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Data Driven Disaggregation Method for Electricity Based Energy Consumption for Smart Homes

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Abstract. Sustainable energy systems must be capable of ensuring sustainable development by providing affordable and reliable energy to consumers. Hence, knowledge and understanding of energy consumption in the residential sector are indispensable for energy preservation and energy efficiency which can only be possible with the help of consumer participation. New energy efficiency methods are developed due to the global adoption of smart meters that monitor and communicate residential energy consumption. Moreover, energy monitoring of each appliance is not feasible, as it is a costly solution. Therefore, energy consumption disaggregation is an answer for cost-cutting and energy saving. Contrary to the non-intrusive load monitoring (NILM) approaches, which are based on high-frequency power signals, we propose a data-driven algorithm that requires only a time-series energy meter dataset, a few appliances' data, and energy consumption data from a consumer-based online questionnaire. Afterward, the proposed algorithm disaggregates whole house energy consumption into nine different energy consumption sectors such as lighting, kitchen, cooling, heating, etc. The energy consumption disaggregation algorithm is applied to datasets of 10 homes under experimentation. One of the homes provides us with the knowledge of 96.8% energy consumption, where only 28% knowledge is reported by monitoring plugs and 68% knowledge obtained by unmonitored means. Finally, the energy consumption obtained by the algorithm is compared with actual energy consumption, which shows the excellent functioning of the developed method.

1. Introduction

Major economic expansions, industrialization, and population growth have resulted in escalated energy consumption and environmental deterioration, posing a threat to long-term development [1]. The total energy consumption in the residential sector is approximated to consume 30-40% of the global production [2]. Still, this figure is anticipated to rise further as the use of appliances and electronic devices increases. In addition, it is necessary to have improved real-time monitoring of specific energy sector usage data at home, which may lead to considerable energy savings. One of the essential things in reducing power consumption is recording electrical appliances' consumption at short intervals. If consumers can monitor the power usage of electric devices, this information can be used to optimize the usage pattern to save 5-15 percent of the electricity consumption [3].

Appliances load monitoring (ALM) can help identify malfunctioning and faulty appliances. Such comprehensive information can assist utility and power companies in improving their home's energy demand forecasting, facilitating demand side management, and even allowing them to segment users more precisely. Furthermore, customers frequently underestimate the contribution of each device to their household's total energy usage, thereby misunderstanding the standard efficient energy-saving methods.

Most of the existing literature regarding ALM mainly focuses on the online available datasets-based classification of appliances, called disaggregation. Contrary to other studies, our research provides smart home monitoring systems that provide comprehensive energy consumption feedback services. Moreover, we propose an energy consumption disaggregation based on nine different energy consumption sectors of smart homes under experiments. In particular, an energy consumption disaggregation algorithm is developed that uses two datasets: one is the data based on the questionnaire from consumers of the smart homes, and the other is a physically monitored dataset using a set of sensors. The salient feature of the proposed algorithm are:

i. Energy consumption Knowledge of overall homes based upon monitored appliances.

ii. Energy consumption disaggregated Knowledge of each unmonitored sector defined.

iii. The algorithm is deployed on the platform. That allows consumers to visualize their feedback on energy consumption.

The paper is structured as follows. Section 2 describes the literature review. Section 3 presents the methodology. Section 4 describes the experimental results. Finally, section 5 concludes the paper.

2. Literature Review

Energy monitoring is a fundamental aspect of the energy management system. It is, therefore, necessary to monitor the energy consumption of a building before taking practical initiatives to minimize energy consumption. Numerous studies have been conducted to understand consumers' energy consumption patterns comprehensively. Disaggregation of energy consumption is an optimal technique to gain deep insights into load monitoring. There are mainly two approaches to disaggregate energy consumption: distributed path monitoring and single point monitoring. In the literature, the first load monitoring method is called Intrusive Load Monitoring (ILM), while the other is called Non-intrusive Load Monitoring (NILM). The ILM approach is optimal due to its distributive nature but at a higher cost as the number of measurement devices increases. On the other hand, NILM is sub-optimal, but the infrastructure cost is low.

A framework and collection of algorithms for implementing novel energy efficiency services using smart meters and smartphones are proposed in [4]. The training procedure for appliance signature detection is greatly simplified using smartphones and a state-of-the-art filtering method. The proposed solution achieved a detection rate of 87 percent in a test with eight simultaneous appliances. In another study [5], authors discussed ILM and NILM approaches to energy disaggregation and the need to address security issues for rapid growth and adoption of such systems. In addition, it is claimed that the improvement of such systems may lead to the strong participation of energy consumers in energy-saving campaigns. Moreover, A pilot project for a Smart Homes Energy Management Monitoring System (SHEMS) based on Tridium's Niagara Framework using Fog (Edge) Cloud Computing with Non-Intrusive Appliance Load Monitoring (NIALM) as an IoT application in energy management was developed in [6]. The SHEMS prototype proposed uses an artificial neural network-based NIALM technique to non-invasively monitor relevant electrical appliances without the need for plug-in electricity meters (smart plugs), completing a two-tier NIALM approach. The SHEMS prototype is based on a compact, cognitive, embedded IoT controller that integrates IoT end devices such as sensors and meters and serves as a gateway for demand side management (DSM) in smart homes.

Research in [7] presented that most datasets in the research are appropriate for pattern-based energy disaggregation (ED) techniques that require a lot of data. Subsequently, optimization-based ED methods have been devised that require information about the operating states of the devices. The development of repeatable state-of-the-art optimization-based ED algorithms is limited by the availability of standard datasets and acceptable assessment measures. Therefore, a dataset with several examples that reflect the various issues given by ED is provided. A NILM approach based on '0-1 sparse coding' was used [8] to disaggregate into one specific appliance from total electricity consumption. Data was collected from two households using smart meters, and the data granularity was 5 minutes. The results show that the "0-1 sparse coding" method achieves 44.8% improved disaggregation accuracy compared to the standard sparse coding method. Authors in [9] discovered that there are concerns with load monitoring and management that need to be addressed, such as more accurate recognition and the requirement for a monitoring system that can monitor as many different types of devices as feasible. More work is needed to include NILM in the energy management of appliances. Finally, electricity customers must promote an energy management culture in homes, workplaces, or enterprises. In another study [10], the NILM approach is used for disaggregation based on load signature composed of macroscopic and microscopic features. Then equipment classification was performed using publicly available datasets. Additionally, applications of energy disaggregation such as disaggregated energy calculations, accurate demand forecasting, and appliance anomalies are also presented.

In [11], the semi-supervised learning (SSL) approach is developed using a variety of signals from the unlabelled dataset to simultaneously learn the classification loss for the labeled dataset and the consistency training loss for the unlabelled dataset. The transformation that generates the samples for consistency learning is based on weighted versions of the DTW Barycentre Averaging method. Using data collected from an Internet-of-Things-based energy monitoring system in the context of a smart home, the process is evaluated and shows excellent results. The work in [12] is based on the values of active power as it examines the effectiveness of the load sharing method using the Random forest Automation Energy Dataset (RAE) and Reference Energy Disaggregation Dataset (REDD) databases, which were collected using the Non-Intrusive Load Monitoring (NILM) measurement method. It explained how to assign labels based on the device combinations used, the device status (ON / OFF), and the appropriate temporal data frame selection. It also evaluated the effectiveness of known machine learning algorithms such as random forest, decision tree, and k-nearest neighbor (kNN). For the RAE and REDD databases, the results show that it is a very effective technique with low computational complexity, with an F1 score of over 95%.

It is found in [13] that providing disaggregated feedback leads to a 5% higher conservation effect than the usual (aggregated) input. Energy consumption can decrease the results of the RAE, and REDD databases are mainly responsible for these conservation effects. Consumers with appliance-level data can more accurately estimate how much different energy appliances consume. In addition, it was pointed out that the impact of smart meter roll-out on energy savings is significantly more significant when appliance-level data is available. Based on a suitable statistical method, it is expected that device-level feedback could increase consumer surplus for German households by about 570 to 600 million euros per year. The authors in [16] believed that engaging consumers in demand-side management activities could lead to achieving energy management goals. An algorithm was applied to 14 households with different use cases for load-shifting activities. An algorithm is applied to 14 homes with varying use cases for load-shifting activities. The results of these simulations showed an average decrease in theoretical flexibility of 53% instead of 66%, measured as the proportion of appliance cycles that are shifted compared to complete processes; in a single household, a maximum deviation of 29% is found.

Finally, the monthly average turned energy per dwelling drops by 32.5 percent, from 27 to 18 kWh.

Authors in [17] wanted to find what involvement the Italian residential sector may play in establishing load flexibility for Demand Response activities. A method of estimating the load profile of a housing cluster of 751 units based on experimental and statistical data was proposed. Fourteen housing archetypes were identified, and an algorithm was developed to categorize the sample units. After analyzing possible flexible loads for each archetype, a control technique was developed for implementing load time shifting. This technique considers both the power demand profile and the hourly electricity price. Calculations reveal that a dwelling cluster in the Italian residential sector has an index of the flexibility of 10.3%, as well as efficiency of 34%. Over the heating season (winter)for the weekends,the highest values have been recorded for flexibility purposes. The authors [18] suggested a technique for analyzing and designing production, self-consumption, and storage system that serves a home user aggregate to optimize electric power demand. They achieved Peak Shaving of the electrical demand power curve by limiting the maximum power absorption from the grid and delivering the balance of the user's power demands via an electrical energy storage system charged from the solar plant during the daily overproduction period. The success of the Peak Shaving approach was assessed using a percentage parameter that depicts the number of grid power absorption peaks averted because of the storage system.

3. Methodology

3.1. Smart Homes Platform

The smart homes platform called DHOMUS, an acronym for Data HOMes and USers, was developed by the National Agency for New Technologies, Energy, and Sustainable Economic Development (ENEA). The platform is aimed at residential customers and aims to make them aware of their "energy data" so that they understand how much energy they use and for what purposes. It also aims to help them marginalize electricity consumption and costs, thus reducing the environmental impact and making the residential customer an active subject contributing to the stability of the national electricity grid. The platform can offer services to residential customers that enable better integration between the individual home and the neighborhood in which it is located. The user, whether equipped with smart devices for the energy management of their "smart homes" or a simple consumer, is the lynchpin of this platform. For both, albeit at different levels of detail, the platform can provide feedback and personalized advice for a more conscientious use of energy to curb consumption, costs, and the resulting environmental impact.

3.2. Smart Homes

ENEA has researched the impact of the electricity system on the environment as part of the Electricity System Research project (funded by the Ministry of Economic Development and comprising a range of research and development activities aimed at reducing electricity costs for end users, improving system reliability and quality of service reduce the impact of the electricity system on the environment and health, enable the rational use of energy resources to ensure the country has the conditions for sustainable development) designed a technical model of the smart homes, shown in Figure 1, are equipped with a range of smart devices such as smart plugs, sensors to measure consumption and comfort, and presence in the homes. All these devices are managed wirelessly, so no connection needs to be installed. The data from the sensors is collected, combined, and transmitted to the DHOMUS platform via the Energy Box, an electrical device connected to the internet.

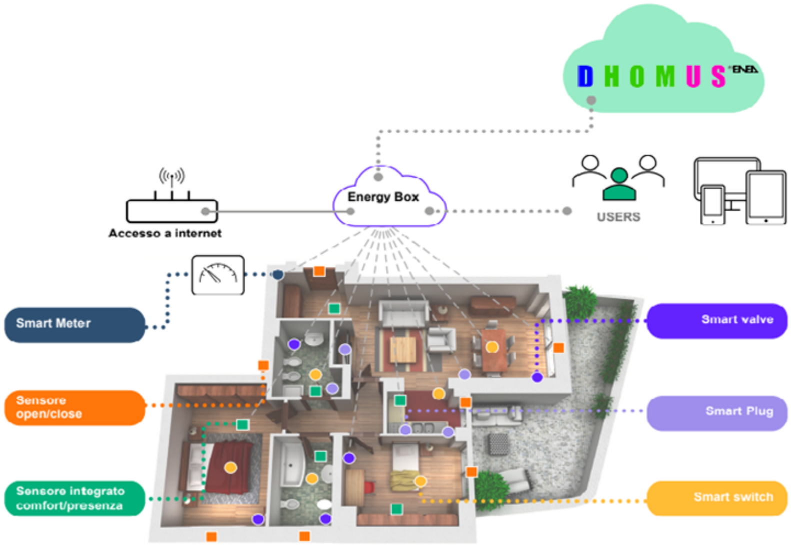

Figure 1: Smart Home
Source [14]

3.3. Data Acquisition Hardware

Table 1 shows the equipment used in the experimental demonstration in Rome. These are commercial sensors provided free of charge to participants in the study. The sensors can communicate via the wireless Z-Wave protocol with the Energy Box (EB), which consists of an Asus Mini PC - PN40 that acts as a gateway for smart homes. This box is made of a PC and is equipped with a USB dongle that acts as an antenna to receive signals from the sensors in the field, with which it communicates via the Z-Wave protocol.

3.4. Data collection

The collected data is stored in the DHOMUS database and then used for data analysis. The dataset contains the energy consumption of smart homes with a data granularity of a quarter of an hour. The data we use contains information from 10 houses representing a particular home as an Energy Box (EB). Also, for the current scenario, we have six months of energy consumption data for (EB1, EB2, EB3, EB4, EB5, EB6, EB9, EB10, EB11, and EB12) for each smart home connected to the DHOMUS platform. However, each EB contains a different number of energy meters, smart plugs, and smart switches. The most important parameters of the data sets can be found in Table2.

Table 3 illustrates the smart homes for experimentation and sensors used for efficiently monitoring the maximum energy consumption.

Table 4 presented the percentage energy meter data collection for six months (June to November 2021) for all smart households. The data presented has a granularity of a quarter of an hour, so for 24 hours, we have 96 observations when the sensors were working and sending 100% of the data correctly. We also counted the number of observations for all months to get some numbers for Table 4. The data collection based on the numbers shows that the collection and recording systems for EB1 worked well in the first four months of the trial compared to the last two months. For EB2, data collection and recording are very poor as the system is switched off for the first three months and hardly works for the next two months, i.e. September and October, but 76% of the data is recorded in November. Subsequently, both the collection and

Table 1: Sensor kits for the experimental demonstration

Sensor	Make/Model	Measured magnitude	Data acquisition interval
Home Energy Meter	Aeotec/ ZW095-C	Instant Power (W)	The data acquisition reporting time according to the technical specification sheet ranges from 30 sec to 300 sec. However, using available parameters, we set the reporting interval to 60 sec for our experimentation
		Accumulated energy (kWh)	The sensor sends a report when it detects a change in Watts of 10%
Smart plug	Aeotec/switch 7	Instant Power (W) .	By default, there are no W thresholds for the sensor to send a report. A report is always sent every 600 seconds. However, in our case, we have set the reporting time to 60 seconds using configuration parameters available in technical specification sheet.
		Accumulated energy (kWh)	By default, there are no accumulated energy thresholds for the sensor to send a report. A report is always sent every 600 seconds. However, in our case, we have set the reporting time to 60 seconds using configuration parameters available in the technical specification sheet.

Table 2: Important Parameters of the Datasets

Parameter	Definition	Units
home id	Energy Box associated with the single house	None
Sensor	Sensor associated with the appliance	None
Timestamp	date in datetime format year-month-day	hour:minutes:seconds
sum of energy of power	power measured by the integrated sensor on the quarter of an hour is therefore energy expressed in Wh	Wh
delta energy	energy detected by the sensor meter remains zero until a consumption threshold dependent on the sensor is exceeded, which can represented as Wh or kWh	Wh or kWh

Table 3: Appliances Information for Smart Homes Under Study

Smart Home	Energy Meter	Dryer	Computer TV	Air conditioner	House lighting	Dishwasher	Washing machine	Water heater and heat pump	Fridge	Coffee machine
EB1	1	1	4	3	1	1	1	1	x	x
EB2	1	1	x	2	x	1	1	1	x	x
EB3	1	x	1	x	x	1	1	x	x	x
EB4	1	x	x	1	x	1	1	x	1	x
EB5	1	x	1	x	x	x	1	x	1	1
EB6	1	1	x	1	x	1	1	x	1	x
EB9	1	1	x	2	x	1	1	1	x	x
EB10	1	x	x	x	x	1	1	x	1	x
EB11	1	x	x	2	x	1	1	x	1	x
EB12	1	x	x	x	x	1	1	x	1	x

collection modules worked better for EB3, even in the month of July when 100% of the energy consumption data was collected. Also, for EB4, 100% data was collected in July and 98% in September, and satisfactory percentages for the other months. Also, for EB5, 100% and 96% of data were recorded in July and August respectively, compared to 67% in June. For EB6, the energy consumption is 0% in July, but 97% in August and September. For EB9, EB11, and EB12, the data for the month of September is 98% and for EB9, the data for the month of August is 97%. Moreover, for EB10, as for EB2, the data collection is very poor and the reason for this type of reading is internet connection problems, so it is better not to consider the data of these houses for the algorithm. Finally, we only consider houses with a good amount of data collected from the smart meter.

Additionally, the involvement of the consumer is made possible by filling Smart Sim questionnaire (SSQ) [15] for their energy uses besides installed sensors. Moreover, SSQ is helpful for knowledge of unmonitored energy consumption when it is not possible to install sensors everywhere in the home.
Overall, 38 different energy consumption devices are identified in the Smart Sim Questionnaire and further subdivided into 9 sectors for better energy consumption disaggregation for unmonitored sectors.

Table 4: Data Collected from Energy Meter

Month	EB1	EB2	EB3	EB4	EB5	EB6	EB9	EB10	EB11	EB12
June	94%	0%	90%	73%	67%	0%	24%	9%	71%	70%
July	98%	0%	100%	100%	100%	56%	100%	26%	73%	56%
August	96%	0%	96%	96%	96%	97%	97%	25%	35%	97%
September	91%	29%	98%	91%	73%	97%	98%	98%	98%	98%
October	84%	37%	84%	84%	84%	84%	22%	84%	35%	83%
November	89%	76%	89%	81%	85%	88%	0%	14%	21%	14%

3.5. Data processing
Our algorithm requires monthly data, while the starting database had quarter-hour data for about three months. For this reason it was necessary to pre-process the data to obtain a

separate CSV file for each month and for each house.
The data collected from the Smart Sim questionnaire (SSQ) were arranged in nine sectors according to the type of appliance. Table 5 presented the detail of each sector.For each month we summed up all the appliances' energy data and put in their specific sector.

Table 5: SS formation from SSQ

Energy Sector	Appliances
Lighting	Interior lighting , Outdoor lighting
EL kitchen	Microwave oven, Oven, Grill, Stove
Refrigeration	Fridge-freezer, Cockpit freezer, other fridge
Cooling	Mechanical ventilation, Fan, Portable dehumidifier, Cooling generator
EL heating	Generator for heating
ACS	ELElectric Domestic Hot Water
[Washing, cleaning, ironing, personal care]	Washing machine, Dryer, Dishwasher, Washer dryer, Vacuum cleaner, Electric broom, Iron without boiler, Iron with boiler, Hairdryer, Hair straightener
Computer/Tv	Desktop computer, Laptop, Modem, Inkjet printer, Laser printer
Other Uses	Heating auxiliaries, Cooling auxiliaries, ACS Production Auxiliaries

3.6. Energy Consumption Disaggregation Algorithm

The main objective of this algorithm is to provide feedback to the consumer about the total energy consumption of the house by monitoring only a few appliances. The proposed smart homes energy consumption breakdown algorithm has been developed to analyse the energy consumption in detail.The flow chart of the proposed algorithm is shown in Figure 2, while the algorithm is shown in Algorithm 1.

Data : SH: is a csv file containing the monthly energy consumption data from the energy metres and smart plugs installed for a specific energy sector. The appliance status is also included in this file if the plug for the specified appliance is present AS =1 otherwise AS =0. For each month we have different SH files. The structure of the file is shown in Table 7. SS: is a csv file containing the data from the Smart Sim questionnaire for all energy sectors of the sampled households. The structure of the file is shown in Table 7.

Equations and Parameters : The energy consumption of nine unmonitored sectors are represented by $S_1, S_2, ...S_9$ and disaggregation can be calculated using all the set of equations employing in algorithm given below:

$$S_1 = SS.Lighting - \sum SH.Lighting \tag{1}$$

$$S_2 = SS_.kitchen - \sum SH.kitchen \tag{2}$$

$$S_3 = SS_.Refrigeration - SH_.Refrigeration \tag{3}$$

$$S_4 = SS.Cooling - \sum SH.Cooling \tag{4}$$

$$S_4' = SS.Cooling \tag{5}$$

$$S_5 = SS.ELheating - \sum SH.heating \tag{6}$$

$$S_5' = SS.ELheating - \sum SH.heating - \sum SH.Cooling \tag{7}$$

$$S_6 = SS.ACSEL - SH.waterheather - SH.heatpump \tag{8}$$

$$S_7 = SS.[Washing, cleaning, ironing, personalcare] - \sum SH.[Washing, cleaning, ironing, personalcare] \tag{9}$$

$$S_8 = SS.Tv/Computer - SH.Tv/Computer \tag{10}$$

$$S_9 = SS.OtherUses = SH.OtherUses \tag{11}$$

Table 6 presents the parameters used in the algorithm for energy disaggregation.

Table 6: Algorithm Parameters

Parameters	Explanation
UN	Unknown Energy
SHME	Monitored Energy
SSUME	Unmonitored Energy information
R	Residue of SS - SH
P_k	Monitoring Plugs

Working of Algorithm : In the first step, the algorithm takes two input files SS and SH, and ensures that the files are from the same month. Then, in the second step, the differences are calculated using a series of equations from 1 to 11 for each of the sectors available in the house. This checks for seasonality, as the months of the year, affect the heating and cooling appliances and their energy consumption. The next, third step is the most important for this algorithm, which initially depends on two factors: the backlog of each unmonitored sector and the status of the appliance. If the backlog for a specific sector is negative, the device status does not contribute much and we set this specific unmonitored sector equal to zero because we have more monitored energy consumption for this specific sector, or we can say that everything is monitored and we could communicate this information to the user as SHME subdivision. Also, in the case where the residue of energy consumption from step two is positive for a specific unmonitored sector, the device status plays an important role in assigning the residue to the disaggregation subdivision UN and SSUME. If all devices are monitored by sensors, e.g. for S1, and the energy consumption reported by SS is higher, which is not possible, we can assign this extra amount of energy to the UN subdivision. If not all devices of sector S1 are monitored, but only a few sensors are available, we can add the extra amount of energy consumption to the subdivision SSUME, i.e. there is a possibility that the extra energy is consumed by other devices of this sector. Finally, step 4 shows the total disaggregation of the house, i.e. the combination of the subdivisions SHME, SSUME, and UN. It can be concluded that with very little information about the monitored energy consumption and with the help of SS it is possible to get a complete knowledge of the energy consumption profile and provide feedback to the consumer. The algorithm is written in Python 3.8 and uses various libraries.

Algorithm 1: Energy Consumption Disaggregation

$Step$ 1:INPUT datasetS[SS,SH]
$Step$ 2:Evaluate Differences SS from SH using equations (1) -(11)
Seasonality Checks [for $S_4 and S'_4, S_5 and S'_5$]
$If month >= 4\ \ \&\ \ month <= 9$
$Use S_4, S_5$
$else$
S'_4, S'_5
$endif$
Step3 : $Disaggregation Allocation \quad to \quad Sectors$
$[SHME, (SSUME, UN]$
$Checks \quad based \quad upon \quad difference \quad from \quad Step2 \quad and \quad AS$
$C1 = R > 0\ \ \&\ \ AS == \forall \mathrm{P}_k : UN \leftarrow R$
$C2 = R > 0\ \ \&\ \ AS == \neg \forall \mathrm{P}_k : SSUME \leftarrow R$
$C3 = R < 0\ \ \&\ \ AS == \forall \mathrm{P}_k : SHME$
$C4 = R < 0\ \ \&\ \ AS == \neg \forall \mathrm{P}_k : SHME$
Step4 : $Output$
$Disaggregation = [SHME + SSUME + UN]$

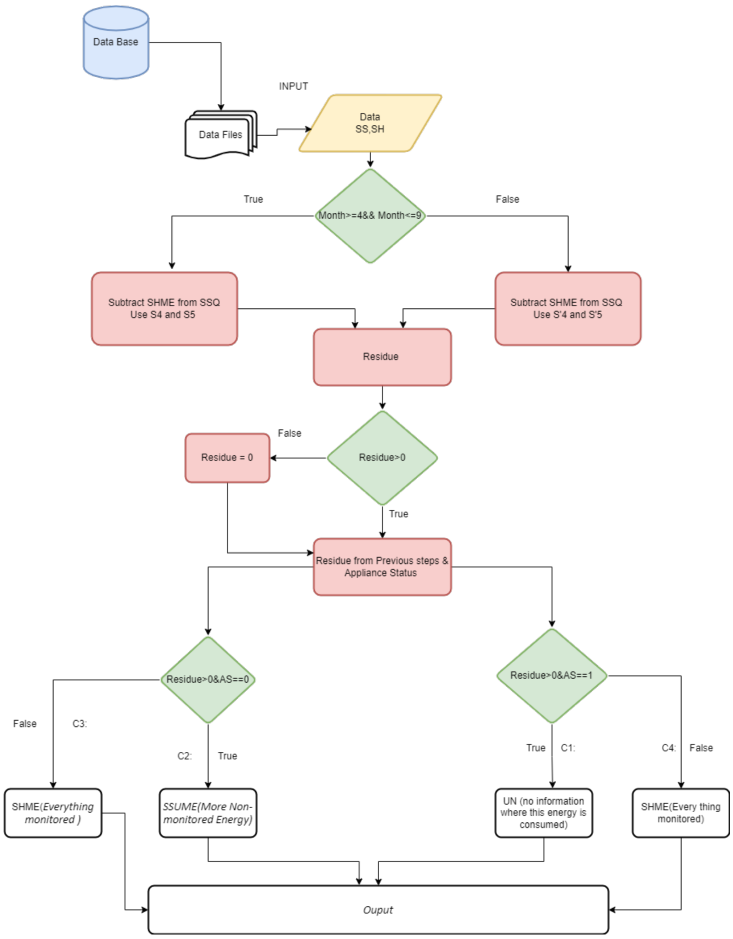

Figure 2: Energy Consumption Desegregation Flow chart

Example Scenario : To evaluate the functioning of the algorithm, an example is presented to explain the disaggregation of energy consumption. The smart house under consideration is equipped with a smart meter that is responsible for measuring the total energy consumption of the house. In addition, three [TV, dishwasher, washing machine] smart sockets are installed in the same house for specific measurements, which are aggregated for a specific energy consumption sector, as mentioned earlier. Furthermore, an important parameter of the disaggregation algorithm is the data provided by the consumer on SS for the same house and for a whole year.

Table 7: EB-3 Summarized Monitored and Unmonitored from dataset

SH	kWh		SS	
Meter	164.34	AS	Enerfy Sector	September
Meter FV	0	0	Lighting	5
Conditioner	0	0	EL kitchen	11
Switch Conditioner	0	0	Refrigeration	12
Dishwasher	9.16	1	Cooling	0
Fridge	0	0	EL heating	0
Fan heater	0	0	ACS EL	0
Coffee machine	0	0	Washing, cleaning, ironing, personal care	73
Vacuum	0	0	Computer / TV	31
Iron	0	0	Other Uses	6
TV	27.48	1		
Thermomix	0	0		
Microwave	0	0		
Washing machine	9.50	1		
Lamp	0	0		
Kitchen	0	0		
Dryer	0	0		
Water heater and heat pump	0	0		
Oven	0	0		

Table 7 illustrates the components from the datasets SH and SS for the month of September, that is stored in CSV files used as algorithm input. In this example, SH displays the energy consumption monitored by three separate plug-in devices. In addition, the device status is an essential algorithm parameter. If a certain device is present during the monitoring period, a 1 is assigned; otherwise, a 0 is assigned. The other data set file comprises the questionnaire data that reveals the energy usage of a certain sector.

The results of our method are shown in Table 8, which contains all of their specifics. In general, three primary components must be accounted for in the output: the first is SHME, which displays the total amount of energy consumed by three distinct appliances across two energy sectors. Both the washing machine and the dishwasher come from the S_7 sector, which is responsible for washing, cleaning, ironing, and personal care. In addition, the amount of energy used by a washing machine is 9.50 kWh, while the energy used by a dishwasher is 9.16 kWh. The remaining information for this sector comes from SSUME, which indicated a total of 69.92 kWh.

Secondly, if there is more than one TV or computer in a given Home, the data must be

Table 8: Energy consumption Disaggregation Monitored and Unmonitored

Final Disaggregation			
SSUME		SHME	
	kWh		kWh
Lighting	6.43	Conditioner	0
EL kitchen	14.15	Switch Conditioner	0
Refrigeration	15.44	Dishwasher	9.16
Cooling	0	Fridge	0
EL heating	0	Fan heater	0
ACS EL	0	Coffee machine	0
Washing, cleaning, ironing, personal care	69.92	Vacuum	0
Computer / TV	0	Iron	0
Other Uses	6.0	TV	27.48
UN	6.0	Thermomix	0
		Microwave	0
		Washing machine	9.50
		Lamp	0
		Kitchen	0
		Dryer	0
		Water heater and heat pump	0
		Oven	0
Total			164.34

combined to show only the total energy consumption of that computer/TV sector. However, in this Home, we only have one TV and it consumes 27.48 kWh of energy. In the SH files, the parameter "AS =1" confirms that this sector is shown with all plugs. So the algorithm showed 0 kWh in SSUME, which means that everything has been monitored.

Additionally, Because there are no plugs available for the other areas of energy consumption, all of the energy that is used must originate from an unmonitored portion of the output. The Refrigeration sector use15.44 kWh of energy, the Lighting sector used 6.43 kWh, and the Kitchen sector used 14.15 kWh of energy. In addition, the cooling and heating sector did not consume any energy as ACS did, and the value of 6 kWh is unknown, which is the same as the value for the other uses sector. Lastly, It can be observed that our algorithm provides us the information about 96.8 % of consumed whereas SSUME provides information on 68% of the energy consumed in the Home. 28% energy presented by SHME subdivision by means of sensors and 4% information comes from UN subdivision

Figure 3 shows a graphical representation of the energy use of EB-3 which further demonstrated SSUME 68% disaggregation sectors in more detail where 4% energy consumed is by the lighting sector. The kitchen sector and refrigeration sector consumed 9% of energy followed by 47% for washing, cleaning, ironing, personal care sector and remaining 3% goes to another use sector.

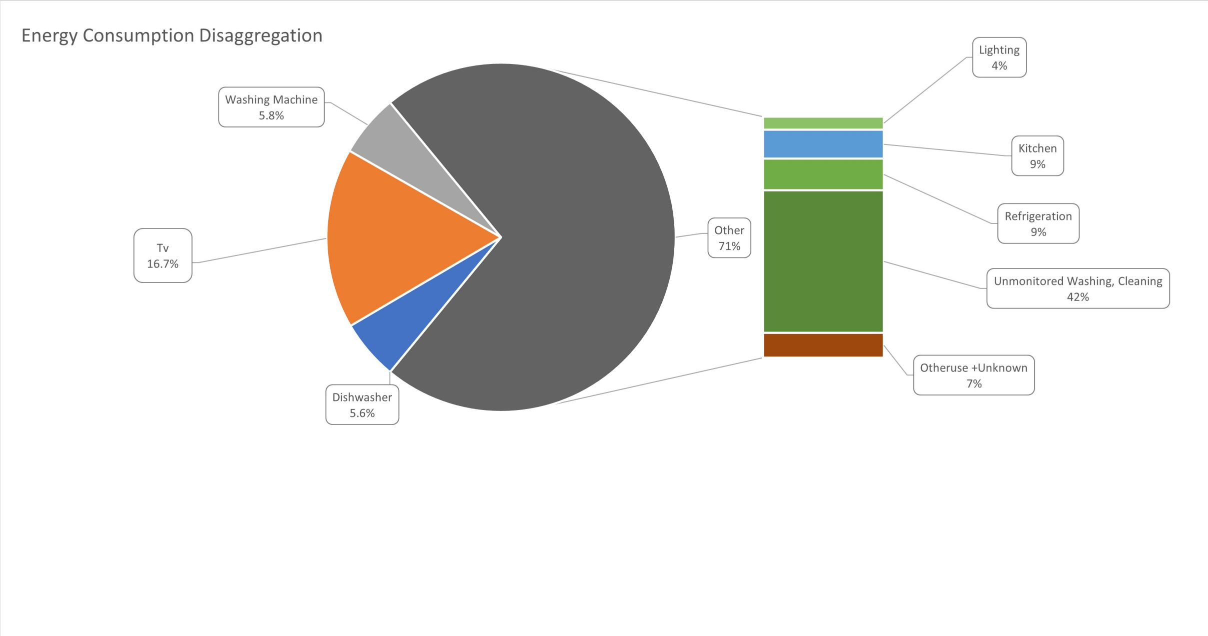

Figure 3: Energy Consumption Desegregation

4. Results

The Algorithm is employed on different Homes for its performance and monthly feedback to the consumer for their energy consumption patterns. However, here in this section, only a few are presented.

Table 9: Energy Consumption Disaggregation EB-3

Energy Sectors	Algorithm Results	Questionnaire Results
Lighting	3.9%	3.6%
EL kitchen	8.6%	8.0%
Refrigeration	9.4%	8.7%
Cooling	0.0%	0.0%
EL heating	0.0%	0.0%
ACS EL	0.0%	0.0%
Washing, cleaning, ironing, personal care	53.9%	52.9%
Computer / TV	16.7%	22.5%
Other Uses	3.7%	4.3%
	monitored	28%
	unmonitored	68.1%
	unknown	3.8%

Table 9 presented the energy consumption disaggregation algorithm output compared with the data acquired by the questionnaire. As discussed in the previous section, this EB-3 is equipped with three plugs beside an energy meter. The Lighting sector of this home consumed

3.9% of overall energy consumption, which have a marginal difference compared to figures provided by the user during the filling of the questionnaire, which is 3.6%. Subsequently, the kitchen appliance reported 8.6% of consumption compared to 8.0% of data from the questionnaire. Furthermore, in the case of the Refrigeration sector, the difference of comparison is 1.1 %, where the algorithm reported consumption of 9.4% of overall consumption. However, cooling, heating, and ACS have 0% consumption for September. The washing, cleaning, ironing, and personal care sector reported 53.9% from the algorithm, whereas 52.9% is extracted from user information. The Computer/Tv sector energy consumption by the algorithm is 16.7% and 22.5% from the questionnaire, but an important factor needs to be discussed. The questionnaire also approximated values, and the gap between these values could be reduced by employing different machine learning models.

The results of the algorithm from Table 9 provide us with phenomenal energy knowledge that we can improve energy knowledge from 28% to approximately 97%.

The output of the Energy consumption disaggregation algorithm compared to the data collected through the questionnaire in Table 10 is presented for EB-12. This EB-12 has three plugs in addition to an energy meter. This home's lighting sector utilized 4.6 percent of total energy usage, a slight variance from the 4.3 percent stated by the user while filling out the questionnaire. Following that, the kitchen appliance indicated 16.1% usage vs 15.2%percent from the questionnaire. Furthermore, 27.44% percent of energy is consumed reported by the refrigeration sector of the algorithm, where the questionnaire results indicated the use of 16.3% of total consumption. Afterward, algorithm results for cooling are 2.3% compared to 2.2%. However, cooling, heating, and ACS all had zero percent usage for this home. There is a big difference between Washing, cleaning, ironing, and the personal care sector. finally, It can be discovered that our algorithm provides us the information about 85 % of consumed whereas unmonitored sectors SS provide information on 44% of the energy consumed in the Home. 41% energy is monitored by means of sensors but we have no information about 15%.

Table 10: Energy Consumption Desegregation EB-12

Energy Sectors	Algorithm Results	Questionnaire Results
Lighting	4.6%	4.3%
EL kitchen	16.1%	15.2%
Refrigeration	27.4%	16.3%
Cooling	2.3%	2.2%
EL heating	0.0%	0.0%
ACS EL	0.0%	0.0%
Washing, cleaning, ironing, personal care	13.4%	40.2%
Computer / TV	19.5%	18.5%
Other Uses	1.6%	3.3%
	monitored	41%
	unmonitored	44%
	unknown	15%

Table 11 presented the Energy consumption disaggregation comparison of home (EB-6) under experimentation with data collected from the consumer of the home. In the energy sector Lighting reported 6.9% consumption by means of the algorithm compared to 7.1% of information provided by the user. Likewise, the kitchen sector consumed 14.1% of the total energy according to our developed algorithm. Moreover, the results of all other sectors can be seen in the table. Lastly, 65% of energy consumption information is provided by the algorithm whereas only 12% of the information comes from sensors which showed the productivity of the algorithm.

Table 11: Energy Consumption Desegregation EB-6

Energy Sectors	Algorithm Results	Questionnaire Results
Lighting	6.9%	7.1%
EL kitchen	14.1%	14.6%
Refrigeration	7.1%	5.0%
Cooling	8.5%	8.8%
EL heating	0.3%	0.0%
ACS EL	0.0%	0.0%
Washing, cleaning, ironing, personal care	4.8%	38.5%
Computer / TV	23.8%	24.7%
Other Uses	1.5%	1.3%
	monitored	12%
	unmonitored	55%
	unknown	33%

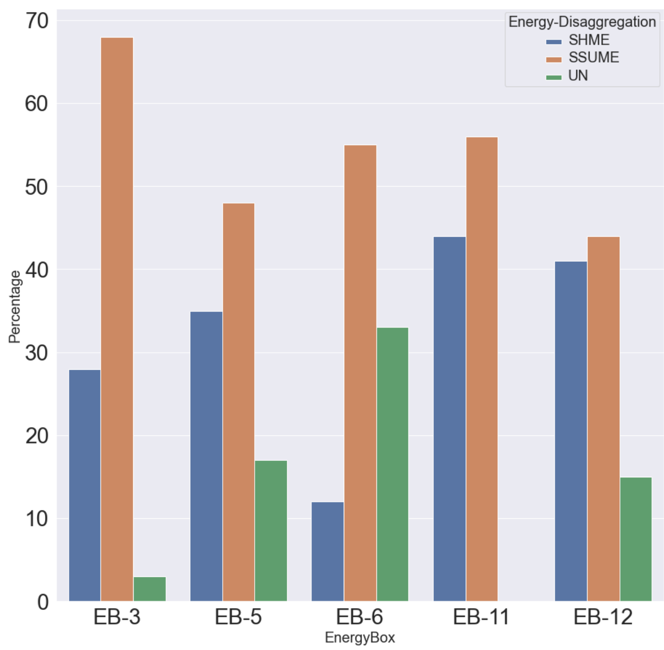

Figure 4: Energy Disaggregation Comparison

The energy disaggregation comparison of five homes is demonstrated in figure 4. Here, it can be seen that EB-6 has the lowest SHME compared to other EB under experimentation, whereas

EB-3 has the highest SSUME and, in the case of EB-11, zero UN. Moreover, the pattern of all the homes is the same less SHME energy consumption and more SSUME, which seconds our motivation that from less SHME to more knowledge of overall energy consumption with the addition of SSUME and the subdivision SSUME is also further disaggregated as already shown as an example in figure 3.

5. Conclusion

This paper proposed an energy consumption disaggregation algorithm based on the ILM approach, which provides an essential service: energy monitoring, energy disaggregation, and feedback for a household. The standout feature of the proposed algorithm is that it allows for energy consumption for various energy utilities of homes with fewer sensors. The dataset used for testing the algorithm is attained from our ongoing project. The comparison with state-of-the-art is impossible due to the non-availability of studies employing such an algorithm, according to our knowledge. The results of three different homes have been presented and compared with consumers' information, showing excellent algorithm performance with slight divergence. The results of the algorithm for EB-3 provide us with phenomenal energy knowledge that we can improve energy knowledge from 28% to approximately 97% compared to four other homes under experimentation. Further work can be done to reduce the unknown sector values. By doing this, energy information will be enhanced, narrowing the energy consumption gap between actual and obtained consumption.

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