$Q_{t_i}^{(n)}\left(z_t^{(n)}\right) := \begin{cases} 1 & if \quad z_t^{(n)} = i \\ 0 & if \quad z_t^{(n)} \neq i \end{cases} \tag{20}$$

Substituting the third term in Eq. (16) with Eq. (19) and Eq. (20), the NILM problem (17) can then be written as:

$$\underset{z^{(1:N)}}{\mathbf{argmax}}\left(-\frac{1}{\left(2\sigma_{th}{}^2\right)}\sum_{t=1}^{T}\left\|x_t - \sum_{n=1}^{N}\boldsymbol{\mu}^{(\boldsymbol{n})}\left(\boldsymbol{Q}_t^{(n)}\right)^{\mathrm{T}}\right\|^2 + \sum_{t=2}^{T}\sum_{n=1}^{N}\log p\left(z_t^{(n)}\middle|z_{t-1}^{(n)},\ \boldsymbol{A}^{(n)}\right) + T\log\frac{1}{\left(\sigma_{th}\sqrt{2\pi}\right)}\right) \tag{21}$$

Note that $\boldsymbol{Q}_t^{(n)}$ is basically a binary vector. Then (21) is actually an integer quadratic programming (IQP) problem.

Since the problem of (21) contains a total of NTK variables, some relaxation should be adopted to tackle the intractable nature of a problem of this size. Considering our focus is on better estimation of demand response potential, we intend that our approach will have the tendency to estimate more correctly for higher power consumption appliances such as air-conditioning and water heater than those with smaller potential such as TV, lighting and laptop.

Algorithm 3 SIQCP NILM Solver

Inputs: $\boldsymbol{x}$, $\boldsymbol{\theta}^{(1:N)}$, σ_{th}
Output: $z^{(1:N)}$
Applying σ_{th} to divide $\boldsymbol{x}$ into $[\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots \boldsymbol{x}_{N_s}]$
For Each Segment $\boldsymbol{x}_i$
  Construct constraints $\mathcal{C}_1$, $\mathcal{C}_2$
  Solve (22) subject to $\mathcal{C}$ for $\boldsymbol{z}_i^{(1:N)}$
Loop
Assign each $z_i^{(1:N)}$ to $z^{(1:N)}$
Return: $\mathbf{Z}^{(1:N)}$

Therefore, we reuse the threshold σ_{th} stating that only power change $|x_t - x_{t-1}|$ higher than the threshold is treated as a state transition. This relaxation rule can be interpreted as if power change between two time steps is lower than σ_{th}, all appliances in the household remain in their operating states as at previous time step $(t-1)$. Therefore, the given sequence $\boldsymbol{x}$ can be divided into a number of segments: $\boldsymbol{x} = [\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x}_{N_s}]$, where N_s is the number of segments. In each segment, it is assumed that no appliances change state. With this rule, we can re-formulate Eq. (21) to a series of smaller segment-wise IQP (SIQP) problems:

$$\underset{z_i^{(1:N)}}{\mathbf{argmax}}\left(\begin{array}{l} -\frac{L_i}{\left(2\sigma_{th}{}^2\right)}\left\|x_t - \sum_{n=1}^{N}\boldsymbol{\mu}^{(\boldsymbol{n})}\left(\boldsymbol{Q}_t^{(n)}\right)^{\mathrm{T}}\right\|^2 \\ \quad + \sum_{n=1}^{N}\log p\left(\boldsymbol{A}^{(n)}\middle|z_{s-1}^{(n)}\right)^{L_i}\left(\boldsymbol{Q}^{(n)}\right)^{\mathrm{T}} \\ \quad + \sum_{n=1}^{N}\log\left(\mathrm{diag}\left(\boldsymbol{A}^{(n)}\right)^{L_i}\right)\left(\boldsymbol{Q}^{(n)}\right)^{\mathrm{T}} \\ \quad + L_i\log\frac{1}{\left(\sigma_{th}\sqrt{2\pi}\right)} \end{array}\right) \tag{22}$$

where L_i is the length of the ith observation segment, and $\boldsymbol{z_i}^{(1:N)}$ is the operating state for all appliances at the ith segment. Note that an appliance can only be at one operating state at a time. Therefore, Eq. (22) is subject to the following constraint in each segment:

$$\mathcal{C}_1 = \left\{Q : \begin{array}{c}\sum_i Q_i^{(n)} = 1 \\ 0 \leq Q_i^{(n)} \leq 1\end{array}\right\} \tag{23}$$

To further relax the problem, we also modify the popular one-appliance-at-a-time constraint in the field of NILM to at most M steps, because it could be quite common for more than one appliance change states at the same time slot. This constraint is formulated as:

$$\mathcal{C}_2 : \frac{1}{2}\sum_{n=1}^{N}\left(\boldsymbol{Q}_t^{(n)} - \boldsymbol{Q}_{t-1}^{(n)}\right)^{\boldsymbol{T}}\left(\boldsymbol{Q}_t^{(n)} - \boldsymbol{Q}_{t-1}^{(n)}\right) \leq M \tag{24}$$

where $\boldsymbol{Q}_{t-1}^{(n)}$ is the solution for nth appliance at time $t-1$. In our simulations, M is set to 2. Since there is a quadratic constraint term, the problem becomes a segmented integer quadratic constraint programming problem (SIQCP).

The pseudo codes of the our NILM solver are given as Algorithm 3, where $\hat{z}_j^{(1:N)}$ represents the solution of appliance states considering only the jth appliance changes its state; $z_i^{(1:N)}$ represents the variable of state assignment for the ith data segment.

By adopting the relaxation rule, the solving of the NILM problem is transformed to solve a small maximum a posteriori (MAP) for each observation segment. The computational

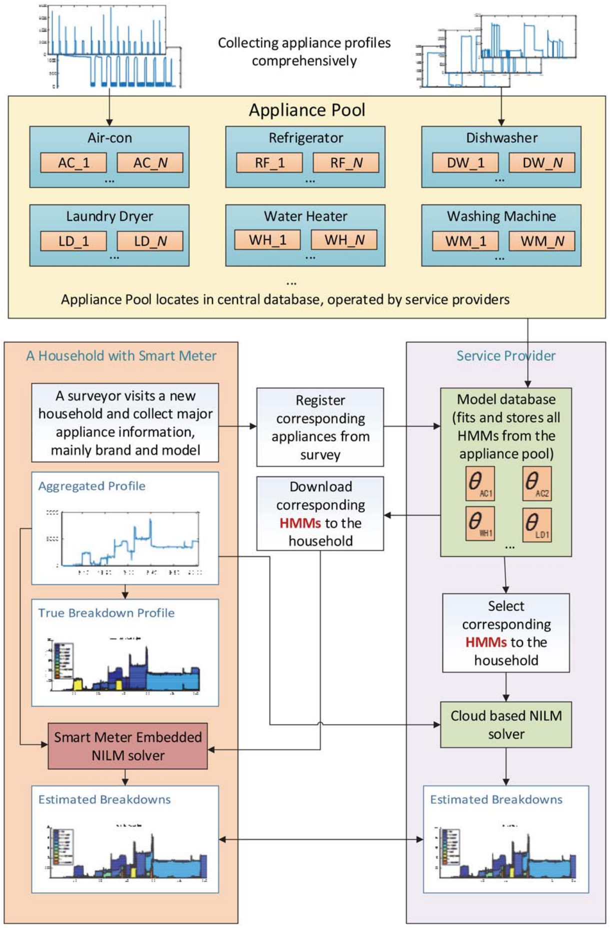

Fig. 6. The NILM implementation architecture.

efficiency is significantly improved while good approximations of the results are also achieved.

IV. The Extensible NILM Framework

One of the benefits of our proposed approach is its extensibility. In this section, a framework of implementing NILM with smart meter infrastructure (SMI) is given to better illustrate how our approach can be easily extended to new households.

The overall architecture of our framework is given as Fig. 6. The NILM service provider could be the utilities, load aggregators, or other agents that specialises in providing NILM service. The service provider maintains a comprehensive database where the typical load profiles of many major popular electric appliances are centrally stored. Appliance models are built based on the iterative k-means algorithm introduce in Section II. For a new household that orders the NILM service, the most straightforward way is to send a surveyor to collect major appliance information and register them into the database. The new service subscriber will be offered two options, either local or cloud-based NILM service. If the household chooses the local NILM service, a new smart meter with embedded NILM algorithm, such as the SIQCP, shall be installed before the main switch of the household. Corresponding appliance models are downloaded to the new smart meter to perform NILM. On the other hand, for cloud-based option, the new household should allow the service provider to access their existing smart meter for the power reading sequences. Then the service provider can perform NILM based on the registered appliance information by selecting the corresponding models, and send the results back to the new customer.

It is worth pointing out that sending surveyors to new customers eliminates the need of installing sub-meters in a new household, which is less intrusive. A general appliance type model is an idea of building a model which can represent a wide range of appliances of the same type [24]. In the future, we will focus on developing a better algorithm which can work with a general appliance type model [24] to make load disaggregation fully non-intrusive.

V. Simulation and Evaluation

In order to verify our approach, we test our framework by using two low-frequency, real-world datasets: REDD [25] and AMPds [26]. Both the fitting and solving algorithms of our proposed framework are coded in Python 2.7. Gurobi [27] is used for solving the integer quadratic programming problem. All tests are run on a desktop with a 3.4 GHz Intel i7 processor and 8GB of memory.

A. Tests on REDD Dataset

Testing our framework with publically available datasets allows better comparison with other works. REDD is one of the most used datasets in the field of NILM. It contains about one month of sub-metered readings for 6 different households sampled at an average frequency of 0.3 Hz. Kolter and Johnson [25] initially used a Gibbs sampler on the REDD dataset and reported results on Houses 1, 2, 3, 4 and 6. Johnson and Willsky [28] tested their sophisticated Bayesian hidden semi-Markov model (HSMM) and a specialized sampler on the 5 selected appliances from the same dataset and reported results under the same evaluation metric. Makonin *et al.* [18] also applied their SparseNILM algorithm on this dataset and summarize the result comparison with the previous works.

To compare with these previous work, we also test our algorithms on the 5 selected loads as in [18] and [28], namely refrigerator, lighting, dishwasher, microwave, and furnace. We use NILMTK, the open sourced non-intrusive load monitoring toolkit [29], to clean up the null readings and down-sampled the REDD data to 1 minute intervals by using a median filter. Although our designed algorithm is able to work with only one typical cycle per appliance, the REDD dataset does not provide typical appliance profiles as [3] does. Therefore, we train our models based on the first week of data from each house to make sure that we capture the ON/OFF event of each appliance at least once. Then we use the rest of the data from each house for testing purpose. The maximum number of states was set to 8 for all appliances.

We also use the same estimate accuracy metric that was initially introduced by [25] and used by [18] and [28] to evaluate

TABLE II
ESTIMATE ACCURACY COMPARISON WITH OTHER PUBLISHED WORK

REDD	Gibbs Sampler [25]	Bayesian HSMM [28]	SparseNILM [18]	SIQCP
House 1	46.6%	82.1%	99.3%	78.4%
House 2	50.8%	84.8%	99.0%	86.4%
House 3	33.3%	81.5%	97.5%	83.5%
House 6	55.7%	77.7%	99.7%	91.6%
Average	46.6%	81.5%	98.9%	85.0%

the performance. The metric is given as:

$$Acc = 1 - \frac{\sum_{t=1}^{T} \sum_{i=1}^{N} \left| \hat{x}_t^{(i)} - x_t^{(i)} \right|}{2 \sum_{t=1}^{T} x_t} \tag{25}$$

where $\hat{x}_t^{(i)}$ and $x_t^{(i)}$ are the estimated power consumption and actual power consumption for the ith appliance at time t respectively, and x_t is the aggregated power at time t.

Our test results and the comparison with other three publications on REDD dataset is given in Table II. It can be seen that our framework performs slightly better than the Bayesian HSMM model and improves significantly by comparing with the Gibbs sampler from previous work. The SparseNILM is by far the best solver in terms of estimation accuracy, which achieves near perfection on the REDD dataset. However, the extra performance of SparseNILM may come from its methodology of viewing a household as a whole and learning appliance dependency through a long phase of training. We will put this into a test using AMPds dataset in the following section.

B. Tests on AMPds Dataset

The AMPds dataset records the current readings of a single house at one minute read intervals for an entire year. The dataset has been cleaned before publication, so it is easier to use than REDD dataset.

Thanks to the release of source code for the SparseNILM algorithm, we can compare our approach with the state-of-the-art more comprehensively. In order to verify the extensibility of our approach, we design various testing scenarios summarized in Table III.

We choose different lengths of training periods from as long as the first half of the whole-year data to as short as only 3 days. We choose a minimum of 3 days is because we need to make sure that each appliance has at least one ON/OFF duty cycle in the training profile. Then we run both algorithms from minimum 1 appliance to all 19 appliances to disaggregate the denoised whole house load profile in the order that released with the SparseNILM demo [18]. We report the overall result by using the estimate accuracy metric (25) and f_1-score. The formulation of f_1-score is detailed in [30] and given as follows:

$$f_1 = \frac{2 \times precision \times recall}{precision + recall}$$
$$precision = \frac{tp}{tp + fp}, \quad recall = \frac{tp}{tp + fn} \tag{26}$$

where tp stands for the true positives, which is the count of correct predictions that the appliance was actually ON; fp is the false positives, which is the count of the OFF appliance events classified as ON; fn is the false negatives, which is the count of the ON appliance events classified as OFF.

TABLE III
AMPDS TESTING SCENARIO SUMMARY

Scenarios	# days for training	# days for testing	# Appliances
Scenario I	First 180	Last 36	From 1 to 19
Scenario II	First 36	Last 36	From 1 to 19
Scenario III	First 7	Last 36	From 1 to 19
Scenario IV	First 3	Last 36	From 1 to 19

The overall results in terms of estimate accuracy and f_1-score for the four scenarios are given in Fig. 7 and Fig. 8. It can be clearly seen that the estimate accuracy drops as the number of appliances grows for both approaches. In Scenario I, SIQCP performs comparably to SparseNILM when the number of appliances is lower than 7, with estimate accuracy about 90% overall. The performance of SIQCP drops significantly to about 70% and keeps dropping slightly as more appliances were added, while the estimate accuracy for SparseNILM drops much more slowly and thus starts outperforming SIQCP when there are more than 7 appliances. However, we have pointed out that our SIQCP approach models appliances separately so that it can work with as few as one typical duty cycle per appliance, while SparseNILM relies on appliance dependency and builds a super-state model for the entire household. Therefore, the length of training shall not affect the performance of our algorithm. This is confirmed by comparing the four scenarios in Fig. 7. When the training length was reduced to about a month, a week or even 3 days, the performances of SIQCP are not significantly affected. On the other hand, the performances of SparseNILM worsen severely after the training length is reduced, especially for the first 7 appliances. In these cases, SIQCP performs considerably better than SparseNILM when the number of appliances is small, and the gaps between performances of the SIQCP and SparseNILM for over 8 appliances becomes smaller. The huge difference in performance for SparseNILM may relate to the dependencies of appliances change over time, or the dependencies between appliances may need longer to fully develop.

Similarly, in terms of f_1-score, the SparseNILM algorithm outperforms our SIQCP solver for a long period of training, achieving almost perfect score for under 5 appliances. The advantage disappears when the training phase is reduced to a week or less. The most obvious f_1-score reduction for SparseNILM also happens on the first 7 appliances being tested. It is likely to imply that the usage patterns of the first 7 appliances changed most obviously in the AMPds dataset, and one week of sub-metered monitoring is not enough to learn appliance dependencies.

In terms of the computational efficiency, the total time complexity of our approach could be about $\mathcal{O}(K^N T)$ in theory, where K is the average number of states of each appliance, and N is the number of appliances and T is the total length of the problem. However, the actual complexity differs from problems to problems, depending on the number of segments in the aggregated profiles and the number of states for additional

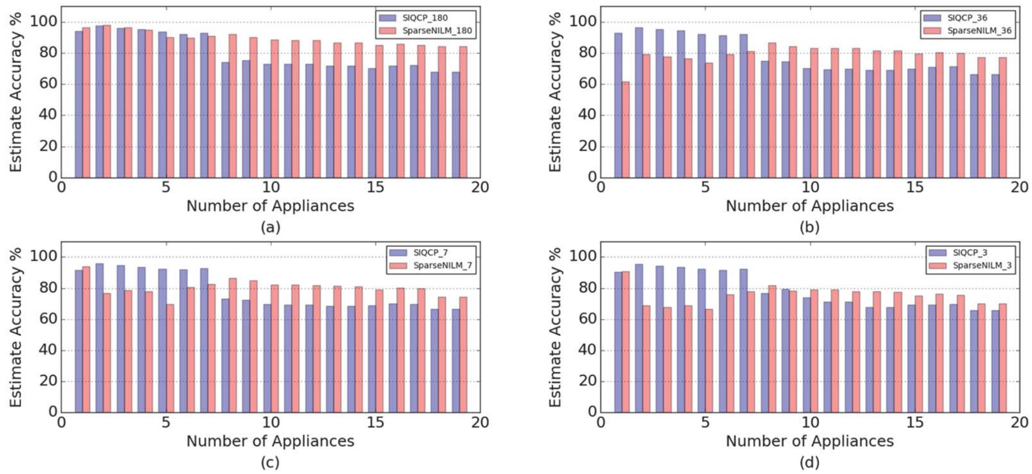

Fig. 7. Estimate Accuracy Comparisons between SIQCP and SparseNILM: (a) Scenario I; (b) Scenario II; (c) Scenario III and (d) Scenario IV.

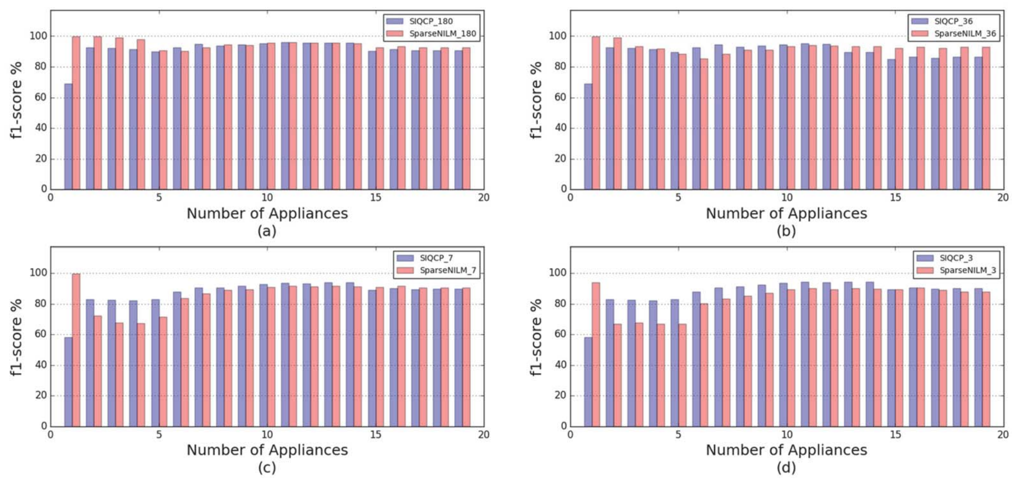

Fig. 8. f_1-score Comparison between SIQCP and SparseNILM: (a) Scenario I; (b) Scenario II; (c) Scenario III and (d) Scenario IV.

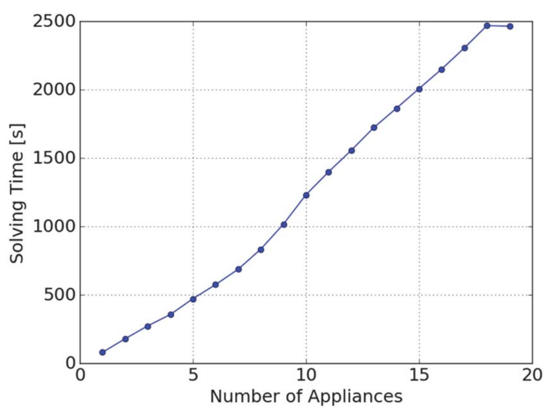

Fig. 9. Computation time against number of appliances.

appliances. Fig. 9 shows the computation times of Scenario IV against the increasing number of appliances. It turns out that processing time grows quicker as the number of appliances increases, but the scalability looks fine in the problem given by AMPds dataset. The last appliance added to the problem is actually the unmetered load. Since we set the problem to be denoised, unmetered load is constantly zero. Therefore, adding it as a one-state appliance does not affect the computational efficiency at all.

VI. Conclusion

In this paper, a complete NILM framework with a model fitting algorithm named the iterative k-means and a NILM solver based on segmented integer quadratic constraint programming is proposed. Appliance load profile with as few as one typical duty cycle can be effectively modelled by our model fitting algorithm. Our simulations also confirm that our solver is robust to deal with models with very short training phase. This feature is ideal for extending the framework to new households without further intrusive sub-metered monitoring. We also propose a potential architecture to integrate the NILM framework with the existing smart meter infrastructure.

There is still plenty of room for improvement in the field of NILM. There may be a trade-off between the extensibility and the result accuracy for various NILM approaches. In future, we are actively seeking adding general appliance type model on top of our current appliance model to eliminate the need of sending surveyors to new customers. Also, we will continue refining or developing better solvers to further improve the performance.

The Source Code

In order to promote better communication in the NILM research community, we have released the SIQCP disaggregator as open source for academic use with the publication of this article. The source code is available for download from GitHub at https://github.com/WilsonKong/siqpnilm.

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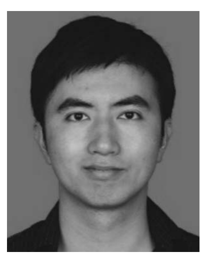

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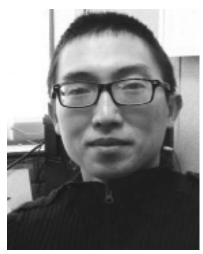

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