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Low Cost Disaggregation of Smart Meter Sensor Data

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ABSTRACT: This paper proposes a novel load disaggregation algorithm, based on non-intrusive appliance monitoring that provides accurate results without the need of the reactive power component. The proposed technique requires the minimum possible number of sensor meters within the smart meter hardware and reduces data traffic of the Advanced Metering Infrastructure (AMI) network since it processes only low frequency smart meter data of the active power component of a residential unit. We propose a three stage process for energy usage analysis, based on pulse extraction, pulse clustering and classification and pulse to appliance association. The smart meter data are decomposed into a discrete set of pulses and each pulse is associated to the operation of the appliances. The outcome of the algorithm is a pulse to appliance association that creates a daily load disaggregation map for the residential unit. In addition, the paper presents an overview and comparison of existing solutions that will help the reader obtain a good overview of the landscape of load disaggregation from smart meter sensor readings.

KEYWORDS: smart grids, smart meter data, signal processing, load disaggregation, non intrusive appliance load monitoring, energy data, big data

I. INTRODUCTION

Over the recent years, the evolution of Smart Grid has created all the necessary foundations for data and command flow in the power grid network. It can now be regarded as an application development platform. New services and applications have emerged to increase customer service offerings but also to enrich demand response programs. Since management is based upon knowledge, one of the most promising directions of investigation is the appliance usage disaggregation. Load disaggregation (also known as appliance usage disaggregation or non-intrusive appliance load monitoring NIALM) is considered as an important service since it provides information about the appliance usage in the household that can help utilities' demand response programs. Load disaggregation is a methodology for recognizing individual appliance signal signatures from aggregated circuit readings. The classification of existing algorithms is based on two general categories. Intrusive monitoring performs appliance disaggregation based on individual meter readings where in the non-intrusive approach, sophisticated signal processing techniques are required to disaggregate individual appliance signals from the total household meter reading [1,2]. Non-intrusive approach is subdivided in supervised and the unsupervised training algorithms [3, 4].

B Proposed Solution

This paper presents a non-intrusive load disaggregation algorithm based on Fuzzy logic and pattern recognition that considers LF data sampling of active power readings. The achieved accuracy is similar to the case of considering the reactive power since we extract knowledge regarding the presence of the reactive component from the variance of the active power component. The proposed solution considers a n-dimensional space for decision making taking into account appliance characteristics, pulse characteristics, user activity and external condition. In the proposed algorithm the user is required to provide information about the number, type, and labelled power value of the appliances in the residential unit. The proposed solution is tested over a real smart meter environment, implementing low cost smart meter equipment provided by Kimatica Ltd. The observed accuracy varies between 70%-99% according to the simultaneous appliance usage in the residential unit. The novelty of the proposed algorithm can by summarized as:

- no need of reactive power since this information is extracted from the variance of the active power

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- outcome is a daily pulse to appliance association per user that is scalable in terms of storage
- considers human behaviour and external data information to minimize error propagation
- is ideal for real applications of current business models since it minimizes costs of hardware equipment

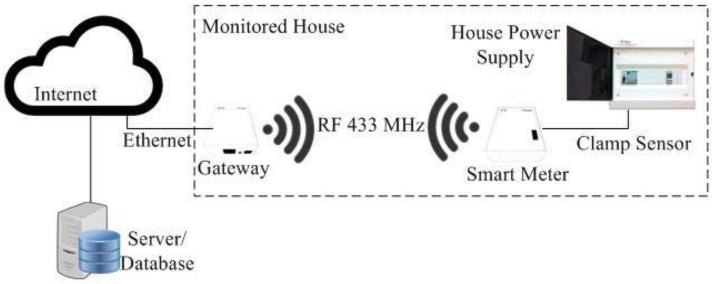

Fig. 1. Monitoring of smart meter energy data

II. STATE OF THE ART AND DIFFERENTIATION

A feature extraction and pattern recognition approach for load disaggregation is given in [5]. The authors focused on event extraction from appliance usage. Event was detected from the switch on/off state of the appliance. In [6] the authors implemented a decision making algorithm, called Committee Decision Mechanism (CDM) to detect appliances over a typical household. An additive Factorial Hidden Markov Model (FHMM) for appliance detection is given in [7]. The proposed solution incorporates a difference FHMM to consider past recording in the detection process. In [8] taxonomy of load signatures of typical appliances is presented accompanied with environmental data used to add new layers on appliance detection and increase accuracy. In [9] the authors propose an application for load disaggregation by considering reactive power component. A HF approximation is given in [10] where current harmonics are used to classify appliances in the household recordings. This approximation can increase accuracy of predictions but requires expensive hardware equipment but also increases communication costs. A classification algorithm for appliance detection based on non-intrusive approximation in presented in [11, 12]. The authors implement clustering and classification algorithms over LF signals. A different approach based on neural network (NN) and supervised training is given in [3]. Neural network is considered an accurate process but it requires high processing power in the cloud. Finally, a survey of load disaggregation techniques and applications is given in [13].

III. ENERGY DATA CHARACTERISTICS

A. Capturing Smart Meter Power Signals

A wireless smart meter is connected to the electrical panel of the residential unit (Fig. 1). The smart meter captures and transmits power samples y(t) (Watt) using a clamp sensor and a radio unit. The sampling frequency was λ=7 seconds (1 sample every 7 secs ~ 0.14Hz). Data is transmitted over an RF 433MHz dedicated wireless channel to the gateway. The gateway is attached to an Ethernet port of user's router and is responsible to push a 15 minute data set to the server/database over the internet. From the database, the third party application provider can use the raw data to perform load disaggregation. Raw data that represents the power consumption of the residential unit is a matrix $Y=(y_i(t):t=1,....T)$, spanning over T=24 hours and $i \in N$, where $N = 3600 \cdot T / \lambda$ is the set of samples per day. The energy consumption over time T is:

$$E = \frac{\lambda}{3600} \sum_{t=1}^{T} y(t) \tag{1}$$

B. Appliances Footprints

A typical power consumption of vector **Y** is presented in Fig. 2. The plot is the superposition of power values of appliances that operate during the day. Assuming that there is a set of M appliances with identifiers j ϵ M, each appliance consumes power equal to $x_i(t)$, then:

$$y_i(t) = \sum_{j=1}^{m<|M|} x_j(t) \tag{2}$$

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Periodic with preparation: thermostatic appliances, like ovens and air condition units that when they are switched on, present a preparation time period (T_{ON}) with constant power consumption $x_j(T_{ON})$ that is followed by on/off states with

$T_{ON}>t_{ON}$ and $T_{ON}>t_{OFF}$, where $x_j(T_{ON})\approx x_j(t_{ON})$.

Static: appliances that create constant power consumption $x_j(t)$=const. While they are on, such as lights and PCs.

Multi State: appliances that are active and present a preparation period with constant power consumption $x_j(T_{ON})$ that is followed by different power states of smaller amplitudes $x_j(T_{ON})> x_j(T_{HOP})$. These are usually appliances with different cycles of operation like washing machines.

Spike: once an appliance is on, there might be a spike associated to its operation due to motors of inductive appliances.

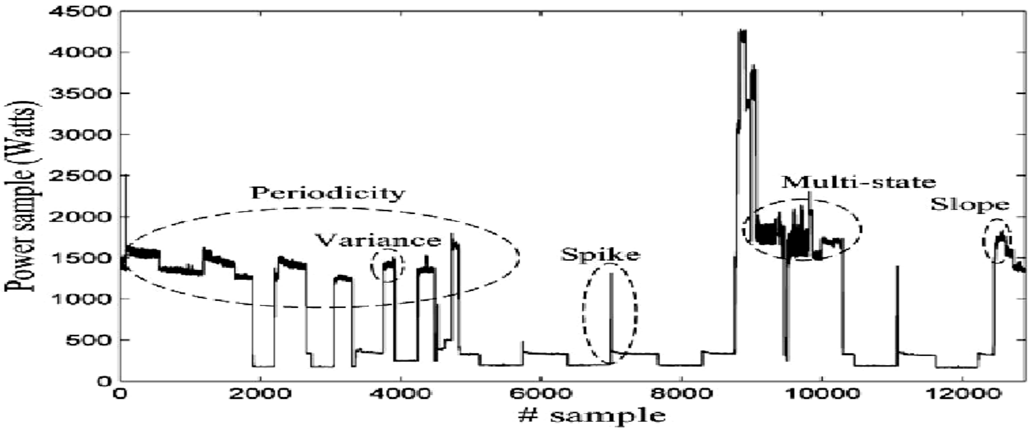

Fig. 2. Raw energy data and information extraction

Variance: a fluctuation of power around the average power consumption. This characteristic is met at inductive appliances and its presence is correlated to a positive reactive power component.

Slope: once an inductive appliance is on, a slope of the power curve is observed for a short time interval. This slope is a unique characteristic of a motor. An interesting survey of load profiles of typical appliances is also given in [14].

C. Decomposition of Appliance Footprint to Pulses

Based on these observations, we decompose the appliance footprint into a set of discrete rectangular pulses Π_n with $n\in\Omega_M$,

D. Integrating Human Behaviour Information to Pulses

The performance of the load disaggregation algorithm can be enhanced by considering human behaviour in the household. This can be modelled as an additional layer of information to the load disaggregation algorithm based on expected usage characteristics.

IV. ALGORITHM DESCRIPTION

A. User Input

This process refers to appliance registration. The user is required to register each appliance in the residential unit by indicating a tabulated power value.

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B. Data Incorporation

There are two types of information that is automatically attached during the registration. The first corresponds to values that include personalized user activity behaviour, such as Timeof Use Probability and Duration of Pulse. Time of Use Probability is defined as a binary vector that indicates the expected time of operation of the appliances, with $T_j^U(t)=\{0,1\}$ indicating if an appliance is most probable to operate a specific time, t of the day or not.
Duration of Pulse is a maximum threshold of the expected duration of a power pulse. For example, a power pulse created by an oven cannot exceed 1 hour of duration.

The second category corresponds to characteristics that exist in typical appliances and are the Look for Neighbours' Pulses, MultiState, Periodicity, Spike, Slope, and Variances

C. Spike Processing

Spikes can be easily detected since they create a high power value on the smart meter signal with a very short time duration. In all cases, spikes have duration smaller than 5 seconds that correspond to one discrete measurement. We detect the spikes of the power signal and store them as information that will be used at the load disaggregation algorithm.

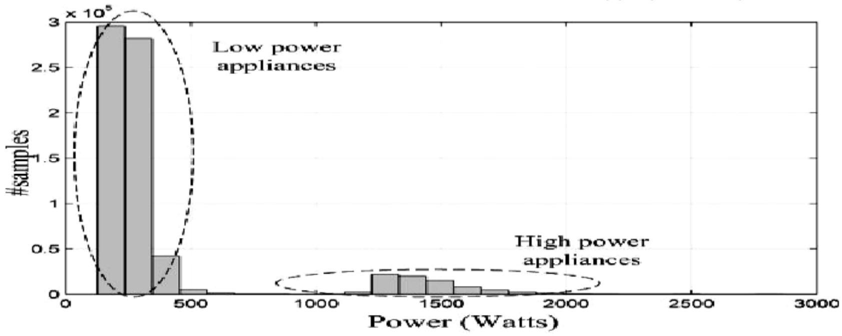

Fig. 3. Histogram of power samples over a two month period for a typical residential unit.

C. Flattening

The simplest and most efficient way to flatten the power signal is to perform a moving average filter. It is observed that most households have two types of appliances. The low power appliances, such as fridge, entertainment equipment, lights, etc., and the high power appliances such as ovens, heat water, air condition units, etc. In most cases, the low power appliances have operational power in the range of 50-300Watts whereas high power appliances operate in the range above 800Watts.

D. Carried Information by Pulses

Pulse slope: assuming $y_i = (y_i(t) : t = t_n, ...t_{n+\delta})$ where $\delta = 14$ times steps (~ 1 minute of smart meter following the initiation of the pulse) then the pulse slope is the slope of the linear regression found as:

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TABLE I
APPLIANCE CHARACTERISTICS MAP

Appliance Type	Name of appliance	Variance	Spike	Slope	Periodicity	Multi State	Neighbor pulses	Sequence of Operation
Resistive	Electric Storage Heater	X	X	X	√	X	X	X
	Oven	X	X	X	√	X	X	√
	Hotplate	X	X	X	√	X	X	√
	Heat Water	X	X	X	√	X	X	√
	Toaster	X	X	X	√	X	X	X
	Hair Dryer	X	X	X	X	X	√	√
	Coffee	X	X	X	√	X	X	X
	Lights	X	X	X	X	X	X	X
Inductive	Vacuum Cleaner	X	X	X	X	X	√	X
	Fridge/Freezer	√	√	X	√	X	X	X
	Air Condition	√	√	√	√	X	X	X
	Washing / Dryer	√	X	X	X	√	X	√
	Dish Washer	√	X	X	X	√	X	√
Capacitive	TV	X	X	X	X	X	X	√
	Stereo	X	X	X	X	X	X	X
	Game/Entertainment	X	X	X	X	X	X	X
	PC	X	X	X	X	X	X	X

V. LOAD DISAGGREGATION

With the aforementioned process, the raw smart meter recordings are decomposed to a discrete set of pulses and each pulse carries unique information that models an appliance `footprint. The outcome of the proposed algorithm is a pulse to appliance association. Each appliance has a discrete set of pulses that models its daily operation.

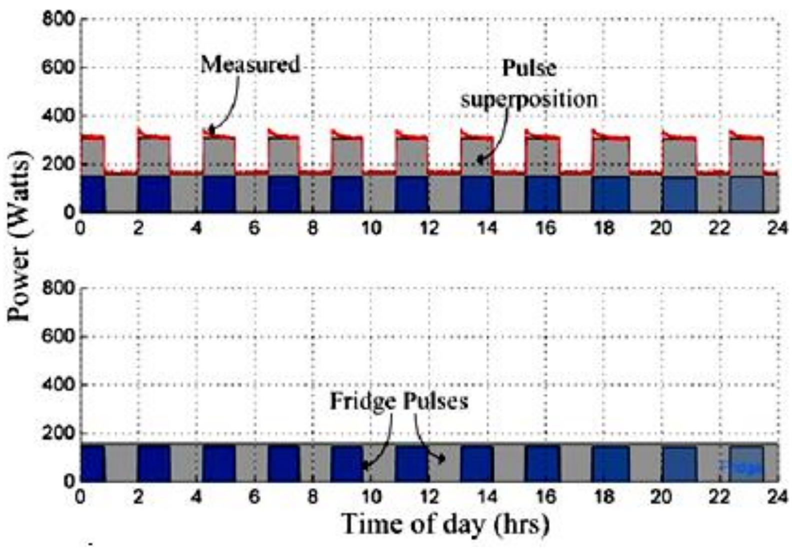

Fig. 4. Pulse to appliance disaggregation for a low energy day

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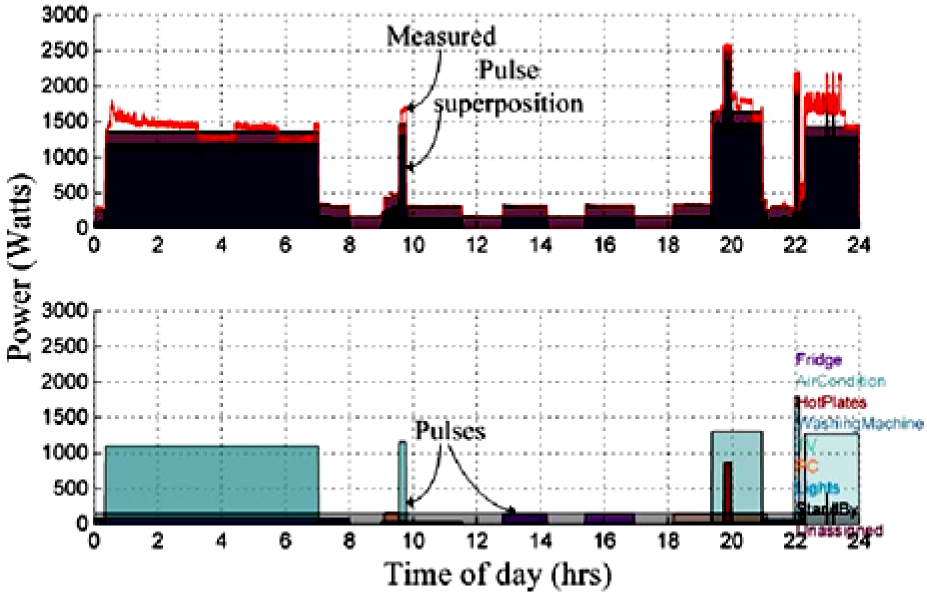

Fig. 5. Pulse to appliance disaggregation for a typical day

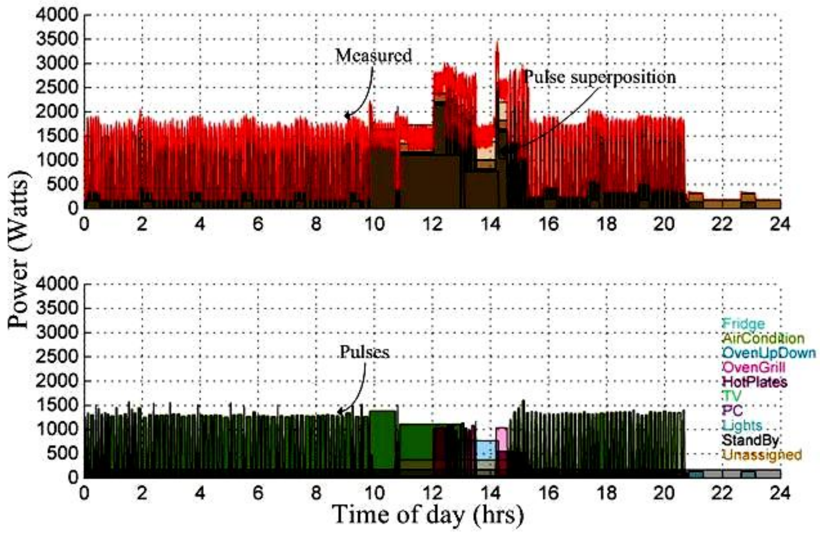

Fig. 6. Pulse to appliance disaggregation for a high energy day

VI. SIMULATION RESULTS

A. Daily results

We examine three case studies. The first refers to an extreme low energy scenario where there was no human activity in the residential unit. Therefore, the energy consumption footprint was a result of the standby power consumption and refrigerator operation. The predictions are presented in Fig. 7 and Table II. The second scenario concerns a typical day with an average human activity (Fig. 8). In most occasions, the proposed algorithm successfully detected the operation of the air-condition unit, the hot-plates and the heat water preparation of the washing machine.

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The third scenario refers to an extreme high energy scenario where the majority of the appliances were operating during the day (Fig. 9). It should be highlighted that this scenario is not met in reality but was used to test the performance of the algorithm. Hotplates and oven operation was successfully detected between 09:55am to 10:04am and 12:12pm to 01:40pm and 02:24pm to 03:35pm. The proposed algorithm made a false detection of the air-condition unit and low power devices such as refrigeration, lights, PC and TV.

VII. CONCLUSION

The paper introduced a novel load disaggregation algorithm that decomposes smart meter power readings into a set of discrete pulses. The pulses are then associated to a registered appliance according to maximum likelihood procedure. The proposed algorithm also considers important characteristics of the appliances signatures, external environmental parameters and human behaviour. These factors are introduced in a *n dimensional* space for decision making. An accuracy of more than 85% was observed. The proposed solution is cost efficient since it does not require reactive power readings at smart meter level and is based on low frequency sampling rates. These are important factors for the real implementation of smart grid energy services in modern business models.

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