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Non-intrusive load monitoring under residential solar power influx

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HIGHLIGHTS

- A novel NILM method which accurately works with residential PV generation is proposed.
- The method scalability was validated by extending to 400 individual houses.
- Total distributed PV generation and DR was reliably estimated in 400 households.
- One-day-ahead DR predictions were made in 400 houses using four days of readings.

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ABSTRACT

This paper proposes a novel Non-Intrusive Load Monitoring (NILM) method for a consumer premises with a residentially installed solar plant. This method simultaneously identifies the amount of solar power influx as well as the turned ON appliances, their operating modes, and power consumption levels. Further, it works effectively with a single active power measurement taken at the total power entry point with a sampling rate of 1 Hz. First, a unique set of appliance and solar signatures were constructed using a high-resolution implementation of Karhunen Loéve expansion (KLE). Then, different operating modes of multi-state appliances were automatically classified utilizing a spectral clustering based method. Finally, using the total power demand profile, through a subspace component power level matching algorithm, the turned ON appliances along with their operating modes and power levels as well as the solar influx amount were found at each time point. The proposed NILM method was first successfully validated on six synthetically generated houses (with solar units) using real household data taken from the Reference Energy Disaggregation Dataset (REDD) - USA. Then, in order to demonstrate the scalability of the proposed NILM method, it was employed on a set of 400 individual households. From that, reliable estimations were obtained for the total residential solar generation and for the total load that can be shed to provide reserve services. Finally, through a developed prediction technique, NILM results observed from 400 households during four days in the recent past were utilized to predict the next day's total load that can be shed.

1. Introduction

Increasing penetration of unpredictable renewable energy sources such as solar photovoltaic (PV) and wind energy have paved the way for many applications of Demand Side Management (DSM) [1]. Due to the intermittent and variable nature of the generation, maintaining the second-by-second balance between the generation and the demand have become a challenging task, unless expensive reserve services are maintained [2,3]. As an economical solution, a DSM application called Demand Response (DR) through Direct Load Control (DLC) has been introduced [4–7]. DLC tries to adjust the demand either by shifting or reducing the consumption in a way that the available generation can be employed efficiently while maintaining a minimum reserve [8]. Furthermore, during a period where network asserts are over-loaded, DLC could be used to minimize distribution losses.

In DLC, utility is directed to shape the customer energy consumption profile by remotely controlling each customer's pre-agreed set of controllable appliances such as heat, ventilation, air-conditioning and

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Nomenclature

Acronyms & Symbols

ACM	Autocorrelation Matrix
CV	Continuously Varying
CS	Cooking Stove
DR	Demand Response
DSM	Demand Side Management
DLC	Direct Load Control
DW	Dish Washer
FN	False Negatives
FP	False Positives
FES	First Elimination Step
KLE	Karhunen Loéve expansion
LHV	Likelihood Value
LM1	Lamp 1: 60 W
LM2	Lamp 2: 100 W
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAP	Maximum A Posteriori
MW	Microwave: 2300 W
MS	Multi State
NILM	Non-Intrusive Load Monitoring
OW	Observation Window
PC	Desktop Computer
PV	Photovoltaic
PES	Pre Elimination Step
PMF	Probability Mass Function
RAM	Random Access Memory
REDD	Reference Energy Disaggregation Dataset
RF	Refrigerator
SES	Second Elimination Step
SS	Single State
SW	Sliding Window
SC	Subspace Component
TP	True Positives
TV	CRT Television
USA	United States of America
WM	Washing Machine

Symbols:

A	affinity matrix
σ	affinity scaling factor
A_{ET}	average execution time
A_{pd}	average accuracy of power assigning
λ_i	average amplitude of ith SC
A_{F_m}	average F-measure
$f_{c(i,n)}$	center frequency of ith SC at nth time instant
$\mathbf{X}$	data window (1 × 10 vector)
D	distance matrix
q_i	ith eigenvector of ACM of $\mathbf{X}$
$F_{m c_j}$	F-measure value of c_j
$Z_{1,..,i}$	set of SCs up to ith SC of OW
i	iteration number; SC number
$\gamma_{c_j,i}$	percentage LHV of c_j after ith iteration
N	length of a SW
L	normalized laplacian matrix
$\widetilde{N}$	number of SCs
K	number of clusters
X_K	Kth eigenvalue of L in ascending
c_j	jth Possible turned ON *appliance/mode* combination
θ_i	phase angle of ith SC
$A_{pa\,c_j}$	power assigning accuracy for c_j
$p_k(t)$	power consumption of kth appliance at time t
$s(t)$	solar power output at time t
z_i	ith SC of OW
n	time instant
$P(t)$	total power consumption at time t
k_T	number of turned ON appliances at time t

smart systems. In this paper, these controllable loads are called as non-critical loads. Even though a smart meter connected at the consumer premises could make the non-critical loads flexible, unless utilities have an idea about the amount of DR available at a given time, the utilities will have to operate expensive reserve services to maintain the second-by-second balance between the generation and the demand [9,10].

In order to estimate the amount of DR available at a consumer premises, individual load activities should be monitored [11–14]. For this purpose, both Non-Intrusive Load Monitoring methods (NILM) as well as intrusive load monitoring (ILM) methods can be suggested. In general, NILM methods have a number of advantages over ILM methods. If ILM is used, the different appliances connected to the Home Area Network (HAN) should send power measurements from each and every appliances to the smart meter continuously. Therefore to implement DR activity such as direct load control with ILM, a bi-directional communication link with high bandwidth is required. Whereas, using a NILM method, only a uni-directional link with a low bandwidth is adequate. Furthermore, the NILM method could be built into a smart meter. It would be able to detect devices as well as faults and improve safety; increasing safety.

Non-Intrusive Load Monitoring (NILM) methods [15] are widely studied and utilized in which, only the total power at the entry point to the consumer premises is monitored to find the load activities [16]. Due to its both low cost and complexity, numerous NILM methods have been proposed in the literature [11,17–24]. These methods enable the identification of turned ON appliances inside a customer premises with their respective power levels non-intrusively.

However, to the best of authors' knowledge, most of the aforementioned NILM methods are unable to identify the individual appliance power levels accurately under the presence of multi-mode appliances such as Washing Machines (WM) and Dish Washers (DW). Further, none of the existing NILM methods have considered the possibility of having a residentially installed solar panels. Furthermore, none of the existing NILM methods have been tested for their applicability under a large number of houses to estimate the total non-critical load that can be shed (i.e. DR) at a given time instant as well as one day ahead.

As a remedy to these common drawbacks of existing NILM methods, this paper introduces a novel NILM method which extends the previously proposed NILM method in [18] by the authors. The proposed NILM method relies on a Karhunen Loéve expansion (KLE) based subspace separation method [18,23] which successfully operates even with only active power measurements collected at a low sampling rate (slower than 1 Hz).

In the proposed NILM method, first, individual appliance operating mode identification technique have been formulated based on spectral clustering and KLE. Through this proposed technique, not only the turned ON appliances, but also the operating mode and power consumption level of each turned ON appliance could be detected at a given time. This stage is essential in determining the total residential critical load and non-critical load power demand values. Also, it plays a vital role in determining appropriate load scheduling schemes under DLC [25].

Further, due to increasing trend of using residentially installed solar