Shedding Light on the Energy Usage of Activity Recognition Systems in Homes *

Alicia Montoro Lendínez[1] [0000-0003-0498-605X], José Luis López Ruiz[1] [0000-0003-2583-8638], David Díaz Jiménez[1] [0000-0003-1791-4258], Macarena Espinilla Estévez[1] [0000-0003-1118-7782], and Chris Nugent[2] [0000-0003-0882-7902]

[1] University of Jaén, Department of Computer Science, Jaén, Spain
[2] Ulster University, School of Computing, Belfast, UK.

Abstract. Activity recognition systems are composed of devices with sensors which, through artificial intelligence techniques, can detect activities performed by people in their homes. Many of these systems are deployed in multi-occupancy environments, so indoor localization approaches are combined with activity recognition systems to achieve discrimination of activities in the same space. The benefits of these systems are numerous such as remote monitoring for anomaly warning or improved safety of the monitored person. Although there is an extensive study on these systems from the technical point of view, there is an important gap in the literature on their energy consumption. This fact is even more relevant considering that one of the most important concerns in society is the prices of electricity and it has had a great variability, with increases, due to the pandemic and the war in Ukraine. This work aims to address this scientific gap through the energy evaluation of a home activity recognition system in two scenarios. First, an ambient intelligence apartment (Smart Lab) of the University of Jaén and, then, a single-family house. The evaluation carried out provides quantitative data considering the data of the year 2022, with a price between 3.125€ and 4.018€ and qualitative data from the point of view of patients, healthcare professionals and researchers.

Keywords: Activity recognition systems · Indoor localization · Energy consumption · Remote monitoring · Sustainable Development Goals

1 Introduction

Activity recognition systems make it possible to know the different activities carried out by one or several monitored people in a specific environment [4]. The advantages provided by activity recognition systems are multiple, such as the detection of certain irregularities in the monitored people's activity (falls, lack of control in the schedule of meals or daily hygiene) [10], help to comply with healthy habits (adequate rest time or physical activity) [9], improve the quality

* Grant PID2021-127275OB-I00 funded by MCIN / AEI / 10.13039/501100011033 and by "ERDF A way of making Europe".

of life of people with a certain degree of physical or cognitive dependence [7] and guarantee their safety and the family members' confidence [22].

Within activity recognition, there is special interest in approaches aimed at detecting activities in multi-occupancy environments [19, 13], i.e. in environments where several inhabitants live and it is necessary to discriminate which activity is carried out by which inhabitant. In multi-occupancy contexts, indoor location systems have played a crucial role in recent years [14, 24]. In this way, when an event is generated by a sensor in the home, the person closest to that sensor is located, associating that event with the interaction produced by the inhabitant in the home. Inevitably, combining indoor location systems for multi-occupancy activity recognition systems requires a larger number of devices and thus higher energy consumption. Among the multi-occupancy activity recognition systems, the ACTIVA system [15, 18] is of particular interest, as it has been tested as a suitable system for activity recognition in elderly people's nursing homes in order to monitor their inhabitants. In addition, the ACTIVA system has the ACTIVA app that allows to visualize the activity of each user in real time and to display notifications for the caregivers of the elderly.

In the literature we can find a wide range of multi-occupancy human activity recognition systems, which evaluate various measures of accuracy, multiple algorithms or various types of sensors, among others [6, 20]. However, until now, no study analysing the energy consumption of activity recognition systems can be found in the scientific literature. The study of the energy consumption of this type of system is very important for its democratisation and viability in the future, since energy prices increase is one of the main problems of the citizens in developed countries [12]. Moreover, this fact becomes even more relevant when the population with the greatest energy concerns includes the elderly, the target population of the vast majority of activity recognition systems [3]. In the context of energy consumption, another important factor to take into account is the current variability of energy prices due to the past pandemic, the current crisis in Ukraine and other factors such as the rising cost of gas, the demand and the cost of carbon dioxide emissions[11] and the fulfilment of the 2030 agenda through the Sustainable Development Goals (SDGs). Specifically, the ACTIVA system is fully aligned with SDG7 in energy and SDG3 in health systems [23, 16].

This work aims to shed light on the energy consumption of a multi-occupancy activity recognition system based on indoor location systems. For this purpose, the ACTIVA [15, 18] system is deployed in two multi-occupancy environments. On the one hand, in the ambient intelligence flat of the University of Jaén called UJAmI [8] and, on the other hand, in a single-family house with 4 inhabitants. Smart plugs to measure consumption are placed in the ACTIVA system devices in order to measure their consumption in the two scenarios. Finally, based on the energy cost in Spain in 2022, the maximum and average cost of this system in the two proposed scenarios are determined in order to provide quantitative data on its use.

The structure of the paper is as follows. Section 2 reviews the indoor location-based multi-occupancy activity recognition system called ACTIVA and presents the existing tools on the market to measure energy consumption. In Section 3 the two scenarios where such a system will be deployed are proposed. Then, Section 4 presents the obtained cost of the energy consumption , the material cost and the total cost in the two evaluated scenarios according to the price of electricity in the year 2022. Finally, the conclusions are presented in Section 5.

2 Materials and methods

This section presents the ACTIVA system and the different devices available on the market to measure energy consumption.

2.1 ACTIVA system

The ACTIVA [15, 18] system is characterised by discriminating multi-occupancy activities with a BLE indoor location approach. The activities that will be monitored in the ACTIVA system in the two scenarios will be the following: daily physical activity, taking medication, sleeping and grooming including showering and brushing teeth. The devices which are integrated in the ACTIVA system and which generate the events according to the interactions of the inhabitants in the home are the following:

- Open/close sensor[3]. Installed both on the main door of the house to know the entrances and exits of the monitored inhabitant and on a box for medicines in order to know the intake of medicines by the monitored inhabitant. It is powered by a CR1632 battery, lasts approximately 1 year and its cost per battery unit is 0.57cts.
- Motion sensor [4]. Installed both in the headboard of the bed to know the time of rest of the monitored inhabitant and in the bathroom focused on toothbrushes to know the daily cleanliness of the monitored inhabitant. It is powered by two CR2450 batteries, lasts approximately 5 years and i its cost per battery unit is 0.90cts.
- Temperature, humidity and pressure sensor [5]. Installed in the bathroom near the shower area to know when the monitored inhabitant showers. It is powered by a CR2032 battery, lasts approximately 2 years and its cost per battery unit is 0.93cts.

In multi-occupancy environments it is necessary to associate each event with the inhabitant who has carried out the interaction that generates the event. For this reason, the ACTIVA system incorporates a location system through RSSI values of the BLE protocol. For this purpose, each inhabitant wears an activity wristband[6] and several Raspberry Pi 4B devices, as BLE beacons, are playing the role of anchor. These Raspberry Pi anchor are distributed in the rooms where

[3] https://www.aqara.com/eu/door_and_window_sensor.html
[4] https://www.aqara.com/eu/product/motion-sensor-p1
[5] https://www.aqara.com/eu/temperature_humidity_sensor.html
[6] https://www.mediamarkt.es/es/product/_pulsera-de-actividad-xiaomi-mi-band-3-oled-puls%C3%B3metro-sensor-frecuencia-card%C3%ADaca-negro-1434035.html

you want to locate the inhabitant and thanks to the BLE takes the RSSI values of the wristband every second. Additionally, one of the BLE anchors plays the role of a central node and is responsible for receiving the events generated by the sensors and the RSSI flows from each of the anchors. This central node is responsible for sending all the information to a server in the cloud which infers in real time, on the one hand, the location of each inhabitant and, on the other hand, the activities under study according to the events generated. In addition, the storage, persistence and visualisation of the data received and the knowledge inferred is carried out on the central server.

Since the purpose of this paper is focused on the energy consumption of the devices of the indoor location-based multi-occupancy activity recognition system, the artificial intelligence-based methods for knowledge inference, which are based on the location proposal of the authors López-Medina et al.[14] and Albín-Rodríguez et al. [2], are not described in detail.

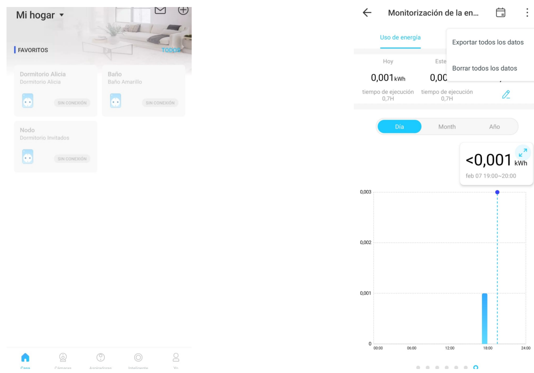
2.2 Measuring energy consumption

This section reviews alternatives for measuring home energy consumption, which are listed below.

- Energy consumption meters. These are devices which are simply plugged into a plug or household appliance and measure their consumption in real time. Normally, they have a screen from which the different variables measured can be displayed. Some examples that can be found on the market Belkin Converse Insight [7] or Kill A Watt [8].
- Smart energy meters. These are more advanced devices than the previous ones. They are connected to the electricity grid and measure energy consumption in real time and, in addition, all the information can be viewed from a website or app. In this way the user can take measures to reduce consumption. Several examples are compared in [1] that try to control the whole home and with artificial intelligence give measures on the user's behaviour to reduce energy consumption in the home. Another example is the smart plugs that have been used in this work Tapo P100[9].
- Energy audits. These are assessments of energy consumption in certain environments. The assessment is carried out by a professional who helps to identify areas where energy consumption can be reduced and what actions can be taken to do so [21].

As mentioned above, the tool for measuring energy consumption in this case study was smart plugs. Specifically, Tapo P100[10] smart plugs have been chosen as they allowed us to visualise the data in real time from the commercial application and to export the data in .csv format for analysis. Fig 1a shows the start screen of the application with the current devices in operation and Fig 1b shows the monitoring of the hourly energy consumption of one of the smart plugs. It should

[7] https://www.belkin.com/uk/support-article/?articleNum=5381
[8] http://www.p3international.com/products/p4460.html
[9] https://www.tapo.com/es/product/smart-plug/tapo-p100/
[10] https://www.tapo.com/es/product/smart-plug/tapo-p100/



(a) Home page (b) Hourly consumption graph

Fig. 1: Tapo app visualisation.

be taken into account that a smart plug was installed at each node and anchor, on the other hand, the sensors have a very low power consumption and are powered externally by button type batteries, so measuring their consumption is not the cost of the inhabitants.

3 Evaluated scenarios

This section presents the two scenarios and their characteristics. In both scenarios, the multiple devices of the ACTIVA system will be installed.

3.1 Smart Lab

The Smart Lab has a total surface area of $25.44m^2$ which is divided into a small hall, a kitchen, a living room with an office and a bedroom with a bathroom inside.

Fig. 2: Layout of the Smart Lab with the distribution of the devices.

In Fig. 2 shows the layout of the Smart Lab of the UJA [8] together with the different devices that have been installed, which are listed below: central node (red), living room anchor (blue), kitchen anchor (blue), bedroom/bathroom anchor (blue colour), motion sensor for brushing (green), motion sensor for resting (purple), temperature, humidity and pressure sensor for the bathroom (yellow), open/close sensor for the medication box (pink) and open/close sensor for the main door (black).

In particular, the central node and the kitchen and living room anchors were fitted with a cooling system. This cooling system includes fan and heatsink. Only, the fan was not installed in the bedroom/bathroom anchor to avoid disturbance and interruption of the inhabitant's rest. The anchors or nodes that include this complete cooling system will have an increase in energy consumption depending on the time the fan is active. Although all fans have been programmed to only turn on if the temperature of the CPU of the Raspberry Pi 4B exceeds 70ºC and turn off when the temperature of the CPU is below 60ºC [17, 5], preventing the fan has an unnecessary and excessive consumption.

3.2 Single-family house

The single-family house consists of two floors. The ground floor has a surface area of $120m^2$ and consists of a small hall, a living room, a toilet, a kitchen with utility room and an outside terrace (refer to Fig. 3).

Fig. 3: Ground floor plan of the single-family house with the distribution of the devices.

The first floor has a surface area of $97m^2$ and comprises three single bedrooms, a bathroom and a double bedroom with its own small bathroom (see Fig. 4). Although four people live in the single-family house, only two will be monitored as in the Smart Lab. Also, in Fig. 3 and Fig. 4 it can be shown the different devices that have been installed in both floors.

The ground floor hosts the central node (red), the living room anchor (blue), the kitchen anchor (blue), open/close sensor for the medication box (pink) and open/close sensor for the main door (black). On the first floor there is the bedroom anchor (blue), the bathroom anchor (blue), the motion sensor for brushing (green), the motion sensor for resting (purple) and the temperature, humidity and pressure sensor for the bathroom (yellow). As with the Smart Lab, the fan has not been installed in the bedroom anchor.

Fig. 4: First floor plan of the single-family house with the distribution of the devices.

4 Results

This section presents the cost results for energy consumption cost, material cost and total cost.

4.1 Energy consumption cost

To obtain energy cost data, the data on the average price per €/kWh was obtained from the TarifaLuzHora[11] website. This website publishes data on the Spanish electricity grid with prices referring to the regulated market and on this data the most expensive day, the most expensive week and the most expensive month could be obtained. Fig.5 shows the history over 2022 of the average monthly price of €/kWh obtained from this website.

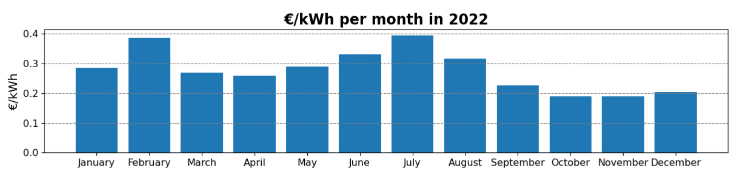


Fig. 5: Average historical data €/kWh in 2022.

Table 1 shows the quantitative consumption data for each device of the ACTIVA System in the Smart Lab scenario and Table 2 for the single-family house scenario.

The first column of Table1 and Table2 shows the devices displayed, the second column shows whether the fan is installed and the third column shows the average daily energy consumption in kWh for each device. To obtain it, the total energy consumption obtained during the experiment according to each anchor or sink is divided by the 21 days of the experiment and the following results are obtained. Then, in the following columns, the energy consumption for the most expensive day of 2022, the most expensive week of 2022 and the most expensive month of 2022 are presented in three sections. For these three cases, the price per kWh

[11] https://tarifaluzhora.es

Table 1: Dialy, weekly, monthly energy consumption from Smart Lab.

Device	With fan	Daily energy consumption (kWh)	Most expensive day in 2022 "8/03/2022"		Most expensive week in 2022 "7/03/2022-13/03/2022"		Most expensive month in 2022 "August"	
			Price for this day (€/kWh)	Total (€)	Price for this week (€/kWh)	Total (€)	Price for this month (€/kWh)	Total (€)
Kitchen Anchor	Yes	1.2915/21 = 0.0615	0.71533	0.044	3.4823	0.214	12.25216	0.754
Living Room Anchor	Yes	1.2915/21 = 0.0615	0.71533	0.044	3.4823	0.214	12.25216	0.754
Bedroom/Bathroom Anchor	No	1.2705/21 = 0.0605	0.71533	0.043	3.4823	0.211	12.25216	0.741
Sink	Yes	1.5015/21 = 0.0715	0.71533	0.051	3.4823	0.249	12.25216	0.876
			Total for the most expensive day in 2022 (€): 0.182		**Total for the most expensive week in 2022 (€): 0.931**		**Total for the most expensive month in 2022 (€): 3.125**	

in €/kWh and the total price per device in €/kWh are shown in two separate columns. And finally, at the bottom, the total price of the entire system with all devices is presented in €.

Table 2: Dialy, weekly, monthly energy consumption from single-family house.

Device	With fan	Daily energy consumption (kWh)	Most expensive day in 2022 "8/03/2022"		Most expensive week in 2022 "7/03/2022-13/03/2022"		Most expensive month in 2022 "August"	
			Daily price (€/kWh)	Total (€)	Weekly price (€/kWh)	Total (€)	Monthly price (€/kWh)	Total (€)
Kitchen Anchor	Yes	1.3608/21 = 0.0648	0.71533	0.046	3.4823	0.226	12.25216	0.793
Living Room Anchor	Yes	1.3608/21 = 0.0648	0.71533	0.046	3.4823	0.226	12.25216	0.793
Bedroom Anchor	No	1.3398/21 = 0.0638	0.71533	0,046	3.4823	0.222	12.25216	0.782
Bathroom Anchor	Yes	1.4406/21 = 0.0686	0.71533	0.049	3.4823	0.24	12.25216	0.84
Sink	Yes	1.3818/21 = 0.0658	0.71533	0.047	3.4823	0.23	12.25216	0.81
			Total for the most expensive day in 2022 (€): 0.234		**Total for the most expensive week in 2022 (€): 1.144**		**Total for the most expensive month in 2022 (€): 4.018**	

It is clear that the daily consumption (expressed in kWh) of the devices installed in the Smart Lab and in the single-family house are different. The main determining factors for these results to be different are as follows:

– The cooling system. Not all devices have the active cooling system (fan) installed. For example, in the case of the bedroom anchor, the fan is not installed so as not to interrupt the user's rest although the use of the fan avoids any overheating of the devices and possible breakage. The central node and the anchors that do have a fan will have a higher energy consumption depending on the operating time of the fan.

– Ambient temperature and ventilation. The Smart Lab is a study scenario where the temperature is kept lower and more stable (above 19ºC) while in the single-family house, depending on the room, there will be different temperatures. For example, the room with the highest temperature (above

25ºC) and the lowest ventilation is the bathroom. Therefore, the fan of this device installed in the bathroom has to work harder and therefore the energy consumption is higher.
- The data flow. While the anchors are simply responsible for obtaining the RSSI value to obtain the location of the inhabitant, the central node is responsible for receiving the data obtained by the anchors and the different sensors installed and sending all the information to the server in the cloud. Consequently, the central node carries out a greater processing of the information and this greater work on the CPU affects energy consumption, which is higher in the central node.

Having examined the different constraints affecting the energy consumption of the various devices, some of the results obtained are specifically discussed.

In the Smart Lab results, a scenario with ideal conditions, it can be seen that the consumption is higher in the central node (*0.0715kWh*) than in the anchors. This is due to the fact that the data processing and CPU work in the central node is higher and, also, the fan has to work harder. Among the anchors, the one that consumed the least was the bedroom/bathroom (*0.0605 kWh*) due to not having the fan installed. Thus, the system made up of one node and three Smart Lab anchors has a consumption price of *3.125€* per month, considering the most expensive month of 2022.

On the other hand, to analyse the results of the single-family house, which is the scenario without ideal conditions, the different temperatures of the rooms must be taken into account. This will cause the fan to work more or less and therefore the devices will consume more or less energy.The kitchen, bedroom, corridor and living room have a temperature of *19ºC* and the bathroom has a temperature of *25ºC*. In the rooms at *19ºC*, the consumption of the anchors is *0.0648kWh* and the consumption of the central node is *0.0658kWh*. However, on this occasion the central node does not have the highest consumption because in the bathroom room there is an anchor that consumes more, *0.0686kWh*. Again, it is the bedroom anchor, without the fan installed, that consumes the least of all the devices deployed, (*0.0638kWh*). So the system consisting of one node and four anchors in the single-family house has a consumption price of *4.018€* per month, considering the most expensive month of 2022.

Energy consumption cost survey In order to ensure economic viability in relation to energy consumption, a survey was carried out among different profiles with different points of view, such as 10 researchers (4 men and 4 women between 25-30 years, 1 woman between 30-40 years and 1 man between 40-50 years) , 6 health professionals (2 men between 30-40 years, 2 men and 1 woman between 40-50 years and 1 man between 50-60 years) and 10 users as elderly people (2 men and 1 woman between 60-65 years, 1 man and 1 woman between 65-70 years and 3 men and 2 women between 70-75 years). The survey's questions was: "Do you consider it appropriate to pay a monthly fee of 4€ as part of the electricity costs associated with the installation of the ACTIVA system in your home? A Likert scale survey was used to collect their opinions on this question, and examples of energy consumption were provided, e.g. the monthly consumption of a 22kWh television is equivalent to 275.48€ in August 2022". The results of this survey are presented in Fig. 6, where it can be seen that the three profiles are in greater percentage in agreement with this fee. Specifically, researchers 69%, health professionals 75% and users 60%.

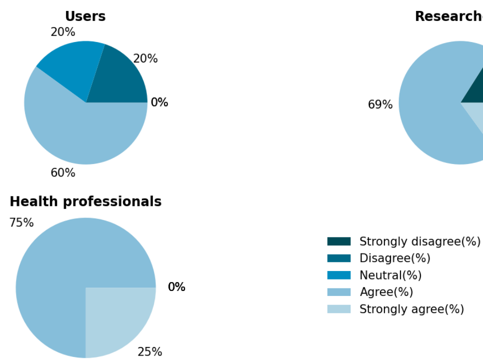


Fig. 6: Results from the energy consumption cost survey

4.2 Material cost.

The material cost of the system will depend on the deployment of devices and sensors. Table 3 presents the material cost in the Smart Lab and in the single-family house.

Table 3: Material cost in Smart Lab and single-family house scenario.

Material	Price per unit (€)	Units in Smart Lab scenario	Units in single-family house scenario
Raspberry Pi Kit	130.65	4	5
Motion sensor + CR2032 batteries	28.99	2	2
Open/Close sensor + CR1632 batteries	19.99	2	2
Temperature, humidity and pressure sensor + CR2450 batteries	22.99	1	1
Conbee II	30.46	1	1
Bluetooth USB	12.99	4	5
Wristband Xiaomi Mi Band 3	55.43	1	1
		Total : 781.4€	**Total: 925.04€**

5 Conclusions and future lines

Up to the present, there are no proposals in the literature that provide quantitative data on the energy cost of activity recognition systems based on indoor location system. This paper has described two scenarios to calculate the energy cost of the ACTIVA system: the Smart Lab of the University of Jaén (UJAmI) and a single-family house. For both scenarios, quantitative data has been obtained regarding energy consumption taking into account historical data on the cost of energy during the year 2022 (most expensive day, most expensive week and most expensive month of 2022). Subsequently, the analysis concluded that the active cooling system (fan) and the ambient temperature of the rooms chosen for the installation of the devices have a strong influence on consumption. Therefore, in the Smart Lab, being a scenario with more favourable conditions, the energy consumption data obtained are lower than in the single-family house. However, for both scenarios, the energy consumption prices obtained are affordable and economic, ranging between *3.125€* and *4.018€* per month, considering the most expensive month of 2022. In addition, a calculation of the material cost of the ACTIVA system in the two scenarios was also carried out.

Finally, it is important to note that the study developed in this work in two scenarios (Smart Lab and single-family house) is only an initial pilot. However, this initial pilot aims to shed light on a new line of research such as energy consumption studies in smart systems based on location and recognition of daily life activities. This type of energy consumption studies could be carried out in different scenarios and with different people monitoring projects in order to align these smart systems with the sustainable development goals of the 2030 agenda.

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