

## Article

# The Impact of Power Definitions on the Disaggregation of Home Loads for Smart Meter Measurements

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**Abstract:** The use of load-monitoring systems in residential homes is fundamental in the context of smart homes and smart grids. Specifically, these systems will allow, for example, the provision of efficient energy management and/or load forecasting for residential homes. To achieve this goal, these systems can be based on the concept of a smart meter. However, a smart meter provides aggregate power consumption, which makes it extremely complex to identify individual home appliances, even using advanced algorithms. In line with this, this paper proposes to analyze the impact of power definitions on the disaggregation of home appliance loads. Moreover, it will also consider the distortion of the voltage grid, which is usually not addressed in the resolution of this problem. This effect will be verified through an approach that is based on a genetic algorithm. The approach will be tested through the use of several scenarios, in which an aggregation of home appliances is used.

**Keywords:** smart meter; appliance identification; load disaggregation; power definitions; grid distortion



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## 1. Introduction

Electrical energy is indispensable in today's world. The increasing reliance on renewable sources, the need for energy storage, and the growth of complex loads have significantly complicated the systems that manage and supply this form of energy. In this way, one of the technologies that has become ubiquitous is the smart meter (SM). In fact, it is predicted that in the future, smart metering will play a very important role in the electrical energy context [1]. Even now, the technology associated with smart meters is already considered very important, especially in Europe. Indeed, countries like Sweden and Finland have strongly adopted this technology [2]. By this means, they intend to be leaders in the transformation to a clean energy economy, in which they combine the use of smart meters with policy measures. However, their use on other continents has also been adopted, such as in the case of the United States, where in 2016, the number of smart meters installed reached 70 million, and this number is expected to be 326 million across Europe by 2028 [3,4].

The use of smart meters integrated into different applications in the electric infrastructure has been proposed. One of the areas in which this equipment has been proposed is

at the power-quality-monitoring level. So, in this context, in [5], a solution is proposed in which an aggregation algorithm is used that must be incorporated into smart meters. Through this proposal, it is possible, for example, to achieve control of a distribution network. Other works in which smart meters were used for PQ purposes have also been published, especially associated with the identification of disturbances [5–11]. Another area in which the use of this technology can be very important is in the context of electrical vehicles (EVs). Over the past few years, several works addressed this aspect. In [12–14], the problem of the integration of EVs in smart grids (SGs) was addressed. In order to facilitate this integration, the use of a technology in which unbundled smart metering is taken into consideration alongside a virtual power plant was proposed [15]. A major advantage of unbundled smart meter usage relies on the fact that it has two completely distinct components (Smart Metrology Meter—SMM and Smart Meter eXtension—SMX). While the SMM is a high-security component, the SMX allows the deployment of new user functionalities [16]. Other works address the problem of the identification of the load patterns generated by electric vehicle charging. To identify these patterns, learning and unsupervised algorithms that use data from smart meters were proposed [17–20].

One of the areas in which smart meters have started to play an important role is at the residential level. In fact, in several countries, in the majority of residential homes, there is a smart meter. This piece of equipment has been used for the monitoring of total household energy. However, several methods have been proposed in order to provide new services based on information from smart meters. So, proposals for the use of this kind of equipment for residential demand response, one of the possible services, have been presented. Thus, in [21], an algorithm for demand response management in which home load management modules are incorporated into smart meters was proposed. This system was developed in the context of a smart grid. Other works, in which smart meters were used in the context of demand response in residential houses, have also been presented [22–27]. Another very important service that can be provided through an SM is the identification of residential appliances. This service can play a very important role in the implementation of several smart applications, such as demand response [28,29], smart billing [30], fault resilience [31,32], and the integration of renewable sources and energy storage [33–37]. In this regard, several techniques and approaches have been presented to provide these services.

For residential appliance identification, there are two main approaches: intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM). The first approach (ILM) is characterized by the use of sensors applied to appliances or to specific points of the load [38,39]. The main disadvantage of this approach is associated with its high costs. In the second approach (NILM), the identification of turned-on appliances is realized by a single point, usually the entry point of the power supply. One of the main problems associated with this last approach is that the identification of turned-on appliances from total electric power is very complex and difficult.

The first NILM techniques were based on the analysis of active and reactive power measurements, in which statistical tools were applied with the purpose of detecting changes in these measurements that are related to the turned-on/off appliances. For example, in [40,41], works are presented in which these kinds of techniques were used. However, these techniques showed some issues in the identification of complex appliances, especially with multiple states. So, other approaches have been used in order to solve this problem. One of the approaches used Hidden Markov Models (HMMs) [42,43], although this presented some problems when the time duration was not relatively constant for each of the states. Other approaches have also been proposed, in which instead of using active and/or reactive power, grid current harmonics, voltage–current trajectory or images were analyzed [44–47]. In the past few years, new approaches have been proposed, for which

interesting results have been obtained. These approaches include techniques based on graph signal processing [48], a cepstrum-smoothing-based method [49], a fuzzy clustering algorithm [50], an artificial bee colony [51] and deep learning [52,53]. A review of NILM techniques can also be seen in [54]. In [55], a cloud-based on-line disaggregation algorithm for home appliance loads is presented. However, these methods have not been studied in the context of grid distortion and the definitions of powers taking into consideration this distortion.

Numerous approaches have been employed to identify individual appliance loads from aggregated smart meter data. However, the impact of different power definitions on load disaggregation has not been extensively explored. This paper aims to investigate the suitability of smart meter measurements, considering grid distortions, for non-intrusive load monitoring (NILM). Different power definitions will be analyzed to assess their impact on NILM. A genetic algorithm-based NILM approach will be employed to evaluate this impact. The proposed methodology will be validated using real-world data from multiple households.

## 2. Power Definitions

Modern smart meters offer a comprehensive set of accurate measurements and calculations, including apparent, active, and reactive power, consumed and produced energy, total harmonic distortion (THD), and more, even under non-sinusoidal or unbalanced conditions. The new generation of smart meters adheres to the recommendations of IEEE Std. 1459–2010 [56] or the DIN 40110–2 [57] to incorporate the latest definitions of apparent power (kVA) and nonactive power (kvar). Since the 1920s, some of the most eminent professors and engineers, such as Budeanu, Bunet, Iliovici, Fryze, Bucholz, Kuster, Shepherd, Zakikhani, Depenbrock, Czarnecki, and Tenti, among others, have proposed and discussed their own power definitions [58]. Despite some mathematical shortcomings, for many years, Budeanu's (Prof. Constantin I. Budeanu) definitions of power were universally accepted by electrical engineers and their organizations. The latest work developed by Prof. Alexander E. Emanuel, published in 2010 [59], is now the most accepted and recognized method. In this section, a brief review of the power definitions proposed by professors Budeanu and Emanuel are presented. As will be seen in the following sections, these definitions are very valuable in the process of NILM.

### 2.1. Budeanu's Proposal

Professor Budeanu created new definitions of apparent power in non-sinusoidal systems and understood that this power has more than two components, which can be represented in a three-dimensional system. The squared RMS (Root Mean Square) harmonic currents can be divided into two orthogonal terms according to (1):

$$I_h^2 = (I_h \cos \theta_h)^2 + (I_h \sin \theta_h)^2 \quad (1)$$

where  $\theta_h$  is the phase angle between the harmonic voltage phasor  $V_h$  and the harmonic current phasor  $I_h$ . From Equation (1), it is possible to obtain the expression of the apparent power squared (2):

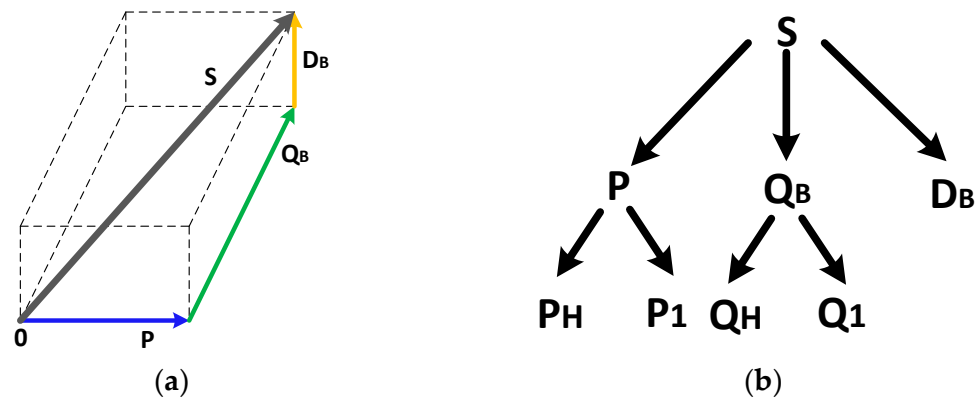
$$S^2 = V^2 I^2 = \sum_{h=1}^v V_h^2 \left[ \sum_{h=1}^v (I_h \cos \theta_h)^2 \right] + \sum_{h=1}^v V_h^2 \left[ \sum_{h=1}^v (I_h \sin \theta_h)^2 \right] \quad (2)$$

Applying Lagrange’s identity, the apparent power squared can be simplified to Equation (3):

$$S^2 = V^2 I^2 = \left( \sum_{h=1}^v V_h I_h \cos \theta_h \right)^2 + \left( \sum_{h=1}^v V_h I_h \sin \theta_h \right)^2 + \sum_{m=1}^{v-1} \sum_{n=m+1}^v \left[ (V_m I_n)^2 + (V_n I_m)^2 - 2V_m V_n I_m I_n \cos(\theta_m - \theta_n) \right] \tag{3}$$

Equation (3) shows that apparent power in non-sinusoidal systems can be decomposed into three orthogonal components, visualized as a right-angled parallelepiped in Figure 1. The diagonal of this parallelepiped, given by Equation (4), represents the apparent power. In the previous equation,  $\theta_m$  is the phase angle between the harmonic voltage phasor  $V_m$  and the harmonic current phasor  $I_m$  and  $\theta_n$  is the phase angle between the harmonic voltage phasor  $V_n$  and the harmonic current phasor  $I_n$ .

$$S^2 = P^2 + Q_B^2 + D_B^2 \tag{4}$$



**Figure 1.** Budeanu’s proposal definition for apparent power: (a) three-dimensional representation and (b) power components (separated into fundamental and nonfundamental).

The first term is the total active power (5) and the second term is called reactive power (6), or Budeanu reactive power,  $Q_B$ . In the previous figure,  $P_1$  is the active power at the fundamental frequency,  $P_H$  is the active power at harmonic frequencies,  $Q_1$  is the reactive power at the fundamental frequency and  $Q_H$  is the reactive power at harmonic frequencies.

$$P = \sum_{h=1}^v V_h I_h \cos \theta_h \tag{5}$$

$$Q_B = \sum_{h=1}^v V_h I_h \sin \theta_h \tag{6}$$

The third term is the distortion power (7). Nevertheless, the usual computation of distortion power is through (8).

$$D_B = \sqrt{\sum_{m=1}^{v-1} \sum_{n=m+1}^v \left[ (V_m I_n)^2 + (V_n I_m)^2 - 2V_m V_n I_m I_n \cos(\theta_m - \theta_n) \right]} \tag{7}$$

$$D_B = \sqrt{S^2 - P^2 - Q_B^2} \tag{8}$$

## 2.2. Emanuel's Proposal

Emanuel's power definition separates fundamental (50/60 Hz) active and reactive powers from non-fundamental components [45]. This definition can be derived from the RMS voltage and current decomposition shown in Equation (9).

$$V^2 = V_1^2 + V_H^2; V_H^2 = \sum_{h \neq 1} V_h^2; I^2 = I_1^2 + I_H^2; I_H^2 = \sum_{h \neq 1} I_h^2 \quad (9)$$

From (9), the result is that the apparent power squared has four terms (10):

$$S^2 = V^2 I^2 = (V_1^2 + V_H^2)(I_1^2 + I_H^2) = (V_1 I_1)^2 + (V_1 I_H)^2 + (V_H I_1)^2 + (V_H I_H)^2 = S_1^2 + D_I^2 + D_V^2 + S_H^2 \quad (10)$$

The first term is the fundamental or 60/50 Hz apparent power (11) and the remaining three terms are the non-fundamental (non-60/50 Hz) apparent power (12).

$$S_1 = (V_1 I_1) = \sqrt{P_1^2 + Q_1^2} (VA) \quad (11)$$

$$S_N = \sqrt{D_I^2 + D_V^2 + S_H^2} (VA) \quad (12)$$

The term  $D_I$  is the current distortion power (see Equation (13)). This non-active power gives information on the amount of VA tied to the current distortion.

$$D_I = V_1 I_H = V_1 \sqrt{\sum_{h \neq 1} I_h^2} (VA_r) \quad (13)$$

The term  $D_V$  (see Equation (14)) is the voltage distortion power, and is proportional to the fundamental component of the current,  $I_1$  and the total harmonic voltage  $V_H$ . It reveals the amount of volt-ampere-reactive caused by voltage distortion.

$$D_V = V_H I_1 = I_1 \sqrt{\sum_{h \neq 1} V_h^2} (VA_r) \quad (14)$$

The last term  $S_H$  is the harmonic apparent power (15).

$$S_H = V_H I_H = \sqrt{\sum_{h \neq 1} V_h^2 \sum_{h \neq 1} I_h^2} (VA) \quad (15)$$

The term  $S_H$  contains the active harmonic power  $P_H$  and harmonic distortion power (16):

$$S_H = (V_H I_H) = \sqrt{P_H^2 + D_H^2} (VA) \quad (16)$$

where the harmonic power  $P_H$  is given by (17):

$$P_H = \sum_{h \neq 1} P_h^2 = \sum_{h \neq 1} V_h I_h \cos \theta_h \quad (17)$$

The harmonic distortion power is given by (18), where  $D_B$  is similar to Budeanu's distortion power, presented in (7). Figure 2 shows the disaggregation of the apparent power according to Emanuel's proposal.

$$D_H = \sqrt{\left( \sum_{h \neq 1} V_h I_h \sin \theta_h \right)^2 + D_B^2} \quad (18)$$

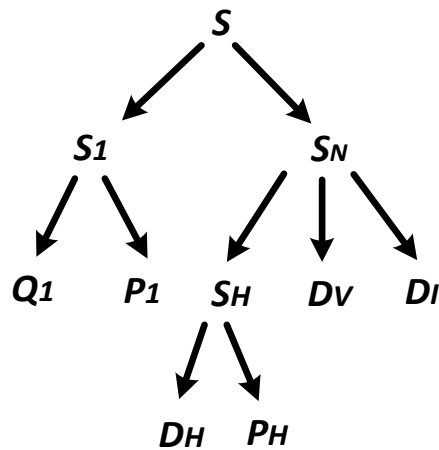


Figure 2. Emanuel’s proposal definition for apparent power.

### 3. NILM Approach Based on the Genetic Algorithm

The type of information obtainable from smart meters depends on the data sampling frequency. For instance, hourly or half-hourly data are sufficient for determining household occupancy. However, to accurately detect individual or multiple appliances, high-frequency smart meter data are necessary [49]. Since the purpose is to provide the ability to identify the turned-on appliances at a specific moment, high sampling frequency is required. This enables precise identification of appliance activation times, a capability inherent in modern smart meters. Smart meter data enables the calculation of power values based on the definitions outlined in the previous section. Unbundled smart meters directly provide voltage and current measurements for each phase, eliminating the need for additional computations (provided by the SMM without additional calculations). The SMM can also obtain the following values: active power value on each phase, reactive power value on each phase, power factor value on each phase, homopolar value of the rms voltage, homopolar value of the rms current, angle between voltages, angle between each phase voltage and current, grid frequency. In this work, and considering that harmonics are available up to the order of 32 [60], we deployed the proper code in the unbundled smart meter SMX component to obtain the values presented in (19) and (20). So, to identify which appliances are on at a specific time  $t$  involves analyzing the aggregated power measurements from the smart meter. In this way, from the point of view of Budeanu’s proposal, the several aggregated powers will be given by:

$$\left\{ \begin{array}{l} P(t) = \sum_{k=1}^{N_{total}} P_k(t) + e(t) \\ Q(t) = \sum_{k=1}^{N_{total}} Q_{Bk}(t) + e(t) \\ D(t) = \sum_{k=1}^{N_{total}} D_{Bk}(t) + e(t) \end{array} \right. \quad (19)$$

where  $P_k(t)$ ,  $Q_{Bk}(t)$  and  $D_{Bk}(t)$  describe the active power, reactive power and distortion power consumptions, respectively, of the specific appliance  $k$  at instant  $t$ , and  $e(t)$  is the noise of the measurement. Regarding the perspective of Emanuel’s proposal, the several aggregate powers are given by (20):

$$\left\{ \begin{array}{l} P_1(t) = \sum_{k=1}^{N_{total}} P_{1k}(t) + e(t), \quad P_H(t) = \sum_{k=1}^{N_{total}} P_{Hk}(t) + e(t) \\ Q_1(t) = \sum_{k=1}^{N_{total}} Q_{1k}(t) + e(t) \\ D_I(t) = \sum_{k=1}^{N_{total}} D_{Ik}(t) + e(t), \quad D_V(t) = \sum_{k=1}^{N_{total}} D_{Vk}(t) + e(t) \\ D_H(t) = \sum_{k=1}^{N_{total}} D_{Hk}(t) + e(t) \end{array} \right. \quad (20)$$

where  $P_{1k}(t)$ ,  $P_{Hk}(t)$ ,  $Q_{1k}(t)$ ,  $D_{Ik}(t)$ ,  $D_{Vk}(t)$  and  $D_{Hk}(t)$  describe the fundamental active power, harmonic active power, fundamental reactive power, current distortion power, voltage distortion power and harmonic distortion power consumptions, respectively, of the specific appliance  $k$  at instant  $t$ .

To identify individual or multiple active appliances, we propose an objective function within a metaheuristic framework. This objective function minimizes the difference between the sum of the powers of active appliances and the total power measured by the smart meter at the grid connection point. The decision variables represent the number of active appliances of each type.

Based on the preceding discussion, objective functions (21) and (22) are defined. These functions aim to minimize the difference between the aggregated power measured by the smart meter and the sum of the powers of active appliances, aligning with Budeanu's and Emanuel's power theories. Emanuel's approach considers fundamental active power ( $P_1$ ), fundamental reactive power ( $Q_1$ ), current distortion power ( $D_I$ ), and voltage distortion power ( $Q_V$ ). By incorporating fundamental power and distortion powers, the algorithm becomes more resilient to grid voltage fluctuations and distortions. To further enhance robustness, the difference between voltage and current waveforms is used instead of considering them separately, allowing higher immunity.

$$\min \left\{ \text{abs} \left( P(t) - \sum_{k=1}^{N_{total}} N_k P_{Tk}(t) \right) + \text{abs} \left( Q(t) - \sum_{k=1}^{N_{total}} N_k Q_{Tk}(t) \right) + \text{abs} \left( D(t) - \sum_{k=1}^{N_{total}} N_k D_{Tk}(t) \right) \right\} \quad (21)$$

$$\min \left\{ \text{abs} \left( P(t) - \sum_{k=1}^{N_{total}} N_k P_{Tk}(t) \right) + \text{abs} \left( Q(t) - \sum_{k=1}^{N_{total}} N_k Q_{Tk}(t) \right) + \text{abs} \left( D(t) - \sum_{k=1}^{N_{total}} N_k D_{Tk}(t) \right) \right\} \quad (22)$$

where  $P_{Tk}(t)$ ,  $P_{THk}(t)$ ,  $Q_{T1k}(t)$ ,  $Q_{THk}(t)$ ,  $D_{Ik}(t)$ ,  $D_{Vk}(t)$  and  $D_{Hk}(t)$  describe the several power consumptions of the specific type of appliance  $k$  at instant  $t$ .

The decision variables represent the number of active appliances of each type ( $N_k$ ). The constraints ensure that the number of active appliances cannot be negative. A value of zero indicates that the appliance is off, while a non-zero value represents the number of identical appliances that are on.

To address the load disaggregation optimization problem, a genetic algorithm from the Illinois Genetic Algorithms Laboratory [48] was employed. This algorithm determines integer decision variables, each representing the number of identical appliances in the aggregate load. Algorithm 1 outlines the proposed load disaggregation approach. To evaluate the algorithm's ability to identify individual appliances, real-world data were collected using sensors on various appliances. These data formed the basis of an experimental database containing power consumption patterns of common electrical devices. The algorithm analyzes the total power consumption and attempts to disaggregate it into individual appliance loads. Alternatively, electrical models of different appliances from various manufacturers can be used to create a synthetic dataset. This solution is currently under investigation and requires further re-

search to provide a comprehensive comparison and identify potential improvements.

**Algorithm 1.** Main work flow of the proposed identification of appliance disaggregation.

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1: Set  $i = 1$ ;
2: Set the maximum number of each equipment;
3: Take 1st aggregation load;
4: Set  $execution = 1$ ;
5: while  $execution$  do
6:   Apply cost function;
7:   Apply the constraint function;
8:   Apply GA for load disaggregation
9:   if  $i =$  number of aggregation load then
10:    Set  $execution = 0$ ;
11:   else
12:     $i = i + 1$ ;
13:    Take  $i$ th aggregation load;
14:   end if
15: end while

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## 4. Results

The proposed load disaggregation approach was evaluated using a dataset of experimental aggregated and appliance measurements collected from various residences under diverse conditions, including different days and times of day.

### 4.1. Appliance Data

The proposed study considered a variety of common household appliances. For each appliance, a dataset of power consumption measurements was collected. Table 1 lists the specific appliances tested and their corresponding power consumption profiles.

**Table 1.** Appliance power consumption levels.

Appliance Name	Power (VA)	Number
LED Lamp (LED)	10	10
Fluorescent Lamp (Flu)	72	3
Vacuum Cleaner (VC)	1180	1
Washing Machine (WM)	2140	1
Dish Washer (DH)	2120	1
Refrigerator (Ref)	105	1
Toaster (Toa)	703	1
Microwave Oven (MO)	1310	1
Coffee Machine (CM)	1405	1
Oven (Ove)	2550	1
Air Conditioner (AC)	1165	2
TV LCD (LCD)	46	2
Laptop (Lap)	105	3
Mobile Phone (MP)	10	3

The algorithm was applied to each observation aggregation load (OAL) of every aggregated power signal associated with each appliance. This process identified the disaggregated load for each OAL. It is worth noting that appliances with varying power consumption levels during their operating cycle can be effectively modeled as state machines with multiple operational levels. This modeling approach does not impact the overall procedure.

#### 4.2. Performance Metrics

To assess the accuracy of identifying appliance combinations in each OAL, a dataset containing total power loads, corresponding appliance combinations, and their power levels was used. The identification accuracy (denoted as AOAL) for each OAL was calculated as follows:

$$A_{OAL} = \frac{C_{DL}}{T_{AL}} \times 100\% \quad (23)$$

where  $C_{DL}$  is the disaggregation appliances identified correctly and  $T_{AL}$  represents the total aggregated appliances. Further, another performance metric for the whole combination of aggregated power loads was defined as the Overall Mean Accuracy (OMA). This measure is obtained by the ratio between the number of OAL, where the appliances were fully correctly disaggregated loads,  $N_{DL}$ , and the total number of OAL,  $N_{TOAL}$ .

$$OMA = \frac{N_{DL}}{N_{TOAL}} \times 100\% \quad (24)$$

The performance of the proposed methodology under various operating conditions (including grid distortions) and appliance combinations will be evaluated using these two metrics.

#### 4.3. Evaluation

The evaluation process considered three approaches described in the previous section: the classical approach using only active power, Budeanu's power definitions, and Emanuel's power definitions.

Table 2 presents the appliance identification accuracy of the proposed methods for aggregated loads calculated using Equation (23). For instance, the first row of Table 2 shows the results for a combination of eleven active and three inactive appliances. For example, the 78.6% accuracy for Active Power with 14 total appliances indicates that the algorithm correctly identified 11 of the 14 appliance loads. It is important to note that multiple units of the same appliance type can be active within a combination. As shown in Table 2, both Budeanu's and Emanuel's power definitions achieved 100% accuracy for several combinations with varying numbers of active appliances. However, Emanuel's power definition consistently outperformed the others in the remaining scenarios.

**Table 2.** Appliance identification accuracy for the proposed methods.

Actual Turned-on Appliances	$A_{OAL}$		
	Active Power	Budeanu's	Emanuel's
8LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1CM + 1Ove + 1AC + 2Lap + 3MP	78.6%	100%	100%
7LED + 1MO + 1MP + 2Lap + 1Fri + 1Toa + 1Ove + 1AC + 1VC	57.1%	71.4%	100%
1LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1MO + 1CM + 1Ove + 1AC + 2Lap + 1MP	100%	100%	100%
8LED + 1MO + 2Lap + 1LCD + 1Toa + 1DH	50%	100%	100%
3LED + 2Flu + 1DH + 1Toa + 1MO + 2AC + 1LCD + 1Lap + 2MP	71.4%	100%	100%
1LED + 1VC + 1WM + 1DH + 1MO + 1Ove + 2AC + 2LCD + 2Lap	50%	64.2%	78.5%

**Table 2.** *Cont.*

Actual Turned-on Appliances	$A_{OAL}$		
	Active Power	Budeanu's	Emanuel's
4LED + 1MP + 1Ref + 1Toa + 1Ove + 1CM + 1AC	50%	71.4%	78.5%
6LED + 3MP + 3Lap + 1LCD + 2Flu + 1DH + 1MC + 2AC + 1VC	64.2%	50%	64.2%
10LED + 3MP + 1Lap + 1Ref + 1Toa + 1Oven + 2Flu + 1WM + 2AC	50%	50%	71.4%
1MO + 1Flu + 10LED + 1WM + 2AC	35.7%	100%	100%

In addition, the results of the OMA of the appliance disaggregation for all the aggregated load combinations (determined by (24)) can be seen in Table 3. The best OMA was 59.8% for Emanuel's aggregated power, which means that in 100 combinations of aggregate appliances, more than 59 combinations were obtained in which all the appliances were correctly disaggregated. This index also showed that the algorithm with Emanuel's proposal is the one that presents the best results. In the case of the algorithm that only uses the active power, the obtained result clearly showed the weakness of this approach.

**Table 3.** Appliance identification accuracy for the proposed methods.

OMA		
Active Power	Budeanu's	Emanuel's
7.6%	41.3%	59.8%

These results emphasize the significance of considering various power definitions. The use of active power alone resulted in poor appliance disaggregation performance. In contrast, the more comprehensive power definition proposed by Emanuel yielded the best results.

It is important to note that all smart meters are subject to intrinsic errors, particularly in the presence of disruptive loads or power supply networks with high Total Harmonic Distortion (THD). This can impact experimental results. In this study, harmonics up to the 32nd order were considered [60]. Data were collected from various locations to capture different THD levels. While some locations exhibited minimal distortion, most modern power networks are affected by distortions due to the prevalence of electronic and disruptive loads.

The previous results were obtained for a grid voltage with a THD of 1.9%. To assess the impact of increased grid voltage distortion, additional tests were conducted with a THD of approximately 3%. Table 4 presents the appliance identification accuracy for this higher distortion level. As expected, increased voltage distortion negatively affected the performance of all approaches, reducing the accuracy of identifying active appliances. The active power-based approach failed to achieve 100% accuracy in any combination. In contrast, Emanuel's aggregated power approach consistently outperformed the others, achieving 100% accuracy in five combinations.

**Table 4.** Appliance identification accuracy for the proposed methods and for a grid voltage with 3% THD.

Actual Turned-On Appliances	$A_{OAL}$		
	Active Power	Budeanu's	Emanuel's
8LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1CM + 1Ove + 1AC + 2Lap + 3MP	50%	100%	100%
7LED + 1MO + 1MP + 2Lap + 1Fri + 1Toa + 1Ove + 1AC + 1VC	42.8%	64.2%	100%
1LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1MO + 1CM + 1Ove + 1AC + 2Lap + 1MP	100%	100%	100%
8LED + 1MO + 2Lap + 1LCD + 1Toa + 1DH	42.8%	100%	78.5%
3LED + 2Flu + 1DH + 1Toa + 1MO + 2AC + 1LCD + 1Lap + 2MP	50%	71.4%	100%
1LED + 1VC + 1WM + 1DH + 1MO + 1Ove + 2AC + 2LCD + 2Lap	42.8%	50%	50%
4LED + 1MP + 1Ref + 1Toa + 1Ove + 1CM + 1AC	35.7%	64.2%	78.5%
6LED + 3MP + 3Lap + 1LCD + 2Flu + 1DH + 1MC + 2AC + 1VC	42.8%	50%	64.2%
10LED + 3MP + 1Lap + 1Ref + 1Toa + 1Oven + 2Flu + 1WM + 2AC	35.7%	50%	57.1%
1MO + 1Flu + 10LED + 1WM + 2AC	28.5%	78.5%	100%

Regarding the OMA of the appliance disaggregation for all the aggregated load combinations, the obtained results can be seen in Table 5. The best OMA is still the one with Emanuel's aggregated power, with a value 54.3%. So, there was a small decrease in this metric when compared with the previous situation. However, with the algorithms with the active power and Budeanu's proposal, there is a severe reduction, namely from 7.6% to 2.2% and 41.3% to 19.3%.

**Table 5.** Appliance identification accuracy for aggregated power loads and for a grid voltage with 3% THD.

OMA		
Active Power	Budeanu's	Emanuel's
2.2%	19.3%	54.3%

Additional tests were conducted with a higher grid voltage distortion of approximately 3.9%. Table 6 presents the appliance identification accuracy results for the three methods under this condition. As expected, the AOAL metric decreased for all methods. The active power-based method failed to achieve 100% accuracy in any combination, with most accuracies below 50%. Budeanu's power-based method achieved 100% accuracy in only one combination. In contrast, Emanuel's power-based method consistently outperformed the others, demonstrating higher immunity to increased grid voltage distortion.

**Table 6.** Appliance identification accuracy for the proposed methods and for a grid voltage with 3.9% THD.

Actual Turned-On Appliances	$A_{OAL}$		
	Active Power	Budeanu's	Emanuel's
8LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1CM + 1Ove + 1AC + 2Lap + 3MP	35.7%	78.5%	100%
7LED + 1MO + 1MP + 2Lap + 1Fri + 1Toa + 1Ove + 1AC + 1VC	21.4%	64.2%	100%
1LED + 1Flu + 1VC + 1WM + 1DH + 1Toa + 1MO + 1CM + 1Ove + 1AC + 2Lap + 1MP	71.4%	100%	100%
8LED + 1MO + 2Lap + 1LCD + 1Toa + 1DH	28.5%	64.2%	71.4%
3LED + 2Flu + 1DH + 1Toa + 1MO + 2AC + 1LCD + 1Lap + 2MP	28.5%	50%	78.5%
1LED + 1VC + 1WM + 1DH + 1MO + 1Ove + 2AC + 2LCD + 2Lap	28.5%	50%	57.1%
4LED + 1MP + 1Ref + 1Toa + 1Ove + 1CM + 1AC	21.4%	50%	64.2%
6LED + 3MP + 3Lap + 1LCD + 2Flu + 1DH + 1MC + 2AC + 1VC	35.7%	42.8%	57.1%
10LED + 3MP + 1Lap + 1Ref + 1Toa + 1Oven + 2Flu + 1WM + 2AC	28.5%	35.7%	50%
1MO + 1Flu + 10LED + 1WM + 2AC	14.2%	57.1%	100%

Table 7 presents the overall mean accuracy (OMA) for appliance disaggregation across all aggregated load combinations. With the increased voltage distortion, the OMA values decreased for all methods. However, Emanuel's aggregated power method exhibited a relatively small decline, maintaining its superiority. In contrast, the active power-based approach suffered a significant drop, with an OMA value approaching zero.

**Table 7.** Appliance identification accuracy for aggregated power loads and for a grid voltage with 3.9% THD.

OMA		
Active Power	Budeneau's	Emanuel's
0.2%	6.3%	50.2%

## 5. Conclusions

This paper proposes a non-intrusive load monitoring approach based on smart meter measurements, considering power grid distortions. The approach incorporates different power definitions and employs a genetic algorithm to optimize the objective function. Real-world data from various household appliances were used to evaluate the proposed method. Results demonstrate that the choice of power definitions significantly impacts appliance identification accuracy. Additionally, grid distortions adversely affect performance, particularly for classical and Budeanu's power definitions. However, Emanuel's power definition exhibits superior robustness against grid distortions.

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