Chapter 13
Non-intrusive Load Monitoring and Its Application in Energy Flexibility Potential Extraction of Active Buildings

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13.1 Introduction

The ever-increasing energy consumption in the residential sector as shown in Fig. 13.1 is of great importance in terms of carbon emissions, global warming, and sustainability issues. Due to the fact that residential demand accounts for 30% of the total demand (Li & Dick, 2018), increasing the role of residential buildings in the power grid from passive consumers to active ones (Clarke, 2021) plays a crucial role in addressing the aforementioned issues. Numerous studies in the area of building energy confirm that reducing energy consumption in buildings requires effective and efficient residential energy management (REM) (Faustine et al., 2020). Therefore, the concepts of residential demand-side management (RDSM) and home energy management (HEM) appear and take an important place in the research and development efforts of science and industry.

RDMS aims to shape customers' consumption patterns to enable more efficient use of energy system resources, improve grid reliability, and reduce emissions by peak-shaving and valley-filling, which results in increasing the second-by-second balance between demand and generation. In this regard, one of the main goals of the active buildings is proposing a cost-efficient way of minimizing energy demand of buildings (Wang et al., 2017). The implementation and success of such programs depend on advanced knowledge of characteristics of loads and the usage pattern of consumers. Therefore, modelling and predicting these factors could be an important support for RDSM and HEM (Zoha et al., 2012).

In this trend, researchers and industry have worked over the last decades to obtain information on household consumption. This information is beneficial for both the

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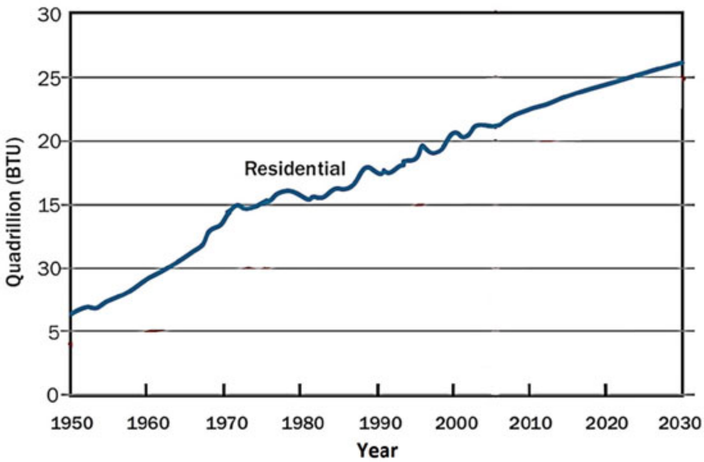

Fig. 13.1 Total primary energy consumption for building in the USA (Hafemeister, 2009)

supplier and the consumer (Devlin & Hayes, 2019). The utility company can use this information to propose different energy management strategies or for control purposes. Consumers can use this information to identify appliances with high electricity consumption and faulty or inefficient appliances. They can also control their consumption to reduce their costs while ensuring their comfort based on this information. Overall, this information can reduce consumption by more than 9% (Aydin et al., 2018; Darby et al., 2006).

Monitoring the consumption of each appliance which is entitled as load monitoring (LM) is one of the useful methods to extract this information (Zhou et al., 2020). Figure 13.2 illustrates the benefits of LM algorithms for consumers and the utility. As it is mentioned in Fig. 13.2, LM provides an opportunity to the utility to extract and characterize the energy flexibility potential of each consumer. Furthermore, studies show that the active building concept is associated more with energy flexibility than self-generation of electricity (Bulut et al., 2016). Therefore, extracting the flexibility via LM plays a crucial role in the efficiency of active buildings.

In the first phase of this chapter, fundamental concepts of load monitoring will be discussed. Then, its application in flexibility extraction of residential buildings will be shown. The schematic of this technique is illustrated in Fig. 13.3.

13.2 Different Types of Load Monitoring

Load monitoring algorithms based on the number of meters and appliances can be categorized into three main groups which will be discussed below.

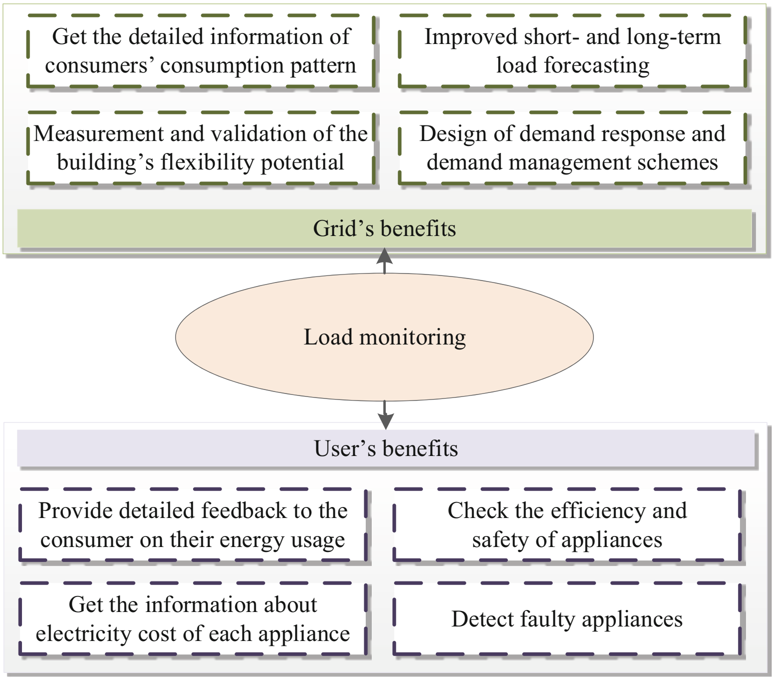

Fig. 13.2 LM benefits to consumers and grid

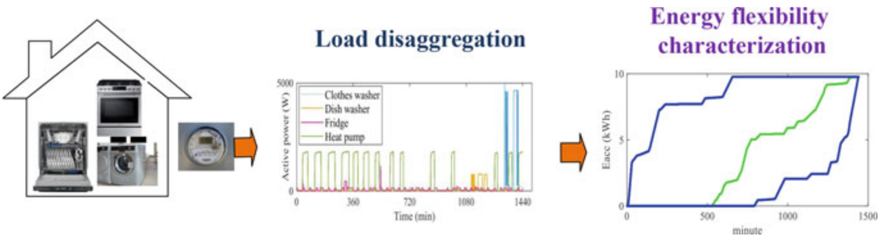

Fig. 13.3 The framework of this study

13.2.1 Intrusive Load Monitoring

The simplest and most accurate approach to obtain the consumption pattern of appliances is to install a meter on each of them to measure, record, and report their consumption which is called intrusive load monitoring (ILM) (Azizi et al., 2020). Figure 13.4c shows the schematic of ILM. However, this approach causes the following concerns:

1. Installing a meter on each appliance is time-consuming (Liu et al., 2019).

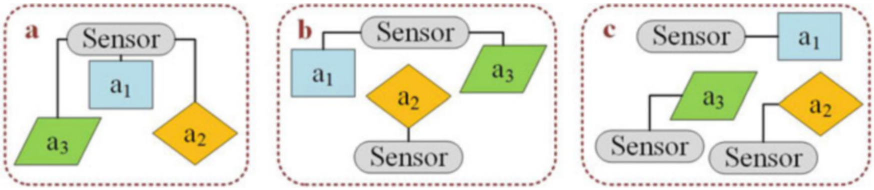

Fig. 13.4 Different types of load monitoring, (**a**) NILM, (**b**) SILM, (**c**) ILM

2. It incurs high costs to the consumer and the utility due to the need for additional meters, cables, etc. (Liu et al., 2019).
3. This approach causes privacy concerns and most consumers are unwilling to take the risk of this approach (Erkin et al., 2013).

Therefore, non-intrusive load monitoring attracts a lot of attention in recent years.

13.2.2 Non-intrusive Load Monitoring

Rather than installing a meter on each appliance individually and measuring its consumption intrusively, Hart proposed non-intrusive load monitoring (NILM) in 1992 (Hart, 1992). The NILM technique aims to obtain the consumption pattern of each appliance by analysing and disaggregating a given aggregate signal measured by existing meters using purely analytical approaches. The schematic of this technique is illustrated in Fig. 13.4a. However, its accuracy is lower than ILM methods. The concept of semi-intrusive load monitoring (SILM) emerged in this field which is the trade-off between cost and accuracy.

13.2.3 Semi-intrusive Load Monitoring

In the semi-intrusive load monitoring (SILM) technique, the set of appliances are divided into some subgroups, and a meter is installed in each subgroup to measure and record the aggregated consumption signal of appliances. Then, the disaggregation approach is applied to each subgroup, separately (Dash et al., 2019). The schematic of this approach is illustrated in Fig. 13.4b. In comparison with ILM methods, SILM reduces the cost and in comparison with NILM increases the accuracy of load disaggregation. The main challenge of these approaches is obtaining a proper number of subgroups based on the consumer's willingness to pay the cost of meters, the infrastructure of the building, and number of appliances.

Due to the fact that NILM does not interfere with the existing building infrastructure, omits the requirement of costly sub-metering, and saves time and protects consumer's privacy, it is more practical and is preferred from different viewpoints

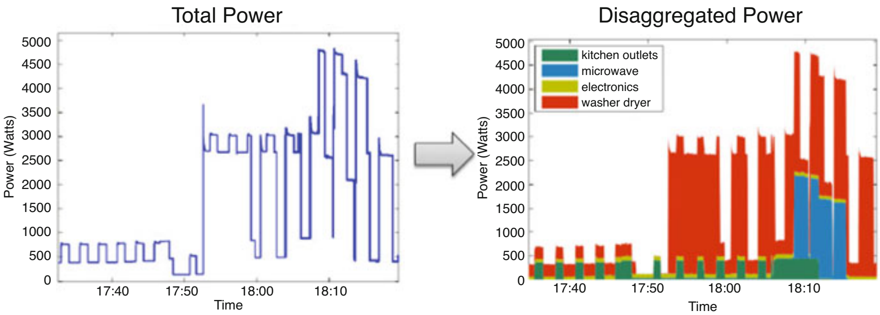

Fig. 13.5 Appliances' consumption extraction based on NILM (Esa et al., 2016)

(Zhang et al., 2019). Therefore, in this chapter, the basic concepts of this technique will be discussed.

13.3 NILM Problem Statement

Non-intrusive load monitoring is a well-known problem that involves disaggregating the total electrical energy consumption of a building into its individual electrical load components without the need for extensive metering equipment at each appliance. This problem can be classified as a blind identification problem, Abed-Meraim et al. (1997) where given the observed output of the entire system (i.e. the household total power consumption), the unobserved sub-states (i.e. the electricity consumption of individual appliances) are to be estimated. The schematic of NILM is shown in Fig. 13.5. Mathematically, NILM can be formulated as an optimization problem and a learning-based problem, which are described below.

13.3.1 Optimization-Based Formulation

NILM algorithms aim to extract the consumption signal of each appliance from the aggregated consumption signal of each consumer, herein denoted by $P(t)$. Considering $\{1, 2, \ldots, N\}$ as the dataset of appliances, and N the total number of appliances, $P(t)$ is sum of the consumption signal of each appliance, $P_i(t)$ as (13.1).

$$P(t) = \sum_{i=1}^{N} P_i(t). \tag{13.1}$$

However, each appliance i, $1 \leq i \leq N$, has m_i operating modes. Due to the presence of noise, fluctuations, overshoots, and spikes, the power value in these operating modes is not fixed in practice. However, by ignoring them and considering fixed values for mode j of appliance i, denoted as x_{ij}, the estimated piecewise constant consumption power of appliance i, $\tilde{P}_i(t)$ is obtained as (Piga et al., 2016)

$$P_i(t) \simeq \tilde{P}_i(t) = \Theta_i^{\mathrm{T}}(t) X_i, \tag{13.2}$$

where element j of the vector X_i shows the fixed consumption of mode j of appliance i. $\Theta_i = \left[\theta_{i1} \ldots \theta_{im_i}\right]^T$ is a binary-valued vector indicating the operating mode of appliance i at time t, defined as

$$\theta_{ij}(t) = \begin{cases} 1 & \text{if } i \text{ operates in mode } j \text{ at time } t \\ 0 & \text{otherwise.} \end{cases} \tag{13.3}$$

In other words, $\Theta_i(t)$ is a binary-valued vector indicating the mode of appliance i at time t that satisfies

$$\sum_{j=1}^{m_i} \theta_{ij}(t) = 1. \tag{13.4}$$

We note that the condition (13.4) guarantees that an appliance cannot operate in two modes simultaneously.

NILM method aims to obtain the consumption signal of each appliance, $\tilde{P}_i(t)$, by determining $\Theta_i(t)$ via minimizing the following error

$$e(t) = P(t) - \sum_{i=1}^{N} \tilde{P}_i(t) = P(t) - \sum_{i=1}^{N} \Theta_i^{\mathrm{T}}(t) X_i, \quad 0 \le t \le T \tag{13.5}$$

13.3.2 Learning-Based Problem Statement

In learning-based NILM problem definition, a training dataset of appliances' consumption exists. The training dataset consists of the consumption or the ON/OFF status of all appliances for a specific period of time. Based on this training dataset, the operation mode of each appliance in each event of the aggregated signal exists. Mathematically, let $A = \{1, \ldots, i, \ldots, N\}$ be the set of appliances, in which N stands for the total number of appliances. TD the training dataset consist of labelled events

$$TD = \{(e_i, l_i) : e_i \in R, l_i \in A, i = 1, \ldots, N_e\} \tag{13.6}$$

where e_i shows the value of the ith event and l_i denotes its respective label (or appliance). N_e stands for the total number of events in the aggregated signal.

Learning-based algorithms extract a model based on the events and their assigned labels. Then, based on the extracted model (learned model), a proper label (or appliance) is assigned to each event of the aggregated test signal.

13.4 Review on NILM Algorithms

The existing optimization-based and learning-based approaches to NILM will be reviewed in this section.

13.4.1 Optimization-Based NILM Algorithms Review

The NILM problem is formulated as a convex quadratic programming in Lin et al. (2016). In this paper, the whole training dataset is used to train the model which increases the computation complexity and time. Furthermore, the proposed method is highly dependent to the training dataset. Therefore, it is not scalable and has low accuracy in disaggregating the consumption of other consumers. Authors in Singh and Majumdar (2017) proposed sparse optimization NILM problem which is solved by dictionary learning-based algorithm. Six different metaheuristic optimization techniques were evaluated in Egarter and Elmenreich (2015) by considering different datasets. NILM is formulated as a stochastic-based optimization problem in Shahroz et al. (2020), and the probability of usage of appliances is defined as the regularization term.

Authors in Suzuki et al. (2008) defined NILM problem as an integer programming (IP) to detect the simultaneously ON appliances and increase the disaggregation accuracy in disaggregating the high number of appliances with multi-operation modes. NILM problem is formulated as a mixed-integer programming (MIP) in Piga et al. (2016), and the results are compared with a learning-based one. Authors in Bhotto et al. (2017) modified the formulation of IP by defining novel boundaries for the appliances. To reduce the computation burden in MIP-based NILM, a window-based algorithm is utilized in Wittmann et al. (2018). To increase the disaggregation accuracy, ILP and clustering algorithm are merged in Ayub et al. (2018). Authors in Azizi et al. (2020) defined constraints based on the transitions between different modes multi-mode appliances to decrease the computation time of the MIP-based NILM method.

All the aforementioned optimization-based NILM algorithms require pre-information about appliances, such as the total number of appliances, the consumption of each operation mode of appliances, their consumption pattern, etc. This information is obtained via involving and asking consumers, the manual datasheet of appliances, or collecting a training dataset which causes new challenges in this field.

13.4.2 Learning-Based NILM Review

Based on the presence of the training dataset, learning-based NILM can be divided into two main groups, supervised NILM algorithms and unsupervised NILM algorithms (Zhao et al., 2020). A brief review of these methods is discussed below.

(1) Supervised NILM Methods

Supervised NILM algorithms aim to extract a proper model from the training dataset which maps each sample or event of the aggregated signal to a specific appliance. Then, based on the extracted model, the test aggregated signal is disaggregated. One of the well-known supervised NILM algorithms is the classification technique which attracts a lot of attention in recent years. NILM is formulated as KNN problem in Schirmer and Mporas (2019) which reduces the burden of computation. Authors in Tabatabaei et al. (2017) and Massidda et al. (2020) proposed multi-label classification-based NILM which results in high accuracy in disaggregating the multi-mode appliances. Deep-learning-based approach is utilized in Singhal et al. (2019) which requires a high volume of a training dataset. To disaggregate the consumption of multi-mode appliances, authors in Shahroz et al. (2020) utilized a novel deep convolutional neural networks-based algorithm.

All supervised NILM methods proved to be accurate in disaggregating high number of appliances and appliances with overlapping power values (Singhal et al., 2019). However, the main challenge in this field is the requirement for a high volume of training dataset that is not in general feasible to collect (Yang et al., 2019). In the last few years, researchers focused on extracting more features and signatures of appliances from small training datasets to address this challenge (Dash et al., 2020).

(2) Unsupervised NILM Methods

In contrast with supervised methods, unsupervised NILM algorithms do not require a training dataset and prior information about appliances. One of the common methods of unsupervised methods is clustering which is used in this field frequently. Authors in Henao et al. (2015) utilized the subtractive clustering method to the events of the aggregated signal to extract a proper number of appliances as shown in Fig. 13.6. In Kong et al. (2016), k-means method is applied on the events of the aggregated signal. The principal component analysis method as an unsupervised method is utilized in Moradzadeh et al. (2020) to reduce the dimension of data and extract the profile of each appliance.

Despite some success in the case where all appliances are type I, these algorithms have been ineffective in dealing with multi-mode appliances (Kong et al., 2016; Dinesh et al., 2019). Moreover, these methods, extract different groups of appliances without assigning any appliances to them.

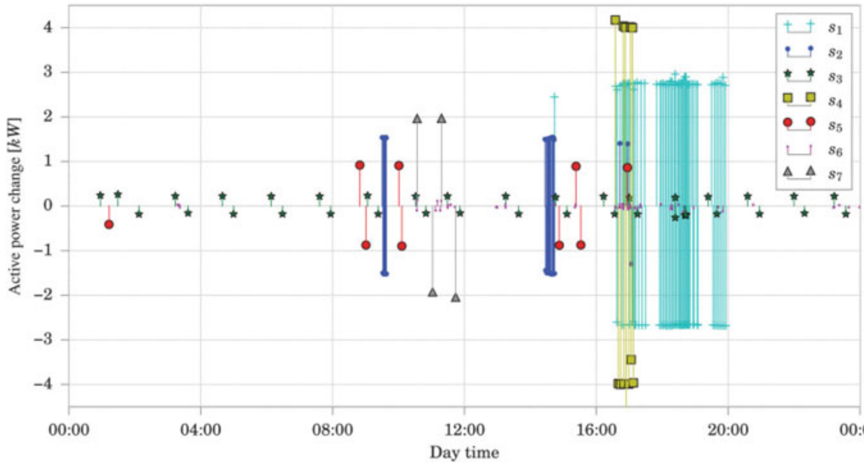

Fig. 13.6 Grouping events based on substractive clustering (Henao et al., 2015)

13.5 Types of Appliances

The accuracy of disaggregation of the consumption of an appliance is highly dependent on its category. Generally speaking, appliances are divided into four main groups based on their number of operation modes and their consumption pattern as discussed below (Zoha et al., 2012):

1. Type I: This type of appliances has two operation modes (ON/OFF modes). Examples of these appliances are table lamp, toaster, etc.
2. Type II: Appliances such as washing machine, dishwasher, stove burner, etc., which have multi-operation modes are included in the type II category. This type of appliances is entitled as a finite state machines (FSM). The switching pattern of these appliances makes them more distinguishable and increases the disaggregation accuracy.
3. Type III: Appliances such as the power drill and dimmer lights are included in type III category that have not fixed number of operation modes which are entitled as continuously variable appliances. Disaggregating the consumption of these appliances is one of the main challenges in this field.
4. Type IV: This type of appliances consumes power 24 h of a day. Examples of type IV appliances are hard-wired smoke alarm and external power supplies.

Figure 13.7 illustrates the power pattern of the first three types of appliances. Among different types of appliances, Type III ones are rarely used by consumers and type IV appliances consume low power. Therefore, disaggregating the consumption of type I and II appliances gains a great deal of attention among researchers.

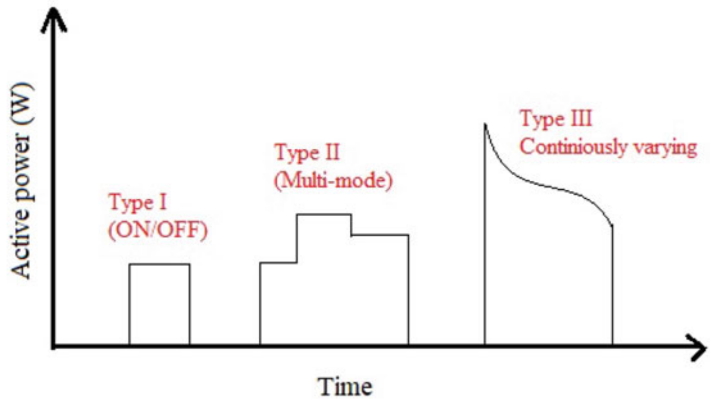

Fig. 13.7 Different types of appliances

13.6 Features/Signatures of Appliances

To disaggregate the aggregated signal, various specific features or signatures of appliances are used. These features or signatures are unique to the appliances and make them more distinguishable from each other. The different types of these features are described below.

13.6.1 Steady-State Features

Steady-state features of appliances refer to longer-lasting changes in power signal when at least one appliance switches its operating mode. The most well-known steady-state features include active and reactive power, current, and current and voltage waveforms (Azizi et al., 2021).

13.6.2 Transient Features

Transient features are short-term fluctuations in power signal before settling to a steady-state condition which include shape, size, duration, and harmonics of the transient. The transient signature of the majority of appliances is pronounced, which makes it suitable for load identification and increases the disaggregation accuracy. However, these features require a high-frequency sampling dataset and specific hardware to collect these data.

a) Active power meter (200$)
b) Active and reactive power meter (300$)
c) Smart harmonic meter (1000$)
d) Meter with waveform capturing function (2500$)

Fig. 13.8 Different types of smart meters vs their cost (Xu et al., 2018)

13.6.3 Non-traditional Features

In addition to the aforementioned signatures of appliances, in recent years non-traditional signatures such as temperature, light, consumers' special usage behaviour, time of day, etc. are increasingly used in disaggregation methods to improve the disaggregation accuracy.

Figure 13.8 shows different kinds of smart meters. Since smart meters of active power have the lowest price, the majority of studies focused on steady-state active power-based NILM algorithms.

13.7 Classification of NILM Methods

Active power-based NILM studies can be broadly divided into two main classes, sample-based algorithms and event-based algorithms which are described below.

13.7.1 Sample-Based Approaches

In sample-based NILM algorithms, by assuming a finite-state machine for each appliance, the total consumption signal is disaggregated based on the pre-learned model of state transitions of appliances (Zhao et al., 2018).

13.7.2 Event-Based Approaches

Event-based methods focused on detecting significant variations in the power signal called events and classifying them based on the specific transitions of appliances (Lu & Li, 2019).

Compared to the sample-based methods, event-based methods are more direct and comprehensive and have low computational complexity and time. Therefore, they have gained a lot of attention in the last years (Azizi et al., 2020). One of the main challenges in these methods is detecting real events. Due to the presence of various noises as shown in Fig. 13.9, event detection plays a crucial role in the disaggregation accuracy of event-based NILM methods (Zhao et al., 2018). Therefore, not detecting any real event or mistakenly considering a fluctuation as an event decreases the accuracy of disaggregation in these methods.

13.8 Evaluation Metrics

Two main groups of evaluation metrics exist in the NILM problem: (1) event-detection evaluation metric and (2) load disaggregation accuracy.

13.8.1 Event-Detection Accuracy Metric

Three famous metrics for measuring the accuracy of event detection can be listed as:

1. False-positive rate (FPR): Ratio of FP to the actual negatives

$$FPR = \frac{FP}{FP + TN}, \tag{13.7}$$

   where FP and TN show the false-positive events (detected non-event as event) and true-negative events (detected non-event as non-event), respectively.
2. F_β: Trade-off between precision and recall

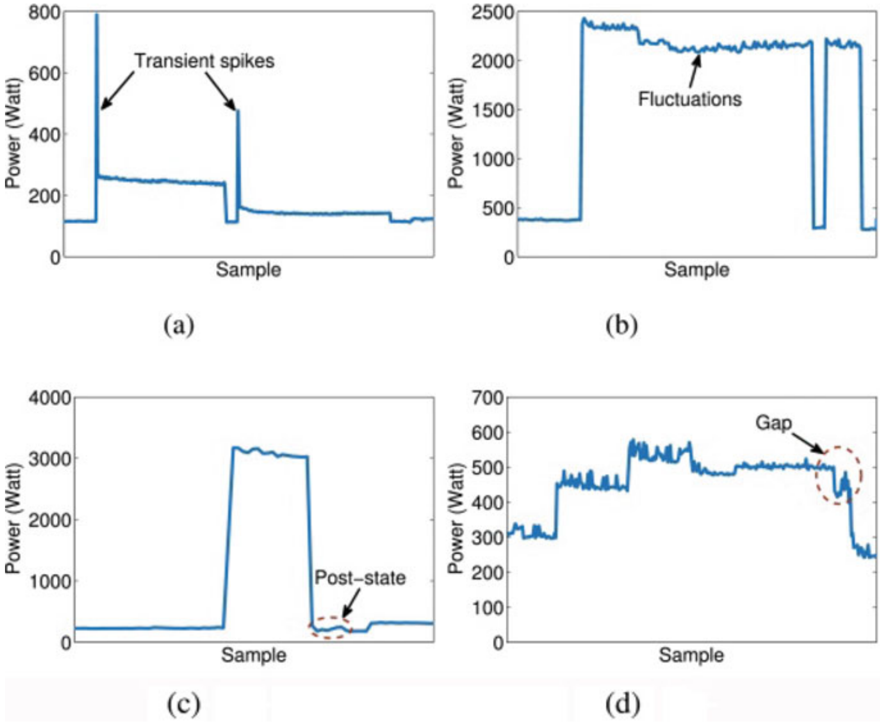

Fig. 13.9 Different types of noises in the measured power signal (Zhao et al., 2018)

$$F_\beta = \frac{(1+\beta^2) \times TRP \times RC}{(\beta^2 \times TRP) + RC}, \tag{13.8}$$

$$TPR = \frac{TP}{TP+FN}, \quad RC = \frac{FP}{FP+TN}, \tag{13.9}$$

where TRP and RC show the precision and recall; TP is true positive, FP is false positive, TN is true negative, and FN is false negative. The weighting factors is shown with β. F_1 score is specific type of F_β in which $\beta = 1$.

3. Overall accuracy:

$$OA = \frac{N_{dis}}{N_{true}} \tag{13.10}$$

where N_{dis} shows number of events and N_{true} stands for the non-events that are detected correctly.

13.8.2 Energy Disaggregation Accuracy

The common energy disaggregation accuracy metrics based on the difference between the estimated consumption of each appliance $\hat{E}_i$ and its actual consumption E_i, for N appliances can be listed as:

1. Relative error (RE): The ratio of the error of disaggregation to the actual power consumption which is formulated as

$$RE = \frac{\sum_{i=1}^{N} E_i - \sum_{i=1}^{N} \hat{E}_i}{\sum_{i=1}^{N} E_i} \tag{13.11}$$

2. Root mean square error (RMSE): This parameter measures the standard deviation of the disaggregation error based on

$$RMSE = 1 - \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - \hat{E}_i)} \tag{13.12}$$

3. Mean absolute error (MAE): MAE measures the average estimated error based on

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|E_i - \hat{E}_i| \tag{13.13}$$

4. Mean absolute percentage error (MAPE): MAPE defines the accuracy as the following ratio

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - \hat{E}_i}{E_i}\right| \tag{13.14}$$

5. R^2: This accuracy metric is defined based on the variance of the data and the residual sum of squares as follows

$$R^2 = 1 - \frac{\sum_{i}^{N}(E_i - \tilde{E}_i)^2}{\sum_{i}^{N}(E_i - \hat{E}_i)^2} \tag{13.15}$$

where $\tilde{E}_i$ is the average of E_i.

13.9 Sampling Frequency

Depending on the sampling frequency of the power signals, NILM approaches are divided into two main groups:

1. High-frequency sampling data: To obtain higher-resolution data and monitor small changes (<50 W), the consumption is sampled with high frequency (>1 Hz). This sampling rate requires specific hardware and contains a high volume of dataset. However, different signatures (steady and transient signatures) of appliances can be easily extracted from this dataset.
2. Low-frequency sampling data: In this case, the data is sampled with low frequency (<1 Hz) with existing meters. Therefore, this type of sampling omits the cost of additional hardware. Steady signatures must be extracted from these datasets.

Due to the low cost and volume of low-frequency sampling data, in recent years researchers have been focused on these dataset in NILM problem.

13.10 NILM Datasets

With the importance of NILM came the need for standardized datasets to benchmark the wide variety of published algorithms. The most popular datasets in this field and their characteristics are listed in Table 13.1.

13.11 Companies of NILM Products

Over the last decade, different companies have developed different NILM products that analyse the total building electricity consumption and extract the consumption of individual appliances based on complex learning or optimization approaches. Based on these results, some of them suggest different energy management and cost-saving strategies to consumers. Table 13.2 shows the list of known companies in this field.

13.12 Application of NILM in Energy Flexibility Potential Extraction

Shiftable appliances, electrical vehicles, and energy storage devices in the residential sector provide flexibility in the power grid. Generally speaking, the energy flexibility potential of each consumer is computed based on the earliest

Table 13.1 Different benchmarking datasets for the NILM problem

Dataset	Sampling rate	Duration	Houses	Ground truth	Country
REDD (Kolter & Johnson, 2011)	1 Hz	Several months	6	Submeter channels	US
UK-DALE (Kelly & Knottenbelt, 2015)	16,000 Hz/1 Hz	2 years	6	Submeter channels	UK
AMPDs (Makonin et al., 2013)	1 min	2 years	1	Submeter channels	Canada
ECO (Kleiminger et al., 2015)	1 s	8 months	6	Submeter channels	Switzerland

Table 13.2 Different NILM companies

Company	Country	Founded year	Description
Bidgely	USA	2010	Load disaggregation and recommendations to save energy
Powerly	USA	2015	Load disaggregation, appliance health monitoring and smart device management
You know what	Belgium	2013	Load disaggregation and anomaly detection
Chai energy	USA	2012	Load disaggregation and identify saving energy oppurtiunities
Watty	Sweden	2013	Load disaggregation

start time and latest finished time for shiftable/flexible appliance (D'hulst et al., 2015). Mathematically, assuming N_{app} shiftable/flexible appliances, the total energy consumption is obtained based on:

$$E_{tip}(t) = \sum_{i=1}^{N_{app}} \int_{t_0}^{t} P^i(n)dn \tag{13.16}$$

where,

$$P^i \triangleq [P^i(1), \ldots, P^i(T)], \quad i \in [1, \ldots, N_{app}] \tag{13.17}$$

in which P^i shows the power of each flexible appliance i.

To extract the energy flexibility potential two parameters are defined as

$$\begin{aligned} P^i_{max} \triangleq [P^i(1), \ldots, P^i(T)], \; P^i(t_\alpha) \geq 0; \\ P^i(t_\beta) = 0; \; \forall t_\alpha < t_\beta \end{aligned} \tag{13.18}$$

$$\begin{aligned} P^i_{min} \triangleq [P^i(1), \ldots, P^i(T)], \; P^i(t_\alpha) = 0; \\ P^i(t_\beta) \geq 0; \; \forall t_\alpha < t_\beta \end{aligned} \tag{13.19}$$

where P_{max} and P_{min} show the power signal when appliance i starts at earliest time and finished at the latest time, respectively.

The energy patterns considering earliest start and latest finished time for appliances is computed based on

$$E_{max}(t) = \sum_{i=1}^{N} \int_{t_0}^{t} P^i_{max}(n)dn \tag{13.20}$$

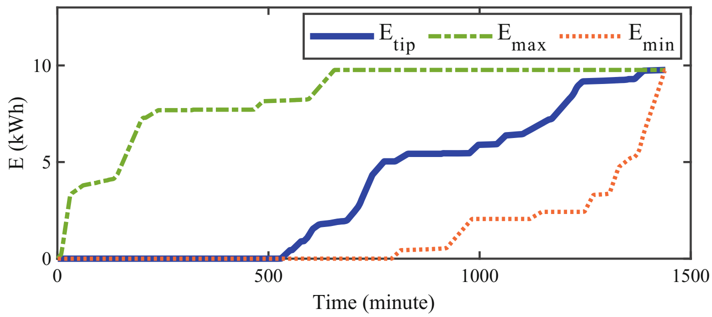

Fig. 13.10 E_{max} and E_{min} vs typical energy pattern

$$E_{min}(t) = \sum_{i=1}^{N} \int_{t_0}^{t} P^{i}_{min}(n)dn \tag{13.21}$$

It should be noted that E_{max} and E_{min} show the boundaries of the energy flexibility of the considered appliances' set as shown in Fig. 13.10.

To compute the energy flexibility of consumers the power signal of shiftable/flexible appliances are required. To obtain them, installing a meter on each appliance (ILM technique) is time-consuming and expensive. Therefore, NILM method must be applied to the aggregated signal of each consumer.

13.12.1 Numerical Results on AMPds

To evaluate the efficiency of the NILM method in the energy flexibility potential extraction the AMPds which consists of minutely measured data is considered (Makonin et al., 2013). Four appliances were considered in this case which include a heat pump, a clothes dryer, a dishwasher, as flexible appliances, and a refrigerator as the most frequent ON/OFF appliance. Figure 13.11 shows the power signal of these appliances and their aggregated one in a typical day.

The event-based optimization NILM method of Azizi et al. (2020) is applied to this dataset which consists of three main steps:

1. **Pre-processing:** In this step, three-point method is applied to the consumption signal of each appliance and the aggregated signal to omit the outliers such as spikes and overshoots, filter the signal and extract events. Then, k-means clustering is applied to events of each appliance to extract the number of their operation modes and their consumption in each mode.
2. **Optimization-based NILM:** Based on the results of the previous step, MINLP is utilized to solve NILM problem in this stage.

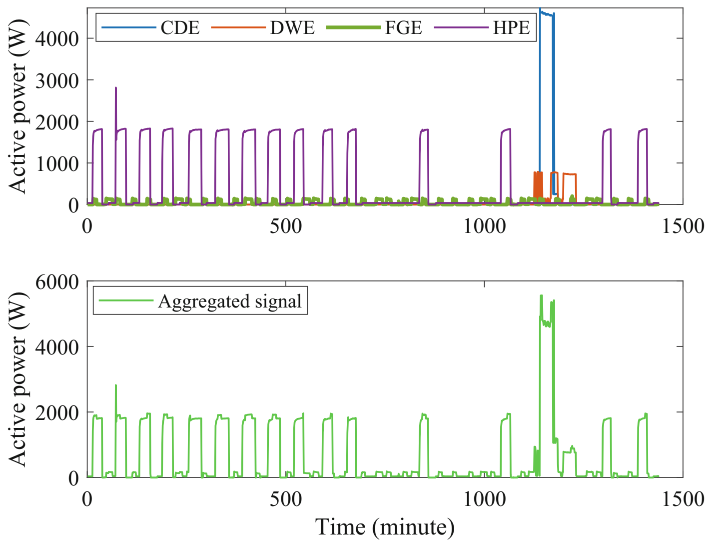

Fig. 13.11 Total power consumption of appliances

Table 13.3 Evaluation metrics of the NILM method

	Apps			
	HP	DW	CW	FRG
RE	0.02	0.12	0.03	0.05
R^2	0.96	0.88	0.97	0.9

3. **Post-processing:** Finally, considering non-fixed consumption values for each operation mode of appliances, the consumption signal of appliances are reconstructed.

Table 13.3 shows the accuracy of the estimated power signals based on (13.11). Based on the extracted power signals of shiftable/flexible appliances (HP, DW, and CW), the boundaries of the energy flexibility are computed which is illustrated in Fig. 13.12. The error between the estimated boundaries and the real ones is less than 5% which shows the effectiveness of NILM methods in energy flexibility extraction of consumers.

13.13 Status Quo, Challenges, and Outlook

In recent years, large amounts of datasets on power profiles have become available, leading to various methods being proposed for the NILM problem. However, there are still some challenges (such as (1) the need for a training dataset for supervised methods, (2) achieving high accuracy in disaggregating the multi-mode appliances, (3) proposing scalable approaches, (4) limiting human contribution

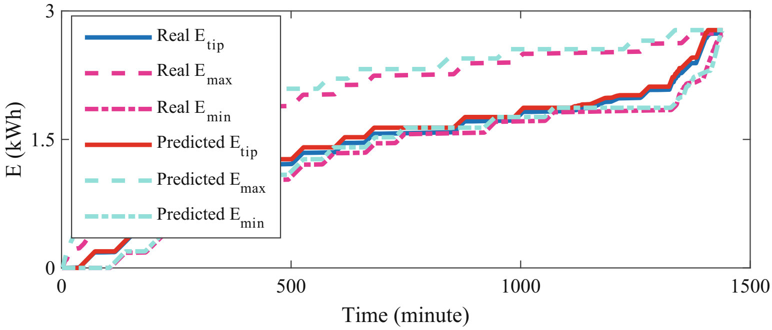

Fig. 13.12 Boundaries of energy flexibility based on (13.20) and (13.21)

during configuration, (5) minimizing hardware complexity and cost, etc.) that have not been addressed yet. Therefore, a practical NILM algorithm should have the following guidelines:

1. The proposed methods should be applicable on low-frequency sampled data (1 Hz or less) which are reported with existing smart meters. The proposed NILM approaches on the high-frequency sample data require specific meters which increases the cost.
2. The accuracy of disaggregation should be more than 80% for each appliance. However, the presence of multi-mode appliances increases the complexity of algorithms and decreases accuracy. Developing a NILM algorithm that could work well in disaggregating all types of appliances regardless of their number of modes is still an unsolved challenge in this field.
3. The majority of proposed NILM algorithms require pre-information about appliances or training dataset. However, to address the privacy concerns of consumers, no training dataset should be required which is still one of the main challenges in this field.
4. The proposed NILM techniques may have high accuracy for specific consumers, while they may have low accuracy in disaggregating the aggregated signal of other consumers. However, the algorithm must be scalable to apply to different residential buildings and consumers.

13.14 Conclusion

Using energy resources responsibly, protecting the environment, and reducing CO2 emissions are key objectives in the development of smart sustainable cities. In this regard, energy management strategies are integral parts of smart sustainable cities. The major goals of energy management programs are extracting information about the consumption behaviour of consumers, proposing proper strategies based on consumer's behaviour in order to peak shaving and valley filling, and finally, increasing the balance between demand and generation. Since more than 30% of total energy consumption belongs to the residential sector, energy management in this sector plays a crucial role to attain the aforementioned goals.

One of the effective tools in residential energy management is non-intrusive load monitoring (NILM). NILM algorithms extract the consumption pattern of each appliance and provide feedback to the consumer about appliances such as their operation condition (normal/faulty), the cost of consumption of each appliance, etc. Furthermore, based on this feedback the energy flexibility potential of each consumer can also be characterized.

In this chapter, we discussed the basic concepts of NILM. To illustrate its application in energy flexibility characterization, four appliances of AMPds are considered, and an optimization-based NILM algorithm is utilized to disaggregate their consumption signal. Then, considering the earliest start time and latest finished time, the energy flexibility of this dataset is extracted.

In this chapter, the energy flexibility of shiftable appliances is computed. Extracting the electrical vehicle consumption pattern using NILM methods and characterizing its energy flexibility potential are one of the main future directions for the researchers who consider reading this chapter. Furthermore, proposing a NILM algorithm that does not require any training dataset and results in high accuracy in disaggregation high number of appliances with multi-mode operation modes can be considered as another future direction for researchers.

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