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Overview of Non-Intrusive Load Monitoring: Probabilistic and Artificial Intelligence approaches

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Abstract. Reduction and conservation of electrical energy consumption in residential buildings is the main objective of Non-Intrusive Load Monitoring (NILM) techniques. NILM detects events and estimate the power consumption of individual appliances by analyzing the aggregate power consumption measured at the service entry. Indeed, our major contribution in this paper is to update research works on NILM methodologies by adding the most recent NILM methods proposed in the literature. In this paper we present an overview of NILM and energy disaggregation methods. Then, we discuss the challenges of this technique to provide useful recommendations for future research.

Keywords: Appliance Load Monitoring, NILM, ILM, Energy disaggregation.

1 Introduction

Residential sector is one of the areas that have seen an increase in energy demand. The energy consumption in this sector is increasing gradually [1], with more than 40% of electricity consumption in buildings at developed countries [2]. Therefore, energy efficiency in buildings will have significant impact on the reduction of overall energy demand.

Reduction of energy consumption in residential buildings can be achieved by Appliance Load Monitoring system (ALM) that gives to consumers information about what appliances and when they are used, how much power they consume and why such consumption. Further, the consumers would be able to understand the relationships between appliances usage and their energy consumption. With this information, the consumers could be able to reduce from 15 to 40% of their annual energy consumption [3].

ALM can be accomplished by two main approaches: Intrusive Load Monitoring system (ILM) and Non-Intrusive Load Monitoring system (NILM) [3, 4]. ILM determine the end users of appliances by distributed sensing methods [5]. In fact, it needs to install one or more sensors at the appliance level. This complex installation makes ILM a limited practically approach. Whereas, the NILM approach requires only a single meter at the main power to monitor appliances. Therefore, the NILM become a feasible approach especially with the advancement in smart grids, smart meters, Artificial Intelligence (AI), and Internet of Things (IoT) [1].

In this paper, we present an overview of NILM framework and the recent proposed NILM methods proposed in the literature. Our major aim is to discuss the research limitation, highlight the challenges and propose useful recommendations for future research. The remainder of this paper is organized as follows: framework of NILM techniques and performance metrics for NILM algorithms are presented in section 2 and 3 respectively. Section 4 illustrated the categories of NILM techniques and the proposed state of the art of NILM methods. Section 5 is dedicated to discuss challenges and future research, followed by a conclusion in section 6.

2 Framework of NILM techniques

Non-Intrusive Load Monitoring (NILM) is a technique of monitoring that uses the aggregate power data of home measured at the service entry to detect the states operation of appliances and their individual consumption [3, 6]. In fact, the idea of this technique is firstly introduced by Hart [7]. The general concept of Harts technique is to analyze the variation of active and reactive power aiming to identify the state operation of appliances in ΔP-ΔQ space by the cluster analysis [4].

The appliances can be classified according to their mode of operation on four types: ON/OFF states, multi-state appliances, Continuously Variable, and permanent consumer devices. More details can be found in [4]:

As shown in Fig. 1, the NILM framework involves three stages: data acquisition, feature extraction and appliance identification.

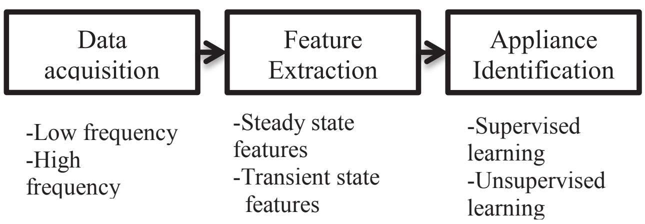

Fig. 1. NILM Framework

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3 Performance metrics for NILM algorithms

To evaluate the NILM algorithms performance, many metrics are used in the literature. These metrics can be classified in three categories: detection metrics, disaggregation or classification metrics, and overall metrics [6]. The used NILM evaluation metrics used in the studied papers of our state of the art are listed in Table 1.

Table 1. Categorized evaluation metrics for NILM algorithms.

Category	Metric	Expression
Detection metrics	ACC (Accuracy metric)	$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{PF}+\mathrm{FN}}$
	F1 (F-Measure)	$\mathrm{F_M} = 2 * \frac{\mathrm{precision} * \mathrm{recall}}{\mathrm{precision} * \mathrm{recall}}$
	MAE (mean average error)	$\mathrm{MAE} = \frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \lvert \hat{\mathrm{Y}}_t - \mathrm{Y}_t \rvert$
Disaggregation Metrics	RMSE (Root mean square error)	$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{t}(\hat{y}_t^i - y_t^i)^2}$
	DE (Disaggregation Error)	$\mathrm{DE} = \frac{1}{2}\sum_{t=1}^{\mathrm{T}}\sum_{i=1}^{\mathrm{K}} \lvert \hat{y}_t^i - y_t^i \rvert^2$
Overall metrics	TECA (Total energy correctly assigned)	$\mathrm{TECA} = 1 - \frac{\sum_{t=1}^{\mathrm{T}}\sum_{i=1}^{\mathrm{K}} \lvert \hat{y}_t^i - y_t^i \rvert}{2\sum_{t=1}^{\mathrm{T}} \bar{y}_t}$

Where TP is the number of correctly detected ON, TN is the number of correctly detected OFF, FP is the number of incorrect detection event ON, FN is the number of ON event not detected, ŷ estimated power consumed, and y true power consumed.

4 State of the art of NILM techniques

The NILM techniques in the literature can be classified into two main categories: Probabilistic approach and Artificial Intelligence approach. In fact, our major contribution in this paper is to update research works on NILM methodologies by adding the most recent NILM methods proposed in the literature by category. In this study, Table 2 lists the Probabilistic NILM techniques and the Artificial Intelligence NILM techniques are summarized in Table 3. In these tables we have mentioned the used features, database, frequency, number of appliances and the performance indicators.

5 Discussion, challenges and future research

- In the studied literature, many researchers proposed different NILM techniques due to the various types and numbers of appliances used in each building. In addition, each appliance has its unique load signature, so no unified load signature can be used for all appliances. Hence, no standard NILM model is presented to deploy at all environments.
- NILM techniques still challenge to identify similar power and low power consumption appliances especially in low frequency. As indicated by [1, 21, 24] it is important to use V-I trajectory as a feature with additional characteristics (appliance usage frequency, time of the day, peak time usage and temperature) to overcome this limit.
- Event detection of appliances in new buildings is still a significant challenge in the NILM algorithm. In fact, the NILM model can learn by supervised or unsupervised methods. Actually, the supervised learning performs better than unsupervised learning technique. However, it requires labeled data [34] which are not easily available. Therefore, more research should be performed on the unsupervised learning methods.
- In [15, 18, 19, 23, 36], authors used the deep learning algorithm to the appliance classification, the results show good performances in the unseen houses. Hence, future works should focus on applying unsupervised learning on deep learning algorithms to achieve better performances.
- From table 2 and 3 we can see that NILM techniques have more accuracy to detect two-state appliances (ON/OFF). However, their performances decrease significantly in identifying some multi-states appliances and continuously variable devices. Therefore, future research should focus on developing NILM algorithms which are able to classify all types of appliances.
- As we mentioned in section 3, there is many metrics used to evaluate the performance of NILM techniques. Thus, it is difficult to compare between these algorithms. So, it is important to standardize the NILM performance evaluation and use the event detection and energy disaggregation accuracy for more understanding of the performance of NILM system.
- Another challenge for NILM system is real time monitoring, which will help consumers to further reduce their energy consumption [2]. Nevertheless, the real time monitoring executed by using online training requires high frequency to capture pattern of appliances. However, the only available data is the total power consumption observations. Hence, the real time monitoring requires expensive devices to acquire load data and complex algorithm. Therefore, there is an actual need to focus on reduction and development of real time disaggregation techniques.

Table 2. State of the art of Probabilistic NILM techniques.

Reference	Year	Features	Method	Database	Frequency	Number of appliances	Performance
[31]	2021	Active power	FHMM based on adaptive clustering	REDD AMPds	Not reported	6	ACC : over 94%
[32]	2021	Power consumption; time of usage	Infinite FHMM model conditioned on contextual features	REDD	Not reported	4	ACC : over 75%
[29]	2021	Not reported	FHMM	Private	Low frequency	6	Precision = 99%
[34]	2019	Active power	device usage estimation algorithm based on Markov model	ECO SMARTENER-GY.KOM UK-DALE	Low frequency	8	Energy share Errore ESE less than 35%
[35]	2019	Not reported	FHMM	REDD	Low frequency	6	F1 : over 80%
[28]	2019	apparent power of transient-state	online NILM method based on HMM	Private	4 KHz	6	ACC : over 90%
[33]	2018	steady state signatures	FHMM	Private	Low frequency	6	Not reported
[16]	2017	active and reactive power at steady state	FHMM	AMPds	Low frequency	6	F1 = 54.1%
[17]	2017	Active and reactive Power	DAE; AFAMAP	AMPds UK-DALE REDD	not repported	6	F1(%) : from 60.4 to 82.6
[30]	2015	Current; apparent power and energy	HMM with sparse Viterbi algorithm	AMPds REDD	Low frequency	5	ACC : over 80%
[12]	2013	current waveform	HMM	private	10 KHz	4	ACC = 97.9%
[13]	2013	Active and reactive power; power factor	FHMM	Not reported	Not reported	5	ACC(%) : from 86.7 to 93.3
[8]	2012	Not reported	Difference HMM	REDD	Low frequency	4	MAE(%) : from 21 to 77%
[9]	2012	Not reported	Difference Additive FHMM	Private	Not reported	7	Precision = 87.2% Recall = 60.3%

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Table 3. State of the art of Artificial Intelligence NILM techniques.

Reference	Year	Features	Method	Database	Frequency	Number of appliances	Performance
[36]	2021	Active power	CNN	REDD	15KHz	Not reported	ACC = 99.59% F1 = 97.37%
[37]	2021	Not reported	Bitcn NILM	REDD UK-DALE	Low frequency	4	ACC = 98.4% F1 = 87.5%
[38]	2021	Not reported	Improved KNN	UK-DALE GREEND PLAID	1/6Hz 30KHz 44KHz	9	ACC = 98.5%
[26]	2020	Not reported	DAE ; LSTM; GRU; Seq to point	REDD UK-DALE	Low frequency	2	MAE(%) : from 60.28 to 90.52
[27]	2020	Not reported	LSTM	wikiEnergy REDD	Low frequency	5	ACC = 99 % F1 = 65%
[25]	2019	active power	Similar Time Window STW algorithm	REDD REFIT	Low frequency	Not reported	ACC(%) : from 78.66 to 97.9
[20]	2018	active and reactive power	DAE	UK-DALE AMPDs	Low frequency	5	F1(%) : from 62.1 to 76.1
[21]	2018	V-I trajectories	CNN	PLAID WHITED	Not reported	11	F1(%) : from 75.46 to77.66
[22]	2018	Not reported	Convolutional sequence to sequence	REDD	Not reported	3	MAE = 27.1%
[23]	2018	Not reported	CNN followed by LSTM	UK-DALE	Low frequency	2	ACC(%) : from 78.66 to 97.9
[24]	2018	V-I trajectory	SVM	REDD	6.4KHz	6	F1 = 94.7%
[18]	2017	current waveform	CNN	Not reported	4 KHz	6	ACC = 99.03%
[19]	2017	transient power	CNN	REDD	1 Hz	7	ACC = 82%
[15]	2015	Active and reactive Power	LSTM; DAE; rectangle	UK-DALE	Low frequency	5	ACC(%) : from 66 to 97
[14]	2014	active power	GSP	REDD	Low frequency	6	F1 = 67%
[10]	2012	real power	KNN	Not reported	Not reported	5	ACC = 86.5%
[11]	2012	Active and reactive Power; Power factor	SVM; KNN	private	Low frequency	6	ACC(%) : over 98.1

6 Conclusion

This paper presented an updated overview of Non-intrusive load monitoring NILM techniques and discussed some of the major challenges of NILM techniques. Due to the non-intrusiveness and less complexity NILM technique is considered as the focused method for Appliance Load Monitoring. Indeed, the presented state of the art showed different Probabilistic and Artificial Intelligence NILM algorithms with good accuracy. Furthermore, NILM still challenges to be deployed at new buildings, detect all type of appliances and real time monitoring In fact, more research has to be driven to overcome these limitations, especially with developing unsupervised NILM algorithms.

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