TESIS DOCTORAL

NUEVAS TECNOLOGÍAS PARA LA MEJORA DE LA EFICIENCIA ENERGÉTICA APLICADAS AL CONTEXTO DEL HOGAR DIGITAL Y LA SMART GRID

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Presentada por **María Rodríguez Fernández** para optar al grado de doctora por la Universidad de Valladolid

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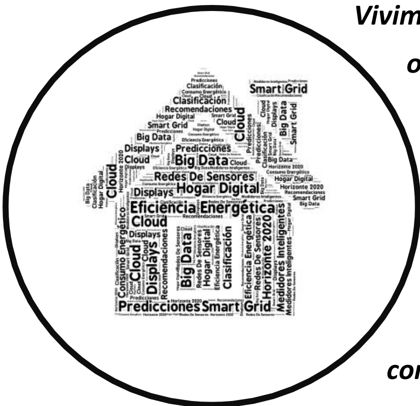

Vivimos en la tierra como si tuviéramos otra a la que ir.-Terry Swearingen.

¿Cuál es el uso de una buena casa si no tienes un planeta tolerable en el que ponerla?-Henry David Thoreau.

El uso apropiado de la ciencia no es conquistar la naturaleza, sino vivir en ella.-Barry Commoner.

P r e f a c i o

Esta tesis es el resultado de la labor investigadora comenzada en 2005, año en el que comencé mis estudios de doctorado. Tras varios años interesada en el estudio de las interfaces de usuario y el aprendizaje automático, pero más dedicada a la docencia, tuve la oportunidad de formar parte de un proyecto que podría contribuir de alguna manera con la sociedad actual y el planeta, enfocando así dichas inquietudes a la mejora de la eficiencia energética, y ahí me vi embarcada en la aventura que aquí se presenta.

En los últimos tres años me he estado moviendo entre la motivación y la desesperación, y al final ese mismo movimiento me ha llevado al final de este viaje, aunque en realidad sólo es una parada en el camino, queda mucho por viajar.

Los que formamos parte de mi generación hemos visto cómo en los últimos años la tecnología ha evolucionado de una forma vertiginosa. Conocimos la vida sin Internet, y ahora vemos como nos rodea de una forma cada vez más ubicua. Sin darnos apenas cuenta, la mayoría hemos pasado a tener como mínimo un dispositivo electrónico del que no nos separamos y desde el que cada vez controlamos más cosas. Pero al mismo tiempo, cada vez somos más conscientes de que si se tira mucho la cuerda se rompe.

Como Ingeniera Informática, me fascina haber podido vivir en la que es seguramente una era clave en la evolución de la sociedad. Como investigadora, creo en el potencial que esto puede tener si sabemos sacarle partido. Como profesora consciente de la responsabilidad de formar a la siguiente generación, me aterroriza pensar cómo la tecnología en manos no adecuadas puede volverse contra nosotros. Como persona, no quiero quedarme parada, viendo cómo esto se nos va de las manos. Como madre quiero dejarle un buen legado a mis hijos.

A g r a d e c i m i e n t o s

Gracias a Javi por ser mi compañero y mi gran apoyo. Son muchos los monólogos monotemáticos que has tenido que escuchar.

A Diego, que llegó en medio de la vorágine a hacer mi vida completamente feliz y se amoldó a este ritmo de trabajo, tanto que ahora ya no hay quien lo pare.

A mis padres, por inculcarme el amor por el estudio, y el afán de superación, sin ellos nada habría sido posible.

Por último, quiero agradecer al Dr. Eduardo Zalama su confianza ciega en mí, siguiendo este trabajo desde la distancia y guiándome cuando no sabía qué camino tomar.

Tabla de Contenidos

Capítulo I:

Introducción

1. Tesis como compendio de trabajos previamente publicados

La presente tesis doctoral se presenta como un **compendio de tres trabajos** publicados en revistas científicas con **factor de impacto**, siguiendo la normativa aprobada por Consejo de Gobierno de la Universidad de Valladolid de 29 de noviembre de 2012 *(BOCyL nº 243, de 19 de diciembre).*

Las referencias completas de los artículos que constituyen el cuerpo de la tesis son las siguientes:

I. M. R. Fernández, A. C. García, I. G. Alonso, and E. Z. Casanova, "***Using the Big Data generated by the Smart Home to improve energy efficiency management***," *Energy Effic.*, pp. 1–12, Jun. 2015.

II. M. R. Fernández, I. G. Alonso, and E. Z. Casanova, "***Online identification of appliances from power consumption data collected by smart meters***," *Pattern Anal. Appl.*, pp. 1–11, Jun. 2015.

III. M. R. Fernández, E. Z. Casanova, and I. G. Alonso, "***Review of Display Technologies Focusing on Power Consumption***," *Sustainability*, vol. 7, no. 8, pp. 10854–10875, 2015.

Los tres artículos originales se recogen en el capítulo 2 de este documento.

2. Introducción general

En la **Unión Europea**, el consumo energético ha ido tradicionalmente ligado al crecimiento económico pero actualmente, aunque la energía sigue impulsando a la sociedad y la economía, el crecimiento futuro debería realizarse con menos energía y menos costes.

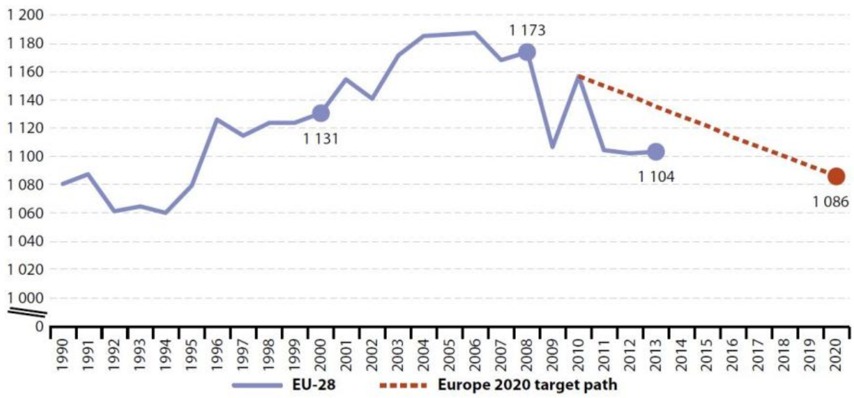

Figura 1: Consumo energético final, EU-28, 1990–2013 (equivalencia en millones de toneladas de petróleo) – Fuente: *Eurostat* (código online tsdpc320)

Es por ello que, aunque en los últimos diez años – tal y como refleja la **Figura 1** – se han llevado a cabo numerosas medidas efectivas para paliar esta tendencia incremental en el consumo, como por ejemplo, la introducción de los certificados de eficiencia energética en los edificios, uno de los principales objetivos de la sociedad actual sigue siendo alcanzar un uso más eficiente de la energía. La **Comisión Europea**, en su marco estratégico en materia de clima y energía para el año 2020 [1] propone el objetivo prioritario para la eficiencia energética de ahorrar energía en un 20% , y aquí se establece el punto de partida de este trabajo.

La propia Comisión Europea establece que reducir el consumo en los edificios es un aspecto clave para alcanzar el objetivo propuesto. Son, de hecho, el campo con mayor potencial de ahorro de energía ya que representan el 44% del consumo de energía final de la Unión Europea.

Hasta ahora, las principales medidas se han basado en reducir el gasto de generación de la energía, fomentando el uso de fuentes de energía renovables o la fabricación de dispositivos de bajo consumo, pero las últimas tendencias dejan paso a una gestión del lado de la demanda, que en este nuevo escenario pasa a ser una parte activa. En la última década ha habido notables avances en este terreno, afianzándose el concepto de Hogar Digital y Smart Grid (también denominada red inteligente, aunque de forma menos extendida) [2].

Un **Hogar Digital** se puede definir como un sistema complejo que integra tecnología y servicios para mejorar la calidad de vida de sus habitantes, prestando especial atención a un uso eficiente de los recursos. La complejidad del sistema reside principalmente en el creciente número de elementos de consumo (desde electrodomésticos inteligentes, a vehículos eléctricos pasando por robots de servicios), que conviven con los elementos eléctricos tradicionales, a la vez que el número de fuentes de energía también es cada vez más variable (renovables, etc.). Además, este sistema se ve influenciado por muchas fuentes de incertidumbre, como la temperatura exterior o el comportamiento de los habitantes. Por su lado, el término ***Smart Grid*** se utiliza para referirse a las redes de distribución eléctricas "inteligentes", donde la electricidad puede ser bidireccional, permitiendo a las viviendas convertirse también en pequeños productores de electricidad y no solo consumidores [2].

El diseño y desarrollo de sistemas de gestión de la energía en los hogares tiene como principal requisito incluir la capacidad de predecir parámetros como la temperatura o la demanda de energía, para poder indicar al usuario cómo ha de consumir. En este contexto, cada vez está más extendido el uso de medidores inteligentes y redes de sensores, que permiten obtener gran cantidad de información de los edificios donde están instalados, como el consumo eléctrico de los electrodomésticos, la temperatura, o el grado de humedad ambiental [3]. Esta información se obtiene en tiempo real, generando millones de bytes de datos, que pueden ser usados como retroalimentación por el usuario para adaptar su comportamiento y aumentar el ahorro [4].

La idea clave es que los datos de consumo por sí mismos no tienen más valor que el dato en sí mismo. La aplicación de procesos de aprendizaje automático sobre dichos datos permitirá obtener diversa información relacionada con el usuario, como por ejemplo sus hábitos de consumo, y usarla para mejorar la eficiencia energética.

Por otra parte, el aumento en el consumo se debe también en gran medida debido a que el número de dispositivos eléctricos por persona crece cada año, como se puede ver en la **Figura 2**.

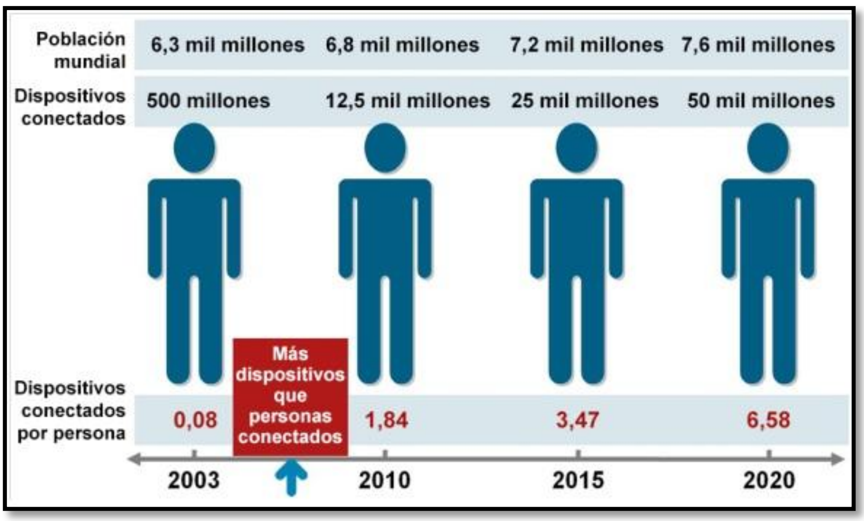

Figura 2: Número de dispositivos por persona – Fuente: *Cisco IBSG* (Abril 2011)

Por tanto, otra forma de fomentar la eficiencia energética es hacer que los componentes electrónicos consuman menos. Dejando aparte las razones medioambientales, esta reducción en el consumo es clave para los fabricantes de dispositivos eléctricos, especialmente aquellos con autonomía limitada. En concreto, uno de los elementos que más influencia suele tener sobre este consumo es el *display* [5] [6].

Tradicionalmente, la reducción del consumo de este elemento se hacía apagándolo durante los períodos de inactividad [7]. También existen estudios que demuestran que un adecuado diseño de la interfaz puede reducir el consumo [8]. Pero recientes estudios de mercado muestran que las últimas tendencias pasan por mejorar la tecnología de fabricación, para que el apartado sea por sí mismo más eficiente energéticamente [9].

3. Objetivos perseguidos

A partir de las ideas del apartado anterior, surgen unos objetivos que se pueden agrupar en dos líneas de investigación que, aunque independientes, están cobijadas bajo el mismo techo de la tecnología al servicio de la eficiencia energética:

Aplicación de técnicas de aprendizaje automático sobre los datos extraídos del Hogar Digital.

El objetivo general es *lograr aprender de los datos que se pueden obtener del hogar, como el consumo o la temperatura, extrayendo de ellos información que de alguna manera se pueda aplicar para la mejora de la eficiencia energética*.

Para lograrlo es necesario descomponer el objetivo en los siguientes:

- Recolectar **datos del hogar** (consumo, temperatura, etc.) con una infraestructura mínima, deseablemente no dependiente de ninguna marca ni producto concreto.

  Además esta infraestructura ha de ser escalable, permitiendo almacenar, procesar y manipular los datos en un tiempo de repuesta aceptable, teniendo en cuenta que la información a obtener en cada hogar puede aumentar, así como el número de hogares adoptando esta solución.

- Aplicar **técnicas de aprendizaje automático** para extraer patrones de consumo que permitan realizar predicciones fiables.

  Un **sistema de predicción** puede aprender patrones de consumo y hábitos de vida del usuario y ayudarle a adaptar sus actividades para alcanzar hábitos más responsables con el medio ambiente, contribuyendo así a un uso más eficiente de la energía.

Además de ahorrar en energía, el sistema puede ayudar a detectar un uso fraudulento de la misma. Por ejemplo, en zonas comunitarias, se pueden aplicar patrones para relacionar cuánto, cómo y cuándo se consume, permitiendo detectar usos no adecuados de las instalaciones comunes.

Por otra parte, conocer el patrón de consumo de cada hora en cada casa permitirá una mejor distribución de la energía.

Además, partiendo de la idea de que el mismo entorno se repite en los hogares, y que dos usuarios (o dos hogares) pueden tener similares perfiles energéticos, se plantea la realización de un recomendador colaborativo, como medida complementaria de ahorro. Una de las técnicas más usadas es el **filtrado colaborativo**, que permite hacer predicciones automáticas (filtrado) acerca de los intereses de un usuario, teniendo en cuenta la información sobre los gustos de varios usuarios (colaborativo). Esta idea ha sido aplicada con éxito en otros escenarios, donde cabe resaltar la plataforma Amazon [10], pero hasta el momento no se ha aplicado al sector de la energía.

Por otro lado, los datos de consumo deberían ser suficientes para permitir **identificar el dispositivo** que generó dichos datos, facilitando así el poder anticiparse a la demanda, lo que permitiría transferir los momentos de carga a períodos más inactivos, haciendo la curva de demanda más aplanada.

- A partir de los resultados obtenidos, el sistema ha de ser capaz de ofrecer **retroalimentación** al usuario y/o a la compañía suministradora de energía.

Reducción en el consumo de las interfaces en el contexto del Hogar Digital.

Otra vía para reducir el consumo, de forma paralela y complementaria a la anterior es hacer que los dispositivos eléctricos por sí mismos consuman menos. Esto será especialmente interesante en aquellos dispositivos con autonomía limitada.

La Agencia Internacional de Energía (*International Energy Agency* – IEA), encargada de monitorizar la oferta y demanda de energía a nivel mundial, tiene por objetivo reducir el nivel de consumo, y para ello está animando a los fabricantes a desarrollar tecnologías más eficientes.

El *display* suele ser un elemento común de los dispositivos eléctricos y, como ya se ha mencionado en el apartado anterior, es uno de los componentes que más gasto energético ocasiona. Por tanto el objetivo general es *reducir el consumo ocasionado por los displays de los dispositivos del hogar*.

El primer paso es en este caso conocer qué tecnologías son las más apropiadas, para luego posteriormente poder analizar la eficacia del diseño de su interfaz.

En los primeros pasos de la investigación se detectó una carencia de información sobre las tecnologías usadas para implementarlos, con lo que se fijó como primer objetivo la elaboración de un **estudio intensivo que comprenda todas las tecnologías utilizadas en la fabricación** de *displays*, agrupadas en relación a su consumo, delimitar aquellas apropiadas para el contexto estudiado (bajo y ultra bajo consumo, pequeño tamaño) y realizar una comparativa de las mismas, en términos relativos.

4. Metodología empleada

4.1. Recolección de datos

Un sistema de adquisición de datos está formado tanto por componentes hardware como software. Respecto a los primeros, es necesaria la utilización de medidores inteligentes en el hogar, que sean capaces de obtener el consumo cada cierto valor de tiempo.

Para independizar la solución del hardware usado, se han usado medidores de dos marcas diferentes. En concreto se han realizado medidas con *EcoManager de Current Cost* [1] *y Plugwise* [2], que se pueden ver en la **Figura 3** (a y b respectivamente).

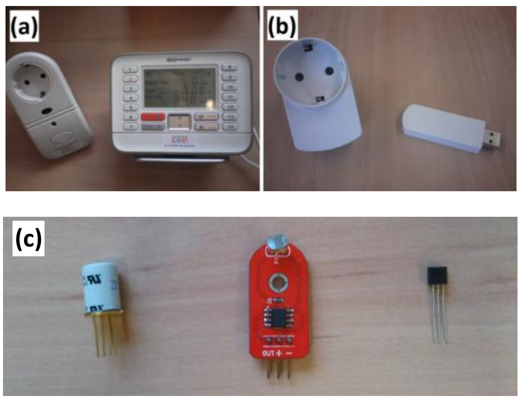

Figura 3: Medidores inteligentes de Current Cost (a) y Plugwise (b) y sensores de Monóxido de Carbono (CO), luminosidad y temperatura – ***Fuente: Elaboración propia***

Ambos se basan en una red de dispositivos que se sitúan entre el electrodoméstico y la toma de corriente y envían datos a otro dispositivo central por medio de radiofrecuencia y ZigBee respectivamente.

[1] http://www.currentcost.com/
[2] https://www.plugwise.com/

Por otra parte se puede recoger otra información del hogar (luminosidad, temperatura, nivel de polución, etc.) por medio de sensores, como los que se muestran en la misma **Figura 3** (c).

Los datos son extraídos de los medidores y sensores mediante un adaptador software, y ofrecidos como servicio energético a través de la tecnología ***Web Service for Devices*** (WS4D) [11]. Este servicio será consumido por los elementos encargados de almacenar y/o procesar los datos, tema que se trata en el siguiente apartado.

4.2. Almacenamiento y procesamiento de los datos

Los datos obtenidos del hogar se almacenarán de forma centralizada gracias a la tecnología **Cloud** [12], haciendo que no sea necesario tener capacidad de almacenamiento en la propia vivienda. Además ofrece otras ventajas añadidas como son la facilidad para gestionar y mantener la integridad, seguridad y disponibilidad de los datos, almacenando réplicas de los datos para ser usadas en caso de pérdida de información.

La frecuencia estandarizada en medición de energía es de una medición cada 15 minutos. Aumentar la frecuencia de las mediciones permite tener un conocimiento más detallado de lo que ocurre en el hogar y realizar así actividades diferentes con la información. Aumentar la frecuencia a una medición cada segundo, por ejemplo, supone un incremento enorme de la capacidad necesaria para almacenar y procesar la información. Igualmente, monitorizar varios dispositivos en un mismo hogar, o desglosar el consumo general en varios dispositivos, supone a su vez un importante incremento. Además, la incorporación de la práctica totalidad de consumidores a estas técnicas de medición supondría un importante incremento de los requisitos de comunicaciones, almacenamiento y procesamiento.

Un hogar bajo estos requisitos de medición, provoca la transmisión y el almacenamiento de 1 KB por segundo. Esto implica la necesidad de un sistema capaz de recibir y almacenar 32 Petabytes por *Millón de usuarios al Año* (PMA). Adicionalmente, será necesario dar soporte al almacenamiento y procesamiento de las operaciones a realizar con toda esta información, que según las funcionalidades que se pretendan ofrecer podría elevar enormemente esta cifra.

Para manejar esta ingente cantidad de datos, las tecnologías tradicionales están bastante limitadas en cuanto a capacidad de almacenamiento y de proceso, por lo que el uso de tecnologías **Big Data** [13] es crucial en esta propuesta. A través de una inversión en tecnología lineal en costes – al ser escalable linealmente – permite cubrir las necesidades de almacenamiento y procesamiento, así como una gestión elástica de la infraestructura de Tecnologías de Información (TI), adaptándose en tamaño según las necesidades. En la **Figura 4** se muestra cómo sería el escenario de aplicación:

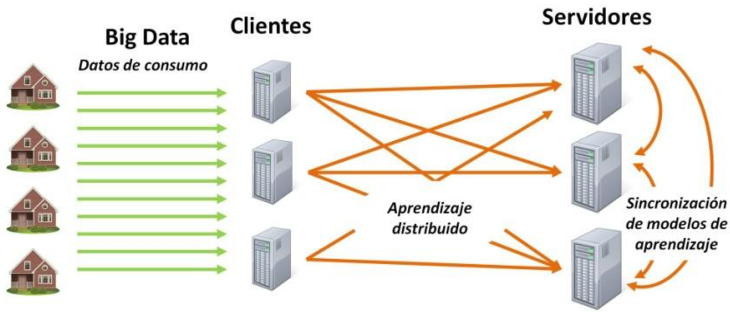

Figura 4: Futuro escenario de aplicación - *Fuente: Elaboración propia*

Big Data, conocida como la tecnología de las tres uves (volumen, velocidad y variedad) da soporte a gran volumen de datos de diversos tipos, procesándolos en un tiempo admisible. Además ofrece soporte para algoritmos de aprendizaje automático, herramientas de minería de datos visuales, monitorización próxima a tiempo real, y una serie de nuevas posibilidades de análisis y procesamiento de la información que ayudarán en gran medida a conseguir los objetivos perseguidos en este estudio, como se verá en el siguiente apartado.

4.3. Aprendizaje automático

Como forma de proceder general, para realizar el aprendizaje automático se ha seguido la filosofía de la **Ciencia dirigida por Modelos** (MDS). El modelado es un proceso que siempre ocurre en la ciencia, en el sentido de que un fenómeno de interés debe ser simplificado para ser estudiado. Dentro de los métodos de modelado, recientes estudios muestran que **SysML** es una manera eficiente de modelar aquellos sistemas que combinan tanto partes software como hardware [14]. En esta investigación, es de vital importancia poder incluir en el modelado del sistema a los dispositivos hardware involucrados, dado que la naturaleza de los mismos puede influir decisivamente en el resultado final.

La metodología seguida consiste en, primeramente formular una hipótesis. A continuación se modela el experimento a realizar para poder demostrarla utilizando SysML. Los tipos de diagramas más prácticos para esta labor son el de bloques – que recogerá los componentes que intervienen – y el de actividad, para clarificar los pasos a seguir. Una vez realizado el experimento se extraen conclusiones. Cabe resaltar en este punto una de las cualidades más importantes de toda ciencia, su carácter provisional. Por tanto, los puntos descritos estarán sujetos a una continua evaluación y corrección en caso necesario.

En los siguientes apartados se verán las peculiaridades de cada uno de los aprendizajes realizados en cuanto a lo que metodología se refiere.

Predicciones

El sistema genera varias veces al día, a partir de cantidades masivas de información, una predicción semanal de consumo para cada usuario. Para realizar este tipo de predicción, se tienen en cuenta factores de consumo propios del usuario, factores de consumo generales, y otros factores externos que son relevantes, como por ejemplo horarios, calendarios de festivos, precios, tarifas, meteorología…

La estrategia aplicada por el modelo, permite definir y ajustar la forma en que el sistema aprende, qué datos son relevantes, qué datos no lo son, y qué datos se deben filtrar o potenciar en el aprendizaje. El uso de un algoritmo de aprendizaje proporciona un mecanismo de memorización, capaz de recordar y olvidar en proporciones adecuadas las situaciones vividas, y de proporcionar un valor coherente para situaciones no ocurridas anteriormente.

Recomendaciones colaborativas

La función de este módulo es la de sugerir a los usuarios la realización de acciones que otros usuarios similares han realizado en sus viviendas y que les han ayudado a reducir el consumo energético.

Para ello será necesario definir la forma de calcular la similitud entre dos usuarios, o lo que es lo mismo, la "distancia" entre ellos. Para calcular esta distancia existen diversos algoritmos, basados en que los usuarios valoran las acciones que toman dentro de un rango de valores, lo que indica su grado de aceptación [15].

En el sistema concreto que se propone en este trabajo, los usuarios no dan una valoración de cuánto están de acuerdo con la realización de una acción, sino que se van a limitar a decir si están de acuerdo o no. Es decir, un usuario o bien no acepta la acción o la acepta completamente.

Para este tipo de valoración los algoritmos más adecuados son los de *Tanimoto* [16], basados en el cálculo del coeficiente de similitud de *Tanimoto* (ver **Ecuación 1**), propuesto en 1960 para clasificar plantas [17].

$$T(A,B) = \frac{C}{A+B-C} \tag{1}$$

Donde:

- A = número de acciones realizadas del usuario 1
- B = número de acciones realizadas del usuario 2
- C = número de acciones realizadas comunes de los usuarios 1 y 2.

Usando esta fórmula se calculan todas las distancias entre los usuarios y se construye una matriz donde se almacenan todos estos datos. En el momento de realizar una recomendación a un usuario, el algoritmo devuelve aquellas acciones que otros usuarios similares han realizado, y que el usuario al que queremos ofrecer la recomendación no ha realizado todavía.

Identificación de dispositivos

En este caso, en la demostración de la hipótesis de poder reconocer el dispositivo a partir de su consumo intervienen muchas variables. Primeramente el algoritmo de aprendizaje a utilizar para entrenar al clasificador supervisado. Dada la cantidad de algoritmos posibles, y el tiempo de aprendizaje del clasificador para cada uno de ellos, se optó por realizar un primer filtro de los mismos, con un número limitado de datos de consumo y la herramienta **Weka** [18], que tiene soporte para la mayoría de algoritmos. Como esta herramienta no ofrece un rendimiento óptimo con el tamaño de datos al que se hizo referencia anteriormente, fue descartada para las pruebas con datos en tiempo real, que se hicieron con **Jubatus** [19].

En una segunda iteración, se realizaron los experimentos en el laboratorio, con mediciones en tiempo real de siete electrodomésticos, a los que se les aplicaron tres configuraciones diferentes (cada una con una cadencia de mediciones distinta – 10 segundos, 1 minuto y 3.75 minutos) y se calculó la tasa de acierto en cuatro momentos diferentes del entrenamiento (a la hora, a las dos, a las cuatro y a las ocho horas).

4.4. Elaboración del estudio de tecnologías de *displays* según su consumo

En un primer paso, se elaboró un listado de todas las tecnologías del mercado. Las tecnologías se clasificaron según su consumo en alto (>250mW/cm^2), medio (100-250mW/cm^2), bajo (10-100mW/cm^2) y ultra-bajo (0-10mW/cm^2). El resultado de esta primera iteración puede verse en la **Figura 5**.

En una segunda iteración, se limitó el estudio a aquellos *displays*, que perteneciendo a las dos últimas categorías anteriores (bajo y ultra-bajo consumo), fueran (o pudieran ser) además de reducido tamaño, ya que las tendencias indican que son aquellos cuya fabricación se está duplicando en los últimos años [9]. En concreto se clasificaron en microdisplays (<1 pulgada), pequeños (1-7 pulgadas), medianos (7-20 pulgadas) y grandes (<20 pulgadas).

Dada la diversidad de tecnologías en cuanto a tamaño y marcas, fue necesario establecer un método estándar para poder realizar la comparativa. El **Comité Internacional de Metrología de Displays** (ICDM) es la referencia tanto para la industria como para instituciones de investigación, a la hora de medir y caracterizar *displays*. En concreto el documento que recoge la información es el *Information Display Measurements Standard* (IDMS) [20].

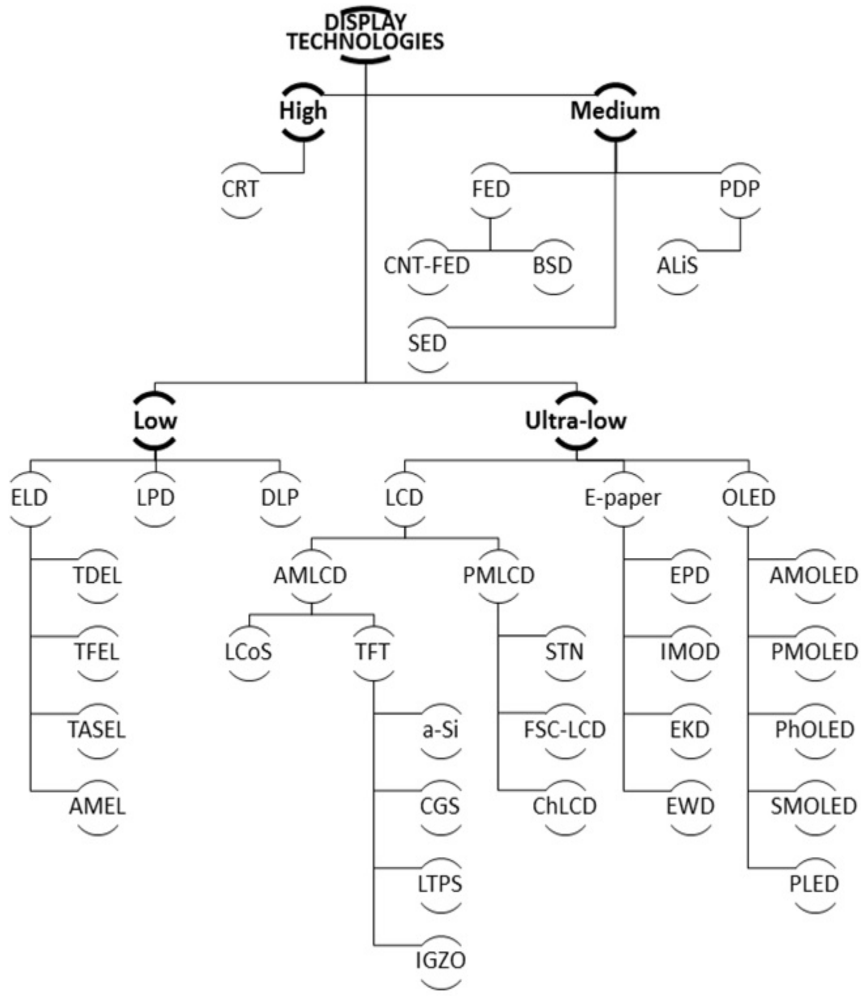

Figura 5: Tecnologías de *displays* estudiadas agrapadas en alto, medio, bajo y ultra-bajo consumo – *Fuente: Elaboración propia*

Existen métricas para obtener un valor relativo en términos de consumo, como las conocidad *Environment Cost of Ownership* (ECO) [21] o *Life Cycle Assessment* (LCA) [22], basadas en el impacto medioambiental de la tecnología. En este trabajo se ha usado la densidad de consumo P_d (medida en milivatios por centímetro cuadrado de pantalla activa), propuesta por Smil [23] (ver **Ecuación (2)**).

$$P_d = \frac{P}{S} \tag{2}$$

Además, teniendo en cuenta la influencia que puede llegar a tener lo que se está mostrando en el *display* con su consumo, se ha considerado adecuado realizar una comparación manteniendo un patrón constante. Para ello se ha usado como medida complementaria la eficiencia de intensidad del *display* (medida en candelas por vatios), definida por la IDMS como el ratio entre la intensidad lumínica I (que es a su vez el producto de la luminancia frontal de la pantalla blanca $\mathrm{L_W}$ por el área activa S – **Ecuación (3)**) y el consumo P (**Ecuación (4)**).

$$I = L_W S \tag{3}$$

$$\xi = \frac{\mathrm{I}}{\mathrm{P}} \tag{4}$$

5. Resultados obtenidos

En la primera línea de investigación se ha propuesto un sistema capaz de extraer un conocimiento extra del hogar, haciendo uso de una infraestructura cada vez más extendida como son los medidores inteligentes y las redes de sensores.

Los datos recolectados son ofrecidos como servicios mediante la tecnología WS4D, y almacenados en la nube. Gracias a la tecnología Big Data el sistema es totalmente escalable y ofrece un buen soporte para realizar el aprendizaje automático. Un esquema de la arquitectura se puede ver gráficamente en la **Figura 6**:

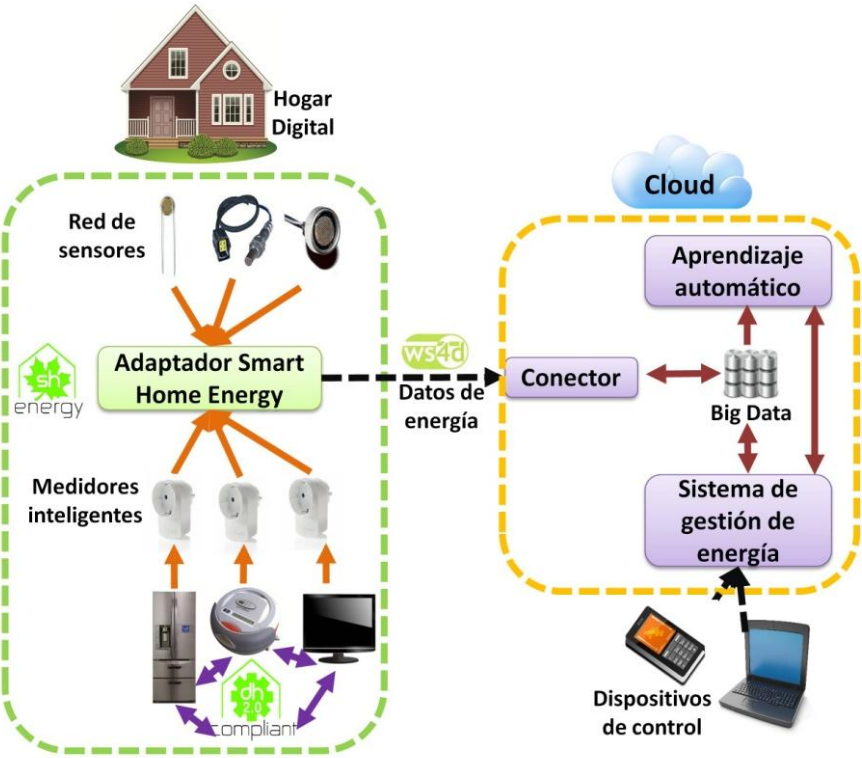

Figura 6: Sistema propuesto – *Fuente: Elaboración propia*

La presentación de esta arquitectura y sus componentes es el núcleo del artículo presentado en esta tesis como **Artículo I.**

El sistema de aprendizaje automático está compuesto por tres elementos principales:

- Un **recomendador colaborativo,** utilizando la tecnología *Mahout*, se encarga de procesar las acciones realizadas por cada usuario para hacer recomendaciones de ahorro a usuarios similares – aplicando para ello los conceptos de perfil de energía y filtrado colaborativo. Para calcular la distancia entre usuarios se ha usado el coeficiente de Tanimoto.

- También es posible extraer patrones de consumo que sirvan como base para la realización de **predicciones**, que también permitirían anticiparse y amoldarse a otras opciones más económicas. La eficiencia de este módulo ha sido evaluada en edificios localizados en dos zonas climáticas diferentes, y se obtuvo una precisión de un 90% en la zona Atlántica.
- Un **clasificador supervisado** ha sido entrenado para reconocer dispositivos a partir de sus datos de consumo, con el principal objetivo de permitir anticiparse a la demanda. Por medio de algoritmos que tienen en cuenta el peso de cada parámetro, se han alcanzado tasas de reconocimiento del 75% tras una hora de entrenamiento. Este valor aumenta con el tiempo, ya que el aprendizaje se hace online. Por ejemplo, el algoritmo *Confidence Weighted* (CW) alcanza tasas de reconocimiento del 100% tras 8 horas de entrenamiento, con lecturas de consumo cada minuto, y entrenando cada 16 minutos.

  Esta parte del aprendizaje dedicada a la identificación de dispositivos ha sido abordada en detalle en el **Artículo II** de esta tesis.

Como herramienta complementaria, se han incorporado **gráficos interactivos y personalizables** para mostrar la información al usuario, lo que le permite gestionar su consumo y mejorar así la eficiencia energética. Por ejemplo, la gráfica de predicción puede realizarse por tramos diarios y ponderarla según la tarifa aplicable en cada tramo, de forma que el usuario pueda acomodar las actividades en el mismo día bajo diferentes tarifas. La **Figura 7** muestra un ejemplo de los mismos.

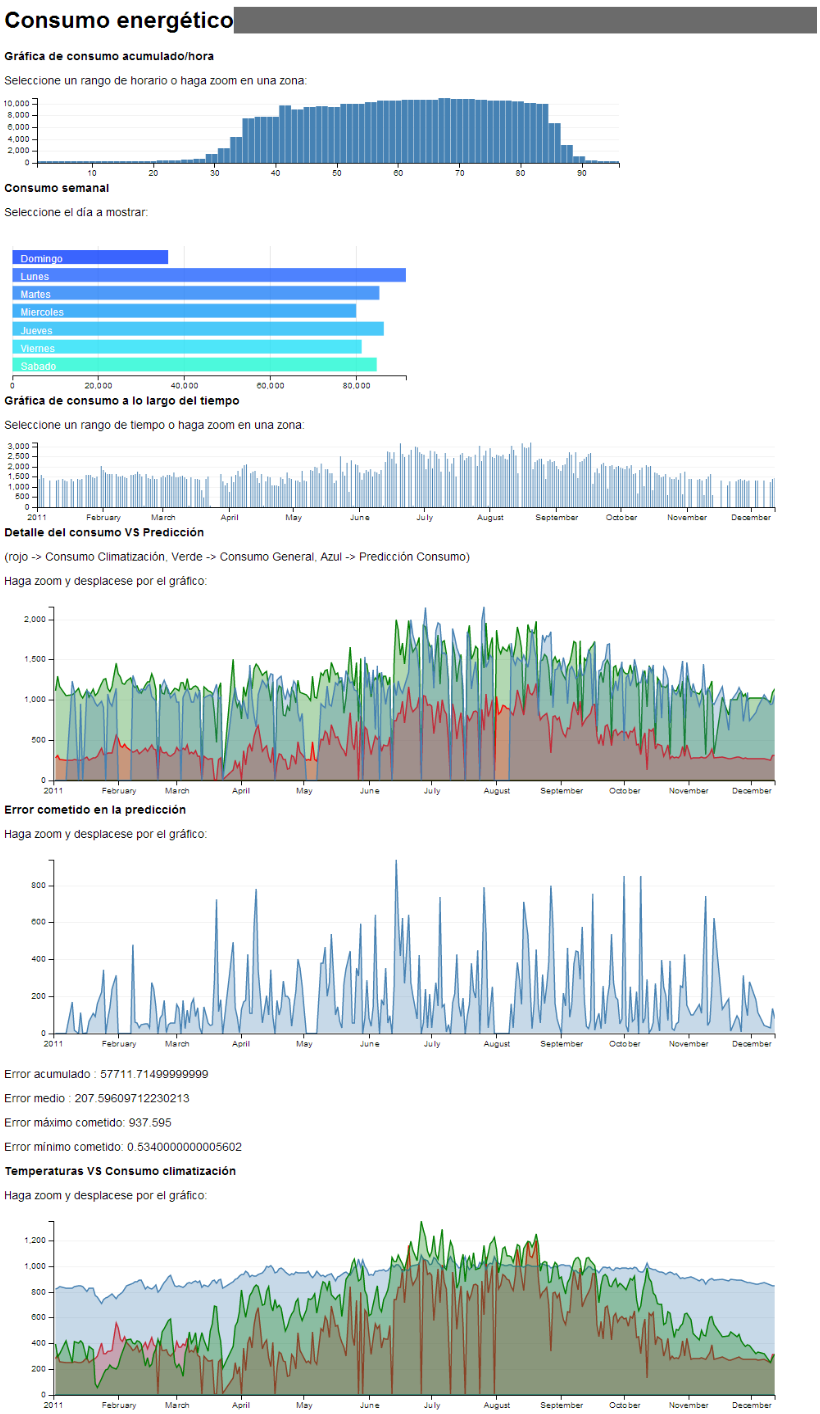

Figura 7: Prototipo de la interfaz Insight de consumo – *Fuente: Elaboración propia*

El modelo ha sido probado y entrenado con edificios ubicados en varias zonas climáticas y se ha obtenido un resultado satisfactorio en todos los casos. La eficacia del sistema de predicción se ha evaluado mediante el análisis de estadísticos. La interpretación de estos estadísticos permite evaluar el error cometido en la predicción y la forma en que este error se distribuye. La idoneidad de la técnica es dependiente de la interpretación de estos estadísticos frente a las situaciones a detectar o evitar.

Las pruebas realizadas, cuyo resultado se muestra en la **Tabla 1**, aportan un resultado de aplicación del modelo sobre datos reales de un establecimiento comercial que presentan los siguientes valores de estos estadísticos:

Tabla 1: Resultados de la evaluación de la eficacia del sistema de predicción por medio de estadísticos

Estadístico	Zona Climática	Interpretación
Media del error absoluto (**MAD**) $MAD = \frac{\sum_{t=1}^{N} \lvert E_t \rvert}{N}$ Donde E_t es el error del pronóstico del período t $E_t = Y_t - F_t$	Atlántica= 237.46 Continental= 207.59	Media de errores de predicción cometidos. Da una perspectiva del error que puede cometerse en una predicción. El valor es similar en ambas zonas climáticas y presenta un mejor ajuste en clima continental.
Media del error absoluto porcentual (**MAPE**) $MAPE = \frac{\sum_{t=1}^{N} \left\lvert \frac{E_t}{Y_t} \right\rvert}{N}$	Atlántica= 0.099 Continental= 0.194	Indica la probabilidad [0,1] de la media de los errores de predicción cometidos. La técnica presenta un mejor valor en el conjunto de datos de clima oceánico.

Estadístico	Zona Climática	Interpretación
Porcentaje de acierto del error absoluto porcentual (**PA**) $PA = 1 - MAPE \times 100$	Atlántica= 90.09% Continental= 80.59%	Presenta el valor MAPE en forma de acierto porcentual [0,100] %, lo que permite comparar el algoritmo en diferentes conjuntos de datos con valores diferentes. La técnica muestra un mejor valor en el conjunto de datos de clima oceánico.
Indicador del error total medio producido en las predicciones **R M S D** $RMSD = \sqrt{\frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{N}}$ $\hat{y}_t$ Valores de la predicción en el tiempo	Atlántica= 333.03 Continental= 281.17	Los errores se encuentran muy repartidos a lo largo del tiempo si el valor es bajo, o muy concentrados en determinados momentos si el valor es alto. Tener errores concentrados puede interpretarse como más conveniente por poder ajustarse como anomalías o poder asociarse nuevas variables no contempladas. La técnica muestra mayor concentración de error en el caso de clima oceánico que en continental.
Desviación estándar (**DS**) $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$	Atlántica= 233.49 Continental= 189.63	Indica la dispersión del error respecto de la media de error, es decir, si el error está concentrado en algunos puntos o repartido uniformemente. En el primer caso, el algoritmo tendría un comportamiento estable en cuanto al error que comete en cada predicción, mientras que en el segundo, existirían grandes variaciones entre diferentes predicciones. La técnica muestra un mejor valor en el caso de clima continental que en el oceánico.

En cuanto a la línea de investigación de interfaces de bajo consumo, el resultado fue un estudio exhaustivo de tecnologías que dio como resultado el **Artículo III** de esta tesis doctoral. En él se tomaron los valores absolutos para el tamaño, peso, brillo, contraste, ángulo de visión y consumo de los *displays* más representativos de cada familia, y se han analizado en términos relativos. Los resultados se pueden ver en la **Figura 8**.

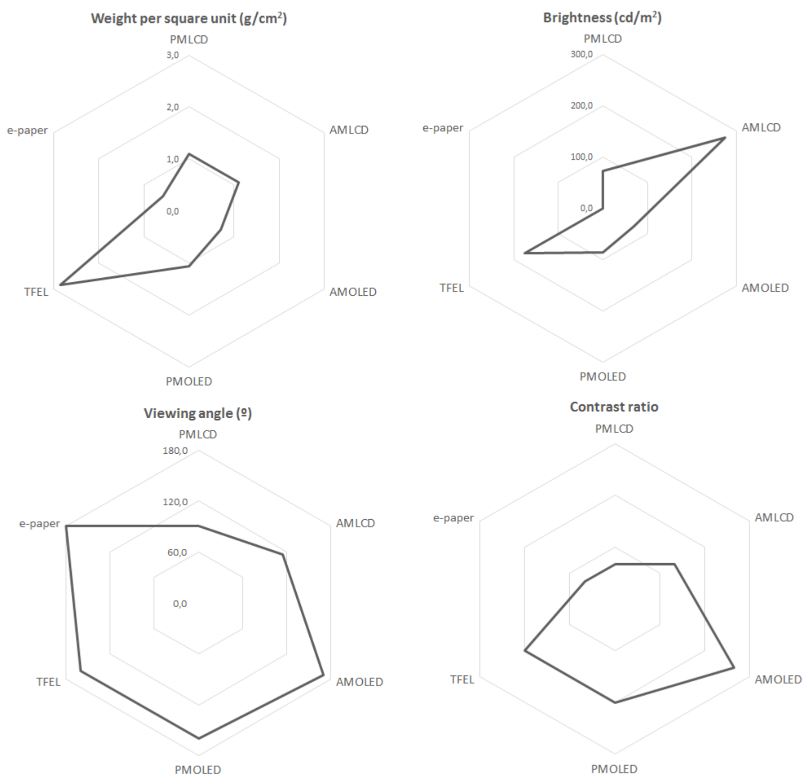

Figura 8: Comparativa mediante gráficos de radar del peso relativo, brillo, ángulo de visión y contraste de las tecnologías estudiadas – *Fuente: Elaboración propia*

Para comparar el peso, se ha considerado éste respecto al área activa y se ha comprobado como todas las tecnologías estudiadas ofrecen valores cercanos a 1 g/cm^2, a excepción de *Thin-film Electroluminescent* (TFEL), con valores medios de 2.9 g/cm^2, y valores máximos de hasta 4g/cm^2.

En cuanto al brillo, cabe destacar el valor extremo de dos tecnologías. Por un lado, *Electronic Paper Displays* (EPD o e-paper) que al carecer de emisión de luz, posee un brillo cero, y en el otro *Active Matrix Liquid Crystal Display* (AMLCD) con valores de hasta 450 cd/m^2.

Para el ángulo de visión, *Liquid Crystal Displays* (LCD) es la que peor resultados ofrece, en contraposición a los 360 grados que puede llegar a ofrecer el *display* transparente TASEL.

En cuanto al contraste, *Pasive Matrix Liquid Crystal Display* (PMLCD) y e-paper ofrecen ratios muy bajos, aunque suelen ser suficientes para las aplicaciones para las que son diseñados habitualmente.

Respecto a los valores de consumo (relativos al tamaño), EPD y *Electro-Wetting Display* (EWD) ofrecen los valores más bajos, aunque hay que tener en cuenta que estas tecnologías son usadas para el desarrollo de displays muy específicos (normalmente monocromo, textuales, etc.). Otras tecnologías como LCD y *Organic Light-Emitting Display* (OLED) ofrecen valores ligeramente superiores pero ofreciendo mejores prestaciones. Por último ELD se presenta como la tecnología con valores más altos de consumo.

Finalmente, en cuanto a la eficiencia de la intensidad del display, se han encontrado claras diferencias dependiendo de si el display es o no emisivo. En un estudio comparativo entre LCD y OLED (teniendo en cuenta sus versiones de matriz activa y pasiva), OLED ha mostrado valores inferiores para displays de pequeño tamaño, mientras que se comporta peor que LCD cuando el tamaño va creciendo.

6. Conclusiones

El conocimiento energético del hogar es un factor clave para lograr un uso eficiente de los recursos. El uso extendido de medidores inteligentes y redes de sensores a nivel residencial, facilita la obtención de la información del mismo, pero esta información, debido a su variedad y tamaño, no es asumible para ser procesada de forma manual, por lo que es necesario recurrir al uso de técnicas de aprendizaje automático.

En la primera parte de la investigación, se han sentado las bases de una arquitectura que, a partir de los datos generados por el hogar digital, ofrece una serie de servicios con el objetivo común de mejorar la eficiencia energética.

Los principales puntos fuertes de esta propuesta son la facilidad de instalación, su flexibilidad - permitiendo obtener información de muy diversa índole -, y su escalabilidad, pudiendo ampliarse tanto a áreas mayores, como a aprendizajes distintos. La tecnología clave para ello es Big Data [24], y su aplicación en el sector de la energía es una idea innovadora. A través de una inversión en tecnología lineal en costes, permite cubrir las necesidades de almacenamiento y procesamiento, así como una gestión elástica de la infraestructura de Tecnologías de Información (TI), adaptándose en tamaño según las necesidades. Big Data da soporte a gran volumen de datos de diversos tipos, procesándolos en un tiempo admisible. Además ofrece soporte para algoritmos de aprendizaje automático, herramientas de minería de datos visuales, monitorización próxima a tiempo real, y una serie de nuevas posibilidades de análisis y procesamiento de la información que encajan perfectamente con el sistema propuesto.

El recomendador colaborativo permite sugerir acciones que ofrecen la posibilidad de ahorrar energía a grupos de usuarios de perfil similar sin necesidad de tener un conocimiento previo de esos usuarios y de sus características.

La posibilidad de realizar predicciones de coste de consumo con tarifa energética para la planificación diaria en tarifas discriminadas, también permite al usuario realizar una mejor distribución en el día de sus hábitos de consumo.

Además de las recomendaciones y las predicciones, se le ofrece al usuario una herramienta para realizar análisis manuales él mismo, que de otra forma serían inabarcables, dada la cantidad ingente de datos que pueden llegar a surgir de un hogar digital.

El método de identificación de dispositivos a partir de sus datos de consumo tiene como principal ventaja respecto a otros métodos similares que se puede aplicar sobre una infraestructura ya existente de *Smart Metering*, lo que la convierte en una solución económica, fácil de instalar e independiente de la marca. Además, al realizar el aprendizaje online, se evita el problema de almacenar la información generada por los medidores.

Otro campo prometedor es la anticipación a la demanda energética. En el sistema propuesto, a través de predicciones y de la identificación de dispositivos se da un paso más para permitir que los comercializadores y empresas de servicios energéticos pudieran realizar una compra más inteligente de la energía.

Un posible paso futuro en la mejora de la eficiencia energética es la de dotar al sistema con la capacidad de simular acciones, para estudiar el impacto que tienen las mismas tanto económico como en el consumo.

En cuanto a la línea de investigación de interfaces de bajo consumo se ha visto que algunas tecnologías, como OLED o e-paper poseen características de bajo consumo intrínsecas en pequeños formatos. De hecho, varios estudios de mercado sitúan a OLED como la tecnología clave en los próximos años, ya que ofrece los mejores ratios de contraste y ángulos de visión, y valores más que aceptables para brillo y peso. Además, la estrecha relación entre el consumo y el número de pixeles activos en cada momento, la hace la más idónea en muchos tipos de aplicaciones.

El papel electrónico es también una tecnología muy prometedora para aquellas aplicaciones que necesiten un consumo ultra-bajo, especialmente si no requieren de actualizaciones de pantalla frecuentes.

Otras tecnologías más maduras como LCD siguen trabajando en ofrecer buenos niveles de consumo en formatos pequeños, para poder seguir siendo competitivos.

Por último, los *displays* electroluminiscentes (ELD), aunque se comportan peor en términos energéticos, ofrecen otras ventajas en situaciones donde el color no es importante pero si otras características como la velocidad, el brillo, el contraste o el ángulo de visión.

Las últimas líneas de investigación en este terreno están explorando nuevos campos de aplicación, como los displays *near-to-eye* (NTE), pensados para estar situados cerca del ojo a través de un dispositivo encajado en la cabeza, o los *displays* flexibles, que, al permitir adquirir diferentes formas abrirían líneas de mercado a nuevas aplicaciones y nuevos tipos de productos. Otros enfoques más futuristas son los *displays* en tres dimensiones. Para obtener una aproximación de aquellos desarrollos que no se han comercializado aun, un buen punto de partida es el análisis de redes de patentes propuesto por Chang [25].

Además de la evolución en la tecnología, otro campo de acción complementario para reducir el consumo es la mejora en la interacción del usuario y la usabilidad de la interface. Las políticas de gestión de consumo del display (DPM) pueden reducir la energía usada por el *display* apagándolo y encendiéndolo según la atención del usuario, pero esta técnica es inaceptable por la degradación que causa en la calidad de la pantalla.

Las principales técnicas sobre las que se está estudiando se dividen en función de si pueden aplicarse sobre displays reflectivos o emisivos. Sobre los primeros se puede reducir la actividad de componentes como la profundidad de color, la tasa de refresco, el buffer o la luminosidad de la luz trasera, jugando con el brillo y el contraste según el contenido a mostrar. En cuanto a los emisivos, aunque pueden aplicarse igualmente las técnicas anteriores, existen estudios más específicos, que se basan en la idea de que la relación entre los niveles de intensidad de color no es lineal, y proponen técnicas como el código de colores RGBW más eficiente que RGB. Las principales líneas de investigación en este campo, tratan de combinar las ventajas de cada técnica, aplicando la más adecuada en cada caso.

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Capítulo II:

Publicaciones fundamentales de la tesis doctoral

Artículo 1: *Using the Big Data generated by the Smart Home to improve energy efficiency management*

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ORIGINAL ARTICLE

Using the Big Data generated by the Smart Home to improve energy efficiency management

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Abstract A Smart Home is able to generate energy-related values such as electricity consumption, temperature, or luminosity without higher infrastructure requirements. The main aim of this research is to extract information from that raw data that could contribute to improving the energy efficiency management. This paper presents a system which, using different Machine Learning approaches to learn about the users' consumption habits, is able to generate collaborative recommendations and consumption predictions that help the user to consume better, which will in turn improve the demand curve. Moreover, from consumption values, the system learns to identify devices, enabling the demand to be anticipated. Taking into account the fact that the amount of energy data is increasing in real-time, the use of Big Data techniques will be the key to handling all the operations and one of the more innovative features of the system.

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Keywords Smart meter · Sensor network · Power consumption · Machine learning · Energy efficiency · Big data

Introduction

The objective of increasing energy efficiency by 20 % was set in the European Union 2020 Strategy as a key factor to achieving long-term energy and climate goals (da Graça Carvalho 2012). Although substantial steps have been taken towards this objective, the European Commission estimated in 2009 that only half of the 20 % objective would be achieved if that trend continued and, therefore, a new energy efficiency [lan was developed in 2011. In this plan, the greatest energy-saving potential lies in buildings (nearly 40 % of the final energy consumption), with such policies as the creation of utilities to enable customers to cut their energy consumption (European Commission 2011).

In the current year, 2015, the Horizon 2020 program is being put into practice as the financial instrument implemented by the Innovation Union, a European 2020 flagship initiative aimed at securing Europe's global competitiveness. In this context, the concept of the Smart Grid is viewed as a key block and is represented in the main road maps throughout Europe (Massoud Amin and Wollenberg 2005).

The core element of Smart Grid is the active participation on the demand side, and this involves two main activities, load shifting and energy conservation programs (Palensky and Dietrich 2011). The first option transfers customer load during periods of high demand to off-peak periods, flattening the load curve, while the second approach encourages customers to reduce their consumption, by such methods as reducing the air conditioning thermostat a few degrees.

Smart Metering (Stromback et al. 2011) is considered to be one of the most cost-effective methods for increasing end-consumer involvement and engagement. This method is based on an intelligent measuring device capable of reporting information about the power consumed. The said information can be managed by the final user to monitor and control the devices in their home, i.e., their own costs and expenses from any device connected to the Internet. If the management is optimum, the final bill is considerably reduced (Venables 2007). Another key enabling technology is the Sensor Network, made up of measuring devices that are distributed and embedded within the environment (Sheth et al. 2008), collecting such information as the temperature or humidity.

In the past, several attempts have been made to improve energy efficiency through the use of Smart Metering (Christine Easterfield 2013), and it is a fact that this type of infrastructure is becoming more widespread, although most of the information obtained from it is not being fully exploited (Jahn et al. 2010). The main aim of this research is to extract information from that raw data that can contribute to improving the energy efficiency management.

In that context, an architecture proposal able to reuse such data to give feedback, which is a possible proven energy saver (Fischer 2008), is presented in this research. The concept of Intelligent Infrastructure is applied—opening up the idea of Smart Grid (Gershenfeld et al. 2010)—and combined with the use of Machine Learning (ML) techniques, which permit learning to be done automatically from the data generated by the home devices, thus generating useful information to improve energy efficiency.

A prediction and recommender system can learn the consumption patterns of a home and thus contribute to the efficient use of energy. Such knowledge includes the technical aspects of behavior and habits of life, so a user can predict the consumption and adapt their activities to achieve more economies (for instance, considering the times with the best rate) and more environmentally responsible habits (Case 2012).

As well as saving energy, the system can help to detect fraud and abuse through consumption behavioral pattern analysis. For example, in communal areas, applying patterns to relate how much, when and how it is consumed, an improper use of the facilities could be detected. Furthermore, by modifying the consumption of final users, it is possible to flatten the demand curve, so the distribution network is optimized as a result of reducing consumption peaks. The knowledge of the behavior pattern of each house, every hour of the week, allows a better distribution of energy to meet demand. This could be generalized to any intelligent service development where low frequency data sampling may be necessary.

Concerning the possible growth of data, the traditional computing technologies have some limitations in terms of the capacity to store and process data, above which specific supercomputers are required, with a very high-associated cost. Big Data technology (Marz and Warren 2013) is able to approach the capabilities of supercomputers using conventional hardware, making it possible to apply the technology to fields in which it was unprofitable before. The use in real-time of Big Data and analytical data techniques applied in this context is the most innovative characteristic of this contribution.

The rest of the paper is organized as follows: firstly, in State of the art, an overview of the most relevant research that has made progress in improving energy efficiency or that has applied similar ideas and successful technologies to other fields. Secondly, a specific system applying the mentioned ideas will be described in Proposed system, with data about the initial results obtained. Finally, the document ends with the conclusions.

State of the art

A Smart Home can be defined as a complex system that integrates technology and services to enhance power efficiency and improve the quality of life (Robles and Kim 2010). It is necessary to take into account the fact that a growing number of consumer items (smart appliances, service robots, or electric vehicles) and different energy production sources (for instance, renewable energies like photovoltaic solar energy) are part of that home. Moreover, it is influenced by many sources of uncertainty, such as the outdoor temperature or the behavior of its occupants (Venkatesh 2008). In fact, user behavior is a key factor to explain households' energy consumption (Gram-Hanssen 2013). There are previous studies (Hargreaves et al. 2010) that show how feedback can change consumption behavior.

The design and development of energy management systems for homes would require the capability of predicting such parameters as the temperature or the energy demand to teach the user how to consume. Previous studies show that predictive models based on neural networks (González Lanza and Zamarreño Cosme 2002; González and Zamarreno 2005) and support vector machines (SVM) (Zhao and Magoulès 2012) are able to predict both the temperature evolution in a building and the consumption of their devices, allowing the preparation of corrective policies to improve the homes' energy efficiency. Regarding the requirements of energy demand, several research works have been carried out in the field of the identification of devices from power consumption using different algorithms of machine learning classification, which would anticipate the energy needs. However, the obtained results are not accurate enough (Berges et al. 2009; Murata and Onoda 2002). Similar classification and pattern characterization problems have been solved in other areas of knowledge, such as Computer Vision (Chechik et al. 2010) or the detection of malicious web sites (Ma et al. 2009), and the basis can be applied to this field of study.

Furthermore, taking into account the fact that the environment under study is repeated in all the Smart Homes and starting from the idea that two users/buildings with a similar energy profile could be interested in the same saving measures, a collaborative recommender system can be used as a complementary energy-saving tool. Specifically, one of the most used techniques for recommendations is collaborative filtering (CF), which filters items through the opinions of other people. It is based on the idea that if the advisors have similar preferences to the user, he/she is much more likely to take their opinions into account (Su and Khoshgoftaar 2009). This kind of tool is used successfully in other fields, such as the best known commercial online companies—e.g., Amazon.com (Linden et al. 2003). However, to the best of our knowledge, it has not yet been applied to the energy field. The fundamental assumption is that if users X and Y rate n recommendations similarly or have similar consumption behaviors (doing the washing at night, air conditioning during August, etc.), hence, they will rate or act on other recommendations similarly.

Regarding the state of the technologies for the realization of the ML process, Weka (Frank et al. 2010) is a matured software that has the advantage of incorporating a large number of training algorithms. It can be used for exploring representative data portions and testing the suitability of different learning methods easily. But for larger amounts of data, as in the case of the environment presented in this research, the tool did not offer a suitable response time, so specific tools for Big Data are needed. The Mahout Apache Project (Owen et al. 2011) and Jubatus Framework (Jubatus 2011) were selected for doing the batch and online learning, respectively. On the one hand, Mahout aims to produce a free implementation of a package that includes the main ML algorithms. The project is very active, but there are still some algorithms to be included, especially for time series classification. Its main advantage over other standalone implementations is the scalability offered when running on Hadoop (Lam 2010). On the other hand, the Jubatus online learning framework (Jubatus WebSite 2011) is a tool which maintains the scalability characteristics of Mahout and, in addition, allows a real-time response to be obtained. It incorporates some weighted algorithms which are the most appropriate for time series classifications.

Proposed system

The proposed system architecture is composed of four main sub-modules:

- The *Data Collection* element corresponds to the Smart Home Energy (SHE) project (SHE Consortium 2012), which obtains the measurements directly from the home.
- The collected values are processed by the *Data Storage* module, which makes them available for the rest of the modules.
- The *Machine Learning* module includes all the algorithms that can be executed massively for each home or user, many times a day, to learn, classify devices, generate recommendations, or predict the consumption using a large set of data for each execution.
- Finally, the *Data Visualization* module is the closest to the user and includes data publishing, allowing the interface to query, receive, and show the data.

The mentioned components will be described in depth in the following subsections.

Data collection

The Smart Home Energy environment, whose graphical description is shown in Fig. 1, is capable of obtaining energy-related information from the Digital Home, such as the power consumed by the electrical devices, the indoor temperature, or the luminosity in a specific zone.

Data acquisition is done by some hardware components—the Smart Meter Network and the Sensor Network—and a software adapter (SHE Adapter) that makes use of the Web Service for Device (WS4D) technology (Web Services for Devices (WS4D) Website (2012)) for making the measurement data available.

Before sending them to the Cloud, the SHE Adapter encapsulates the measurements obtained from the home into an object. Each measurement has an address, a location, and a time. Besides, for consumption values, the smart meter identification, the associated appliance, and the measured consumption value are also provided. In the case of the sensors, only the sensor code and its measure are needed.

Data storage

The collected energy-related data from the SHE environment is centrally stored by means of Cloud technology, which does not require a large infrastructure at home and, moreover, provides facilities to manage and maintain the integrity, security, and availability of data (Rhoton and Haukioja 2011).

The standardized energy measurement rate is 15 min (Franks 2012), due to the limitations of older technologies. If the rate increases, which is possible, thanks to Big Data, more detailed information would be offered, improving our understanding of what happens at home. Decreasing it, however, would represent a huge increase in the information storage and processing capacity, but further possibilities of extracting value from the information would be added. Furthermore, the incorporation of consumers to these measurement techniques would be a remarkable increase in communications, storage, and processing requirements.

Specifically, in the system, each home submits consumption information every minute, which means 525,600 samples per year. As other environmental parameters such as temperature or humidity are also measured, the number of samples per year in the system rises to more than three million. Each sample causes the transmission and storage of 1 kbps, so each home generates 3,229,286,400 bytes of information per year. Considering a population of ten million homes, a system able to process, receive, and store 32 PB of information per year is needed. Additionally, it would be necessary to support the execution of the operations to be performed with all this information, which could greatly increase the needs, and also to give support to remote user access.

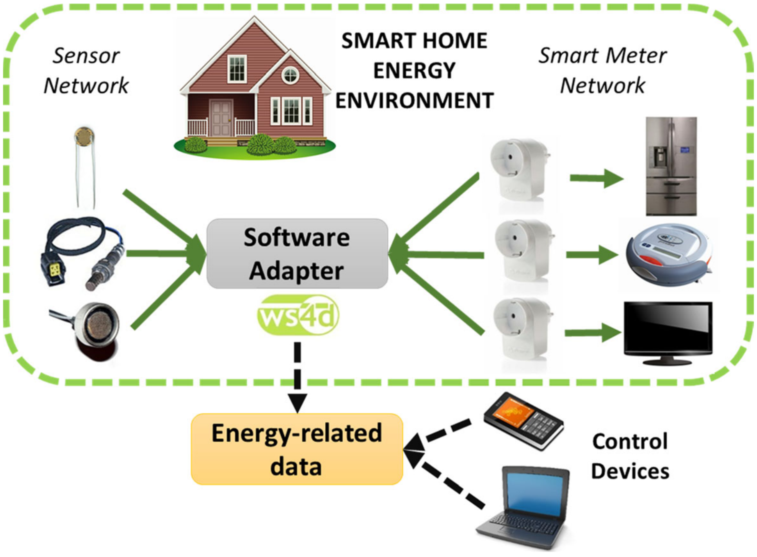

Fig. 1 Smart home energy environment

The storage needs are covered through a cost-linear investment technology based on Big Data. A distributed file system capable of storing up to the order of petabytes of information is the key to the storage management. The system self-manages the integrity of data through replication, without requiring backups or RAID disk enclosures. HBase technology is used to achieve real-time random access to databases consisting of large tables (billions of rows and millions of columns) through a Hive motor (Vora 2011).

Application of Machine Learning techniques to the collected energy-related data

Machine Learning is a technology for mining knowledge from data and then applying it to the new data. A common practice in machine learning to evaluate an algorithm is to split the data into two sets, the training set on which we learn data properties and the testing set on which we test these properties. Depending on the learning problem, the learning can be supervised (inputs and desired outputs are known) or unsupervised (unknown labels), and the technique is slightly different, so the learning details will be given in each subsection.

Appliance recognition module

This module's objective is to identify which device has the highest probability of generating a specific unlabeled consumption record. For this purpose, this module trains a classifier using supervised Machine Learning techniques.

Taking into account the fact that power consumption data is an infinite time series, the online learning approach was considered the most suitable option, offering simple, fast, and less-memory demanding solutions, avoiding re-training when adding new data since the model is generated incrementally.

The solution—graphically described in Fig. 2—follows a Jubatus client/server structure. The Classifier Tester processes the Big Data stream and composes the Training Datum (nomenclature used by Jubatus). Specifically, it is made up of the minimum and maximum values, the mean, sum, deviation, and variance. Finally, the Fast Fourier Transform (FFT) was used to introduce the frequency aspect.

The classification process involves two main operations that can be performed in parallel (50 % of the measured data is used for each one):

- *Training the model*. The *train* function of the Classifier Client receives the labeled record (list of tuple of datum and its label, following the Jubatus nomenclature) and returns the number of trained datum. In each of the iterations, the Classifier Server obtains and saves a new version of the model.
- *Classification*. The model is tested with unlabeled data. It receives the list of datum to classify and returns a list of estimated results, specifically, for each label, the probability of having generated the input record. The score, which represents the possibility of belonging to each class, is calculated as the inner product of the model coefficients and the feature vector. In this step, it is possible to adjust the

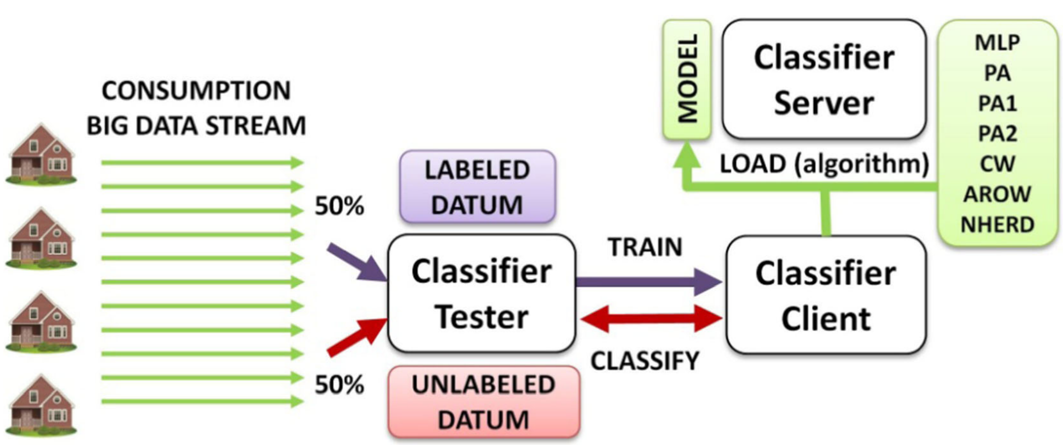

Fig. 2 Appliance identification process

input variables and configure the learning algorithm in order to improve the accuracy of the classifier.

The accuracy of the classifier is calculated as the number of times that an unlabeled record is classified in the correct class in relation to the total number of tests carried out. Both the first and second choice were taken into account, considering the weight of the second as half (Stamatatos and Widmer 2005).

The results shown in this work were obtained by training the Jubatus classifier with the consumption values of seven appliances situated in the Smart Home (CRT monitor, LCD monitor, heater, lamp, fridge, printer, and smart TV), sending measures at a 1-min rate (hence, the duration of each training iteration is 16 min). The experiment has tested all the training algorithms implemented in Jubatus. They can be classified in three families according to their basis:

– Perceptron (McDonald et al. 2010), the classical online learning algorithm performs a multi-class classification based on a set of weight vectors (one for each class), which are updated according to the prediction results, leading to the segmentation of the data space. Based on this, Passive Aggressive (PA) (Crammer et al. 2006) is offered by the tool in three different implementations (PA, PA1, and PA2), but it does not offer optimum results in multi-class classification.
– Confidence Weighted (CW) (Crammer et al. 2009a, b) is based on the notion of a parameter confidence measure, as an improvement over the aforementioned methods. Maintaining this idea, Adaptive Regularization of Weights (AROW) (Crammer et al. 2009a, b) also offers large margin training and the capacity to handle non-separable data. Normal Gaussian herding (NHERD) (Crammer and Lee 2010) is an attempt to improve learning when some noise is present.

The evolution learning rate of the classifier for each algorithm can be seen in Fig. 3, where the accumulated accuracy in the first 15 iterations (4 h of training) is shown. The best performance (about 74 % recognition rate) was obtained using weighted algorithms, such as CW and AROW, which, moreover, are the fastest, presenting values above 60 % of success after 30 min of training.

Collaborative recommender

The function of this module is to suggest actions to the users that other similar users have done in their homes, helping them to reduce their energy consumption.

To this end, it will be necessary to define a method for calculating the similarity between two users, i.e., the "distance" between them. When two users are "close" enough, they are considered as belonging to the same

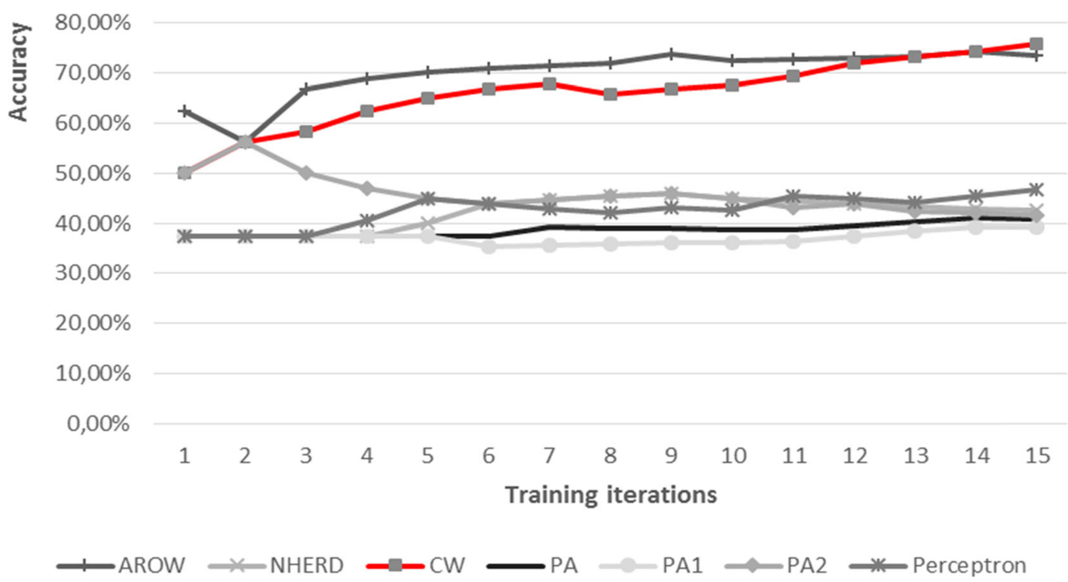

Fig. 3 Evolution of the accumulated accuracy of the classifier for each tested training algorithm

"neighborhood"—virtually speaking—and therefore similar recommendations are offered to them.

The Pearson correlation coefficient and the Euclidean distance are two valid values, which are based on the degree of acceptance of the actions that the users chose. In the specific solution proposed in this work, the users can agree (value 0) or not (value 1) with the completion of an action. In this context, the most appropriate algorithms are those of Tanimoto (Cechinel et al. 2013). The Tanimoto similarity coefficient can be expressed as (1), where A and B are the number of actions carried out by the two users whose similarity is calculated, respectively, and C corresponds to the number of actions common to both users.

$$T(A,\ B) = \frac{C}{A + B - C} \tag{1}$$

From the formula, the distances between all the users are calculated and stored in a matrix. When a recommendation is required to be given to the user, the algorithm returns the actions that most similar users have done and that the user has not yet carried out.

As for implementation, specific tools such as Mahout already incorporate these algorithms. The basic steps are to build a recommendation engine, and from there, generate recommendations. A sample code can be seen in Fig. 4.

Predictions

The system generates a weekly consumption prediction for each user. This massive information can be handled because the algorithms are implemented using Big Data technologies, which enable the code to be parallelized and the calculations to be performed for N users in a distributed way (cluster of machines), with a linear function of associated costs.

To make this kind of prediction, which can be seen in Fig. 5, specific and overall consumption factors are taken into account, as well as other relevant external factors, such as holiday schedules, prices, or meteorology. The graph allows the user to zoom over it and to compare the consumption (in green) with the prediction (in blue). The temperature (°C) is also shown (in red) as it is a representative input to guide the learning process, since the air conditioning consumption is a relevant parameter in business buildings and offices.

Regarding the methodology, the system tries to learn the behavior under certain climatic conditions, also considering social or behavioral aspects. In the first iteration, the variations in the prediction were analyzed and different patterns of day were found (holidays, holidays with commercial time schedule, holidays with full business hours, etc.). This point was solved by typifying the days and creating different units of knowledge for each of them.

To consider the seasonal variation, the system first determines whether the type of day corresponds to a day in winter, spring, summer, or fall, depending on the weather, and applying the acquired knowledge of the season.

Therefore, the system learns and predicts a differentiated "unit of knowledge" corresponding to the time range (morning, noon, afternoon, evening, night), the range type (spring morning, noon summer, etc.), the type of day (weekday morning spring, festive, festive opening noon), and the day except holidays (Monday spring morning business, etc.), obtaining 140 units of knowledge.

The system could determine which ML algorithm is applied in each unit of knowledge, which is different from one user to the next and even some seasons of the year, schedules, and other ranges.

The system learns in each case, i.e., how the user behaves on Monday mornings in spring, on Sunday

```
//Get the neighborhood of similar users
UserNeighborhood neighborhood = new NearestNUserNeighborhood(neighborhoodSize,
userSimilarity, dataModel);

//Create the recommmender
Recommender recommender = new GenericUserBasedRecommender(dataModel, neighborhood,
userSimilarity);
User user = dataModel.getUser(userId);

//Get the five best recommendations
List<RecommendedItem> recommendations = recommender.recommend(userId, 5);
TasteUtils.printRecs(recommendations, handler.map);
```

Fig. 4 Sample code for generating collaborative recommendations

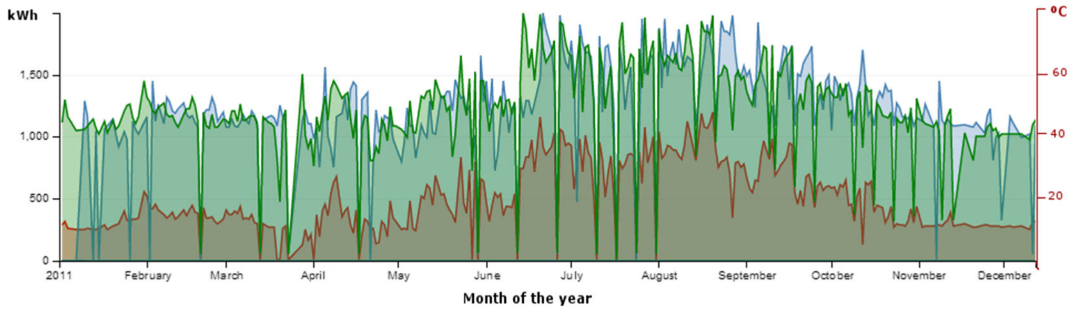

Fig. 5 Expandable graphic prediction generated by the systems, in comparison with the real measure

afternoons in fall, etc., and depending on the day to predict, the system selects the appropriate unit of knowledge, which relearns from the new measurement.

The strategy used by the model allows the way in which the system learns to be defined and adjusted, enhancing the use of relevant data and filtering the irrelevant data.

The model has been trained and tested over 2 years—one for training and one for testing—using the information (temperature, humidity, and consumption) generated by two buildings located in different climatic zones, specifically, Atlantic (a seaside city of northern Spain, Vigo) and Continental (Madrid, located in the center of the country) climate zones. The model is able to learn from the data how energy consumption is correlated with humidity and temperature measurements and then get the prediction for 1 week ahead. The value used for testing is actually the corresponding measured value for the second year. The effectiveness of the prediction system has been evaluated by statistical analysis. The interpretation of these statistics permits the error in the prediction to be calculated and the way in which that error was distributed to be evaluated and thereby adjust the learning model.

From the results listed in Table 1, some conclusions can be drawn. The MAD value offers an insight to the error that can occur in a prediction, and it is similar in both climatic zones. Besides that, MAPE, defined as the probability (between 0 and 1) of the average prediction errors, presents a better value in the oceanic climatic zone. The PA can be calculated from MAPE to compare different datasets. This technique shows a better value in the oceanic climatic zone. In the context of our system, we can predict with that confidence how much and in which way a user has consumed, taking the recorded consumption of last year. Considering the RMSD values, the errors are well spread over time if the value is low or very concentrated at certain times if the value is high. Having concentrated errors can be interpreted as more convenient for adjusting to anomalies. The oceanic zone shows a greater concentration of error than the continental zone, according to this technique. Finally, the SD is considered as an indicator of the error dispersion regarding the average error. Since the error is concentrated at certain points, the algorithm has a more stable performance regarding the error committed in each prediction than if the error was uniformly distributed because it would mean that wide variations exist between different predictions. The continental zone offers a better value in that case.

Data mining and insight

The information is presented to the user using highly expressive visual graphics, thanks to Data Mining and Insight technologies, which permit the user to view a lot of varied information at a glance, thus avoiding having

Table 1 System efficiency evaluation results by means of statistics

Statistic	Atlantic climate zone	Continental climate zone
Median absolute deviation (MAD)	237.46 kWh	207.59 kWh
Mean absolute percentage error (MAPE)	0.099	0.194
Prediction accuracy (PA)	90.09 %	80.59 %
Root mean square deviation (RMSD)	333.03 kWh	281.17 kWh
Standard deviation (SD)	233.49 kWh	189.63 kWh

many disjoint element graphics. In addition, inspection capabilities are provided, allowing the user to select sections, filtering the remaining information in order to draw conclusions.

A relevant graph is the "Heat Map" of consumption, where the consumption is represented by a disk comprising seven concentric circles (one for each day of the week) and 24 segments (one for each hour of the day), wherein the color corresponds to the intensity of consumption (to higher consumption, greater intensity of blue). This graph helps the user to know his/her consumption pattern, showing the differences in consumption between weekdays, which can help to improve the associated habits. Moreover, it facilitates the detection of anomalies that may be caused by device failures, which cause higher consumption. For example, Fig. 6 shows a higher consumption from 0700 to 2100 h on weekdays. Besides, two consumption anomalies can be distinguished, a fall on Saturday between 0200 and 0300 h and a rise on Monday between 0000 and 0100 h.

Relations between the modules

The elements described in the current section can be seen graphically in the SysML Block Diagram of Fig. 7 (dotted rectangles), which includes both hardware and software elements.

At the top of the hierarchy, the *SHE Adapter* collects the values such as the consumption from the home. The obtained data is then processed by the *Data Storage* module, which follows the concepts of Lambda Architecture (Fan and Bifet 2013), decomposing the problem into three layers:

- The *Acquisition block* collects the data from the SHE Adapter, to make it available for the Batch and Real-time blocks.
- The *Real-time block* is needed to provide a real-time monitoring and control services to users through a Graphical User Interface. This layer needs to aggregate the data, using typical functions, such as average and summarization for each user, group of devices, and time intervals, in a near real-time continuous computing.
- The *Batch block* includes several components to store and process the data, applying Data Mining and Machine Learning algorithms to acquire a customized knowledge pool for the home energy consumption.

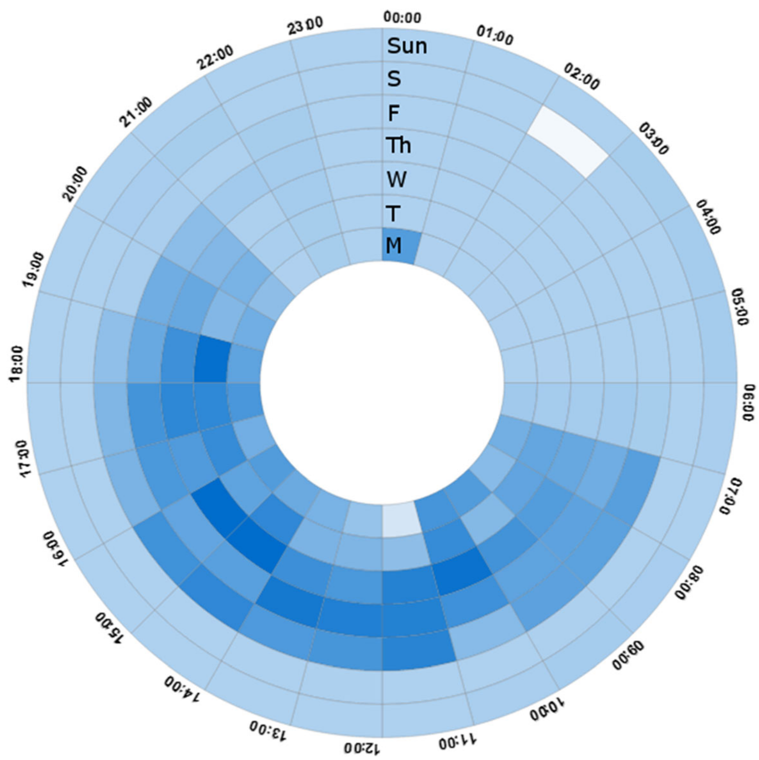

Fig. 6 Heat Map of air conditioning consumption

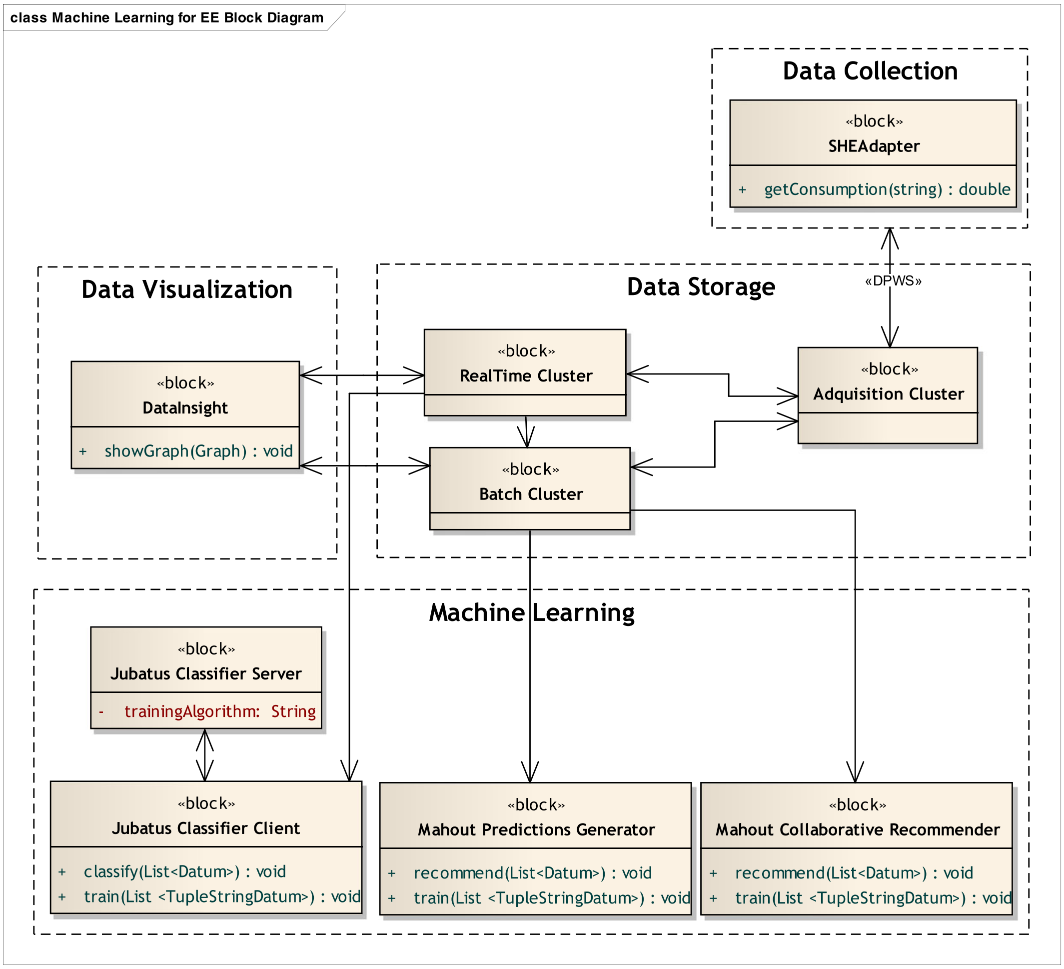

Fig. 7 Proposed system SysML block diagram

The stored data is then available to be used both by the *Data Insight* block to generate interactive graphs and *Mahout* and *Jubatus* instances, which will execute the learning over them, as was described earlier in the section.

Conclusions

The knowledge of household energy is a key factor in achieving the efficient use of resources. The widespread use of Smart Meters and Sensor Networks at residential level facilitates the obtaining of data, but due to their variety and size, it cannot be directly used to make conclusions that help to improve the energy efficiency.

The architecture of a four-module system based on Machine Learning techniques, combined with Big Data technology, has been presented in this work. Big Data allows large volumes of varied data to be managed and offers support for ML algorithms, Data Mining visual tools, near to real-time monitoring, and other information analysis and processing possibilities that fit perfectly with the requirements.

The Data Collection module is based on the data generated by the Smart Home Energy project, so the solution does not require investment in infrastructure. Moreover, it could be applied to any other similar smart environments.

Cloud technology offers an elastic and resilient solution without requiring a high-capacity storage infrastructure at the household level. Besides, the layered design allows both a batch and a continuous real-time processing of the measurements to be done, working with a large set of data taken over time from a large set of homes and historical database (Data Storage module).

The Machine Learning module is composed of three elements. First, a supervised classifier is trained to recognize each device from the consumption data, with the aim of being able to anticipate its consumption demand. By using some weighted algorithms, recognition rates above 74 % have been obtained, a value which improves with time, since the learning is done online. A potential improvement could be the use of clustering techniques in a previous phase in order to find out which category the device belongs to and therefore reduce the number of candidates that the classifier would need to screen it with. Furthermore, by applying the concept of user energy profile, a collaborative recommender processes the user actions in order to make energy-saving suggestions for similar users. It is also possible to extract consumption patterns and thus allow predictions to be made to anticipate and adapt to other cheaper options. The efficiency of this module was evaluated in buildings located in two different climatic zones, and an accuracy of 90 % has been achieved in the Atlantic Zone.

A useful complementary tool—belonging to the Data Mining and Insight module—, is the incorporation of interactive and customizable graphs to show the information to the user, who is able to manage the energy consumption and consequently improve the energy efficiency.

Summarizing, a complete infrastructure to improve the energy efficiency from the data generated by a smart environment has been proposed. The main advantages of the solution are that it is open, distributed, and scalable. The application of Big Data technology allows the information to be analyzed in more detail than with traditional technology, and the application of it to the energy sector is an innovative idea.

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Artículo 2: *Online identification of appliances from power consumption data collected by smart meters*

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SHORT PAPER

Online identification of appliances from power consumption data collected by smart meters

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Abstract The efficient use of resources is a matter of great concern in today's society, especially in the energy sector. Although the main strategy to decrease energy use has long been focused on supply, over the last few years, there has been a shift to the demand side. Under this new line of action, demand-side management networks have emerged and extended from the household level to larger installations, with the appearance of the concepts of Smart Grids and even Smart Cities. The extended use of Smart Meters for measuring residential electricity consumption facilitates the creation of such intelligent environments. In this context, this article proposes a system which extracts value from the collected consumer information to identify the appliances belonging to that smart environment by means of machine learning techniques. Considering the large amount of information that would be handled when millions of homes were sending data, big data technology has been used. An experiment to evaluate the classification method was carried out with seven devices and three different configurations. The results are also reported, achieving promising results, with recognition rates of 75 % after 1 h of training and 100 % after 4 h.

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Keywords Smart meter · Power consumption · Big data · Machine learning · Supervised classification · Energy efficiency

1 Introduction

The European Union (EU) aims to reduce its Green House Gas (GHG) emissions and its total energy consumption by 20 % by 2020 [1]. Although incorporating renewable energy sources to the supply has been an important energy strategy in Europe and world-wide, the importance of energy management on the demand side has recently been discussed [2]. In Europe, for instance, the building sector represents 40 % of the total energy consumption; thus, incorporating in-home management systems at household level can represent a promising line of action to achieve the EU 2020 targets.

These systems have advanced metering infrastructures that monitor home energy consumption, elaborate personalized energy profiles, and settle the basis for energy behavior modifications. This type of infrastructure is becoming more widespread, and most of the information obtained from it is not being fully exploited [3]. By learning from the consumption data to anticipate the final user's energy demand in the short–medium term, the efficiency of the energy sector would consequently be improved [4].

Furthermore, one of the main obstacles to solve—as the Spanish Electrical Grid Platform has pointed out in its Research Agenda [5]—is the lack of standard and open communications protocols to guarantee interoperability between equipment made by different manufacturers. The Digital Home Compliant (DHC2.0) [6] protocol, which has been applied in various fields such as health-based

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scenarios [7], arises with the aim of solving these needs. Currently, any DHC aware device should implement its own software adapter, which acts as intermediary with the DHC Network. A better interoperability of the system would be achieved by automatic deployment of the specific adapter. To do this, it will be necessary, on the one hand, to automatically generate the code for that adapter and secondly identify the device to run the appropriate code.

In this context, this proposal seeks to extract the collected consumption data from these real-world environments and use them to discover the elements that integrate them, identifying which appliances have generated that consumption. On the one hand, the first step would be to anticipate demand. Moreover, this will permit itemized electricity bills and targeted energy saving advice. On the other hand, it will provide the DHC protocol with the necessary feedback to automatically deploy the specific adapter to permit the appliance to be part of the network.

Concerning the possible growth of data—increasing the number of appliances in the home, or the number of homes belonging to the grid—the traditional computing technologies have some limitations in terms of the capacity to process data, above which specific supercomputers are required, with a very high associated cost. Big Data technology [8] is able to approach the capabilities of supercomputers using conventional hardware, making it possible to apply the technology to fields in which it was unprofitable before. The large amounts of consumption data can be processed by a classifier system to automatically perform an online learning. Moreover, the application of machine learning (ML) algorithms running over big data technologies provides the system with faster response times and scalability, which are the most innovative characteristics of the contribution.

The document is organized as follows: First, in the state of the art section, an overview of relevant automatic identification mechanisms is set out. Then, the way in which consumption data are collected and processed by the system using machine learning techniques is described in Sect. 3. The experiment carried out to test the proposed environment is described in Sect. 4, as well as the discussion of the obtained results. Finally, the document closes with the conclusions and future work.

2 State of the art

The field of the automatic identification of electrical devices based on power consumption has been explored over more than two decades in several studies. The first proposals [9, 10] had to limit their testing infrastructure to a single Smart Meter located at the point of entry/exit of the house due to the price of the technology. Therefore, the identification of the specific power consumption record belonging to each individual appliance was done afterward. A remarkable method, the non-intrusive load monitoring (NILM) proposed by George Hart [11], was able to recognize a representation of a finite state machine consumption of an appliance over time, given the consumption changes (up and down) [12]. However, the algorithm was able to identify only on/off appliances and appliances which could be described as finite state graph.

After years of relatively little research in the field, perhaps driven by the new possibilities that have arisen around the concept of Smart Grid and new technological opportunities, it seems that new ideas have emerged strongly. Based on these new developments, two main approaches to identify appliances are distinguished.

The first approach obtains very accurate data under a low measuring rate [8]. This method requires simple software but special hardware, so it does not fit with the initial idea of using the power consumption data obtained by an existing Smart Meter network located in a smart home environment.

The other main approach, where this work is framed, proposes to measure large amounts of data but not very accurately. Therefore, more complex software, commonly based on ML techniques, is needed to analyze the data. Different ML methods can be used depending on the characteristics of the data and the goal to be achieved. In Table 1, several studies are listed, checking the values for

Table 1 Comparison of ML-based appliance recognition studies

References	Plug-based meter	Online training	No appliances	Reading rate	Training algorithm	Accuracy (%)	Scalable
[13]	NO	NO	5	10 s	HMM	75–95	NO
[14]	NO	NO	3	15 min	ANN	80–97	NO
[17]	NO	NO	6	10 s	DTW	10–95	NO
[18]	NO	YES	8	1 s	KNN	70–90	YES
[19]	NO	YES	9	5 s	DBN	92–99	YES
[20]	NO	NO	13	1 s	K-means	60–97	NO
[21]	YES	NO	10	10 s	KNN and GMM	84–94	NO

the more remarkable features of our solution, as well as the configuration and results of their experiments.

Zia et al. make use of Hidden Markov Models (HMM) to recognize the individual appliances from combined load [13]. However, the complexity of the HMM models increases exponentially as the number of target appliances increases, which limits the applicability of this learning method. Artificial Neural Networks (ANN) are applied by Prudenzi to find out the patterns of use of home appliances [14], and although the extensibility is better (input feedback), exhaustive training for each appliance is needed. In the same way, Murata and Onoda estimate the behavior of the appliances from the total load demand curve thanks to radial basis function networks [15]. Baranski and Voss use Genetic Algorithms for the same purpose [16]. A weighted algorithm such as Dynamic Time Warping (DTW), used by Zaidi, also gives uncertain results when the number of loads increases [17].

Berges et al. present a new approach by means of online learning. The proposed solution, based on K-Nearest Neighbor (KNN), is scalable, but the tests have been carried out with laboratory generated data so far [18]. Lin et al. follow the same idea, but using a Dynamic Bayesian Network (DBN) [19]. However, online learning is not enough for learning from Big Data streams, in which thousands of samples arrive each second.

A different clustering method based on k-means is proposed by Simon, Liang, and Cheng. They measure the consumption of all appliances in the house a priori and record them, which limits its scalability. However, there are several drawbacks and challenges, as highlighted by the authors; the accuracy of the classifier is low for some types of appliances, due to consumption similarities. In addition, multi-state appliances form several clusters due to the multiple states [20].

If we add the technological advances in the field of Smart Metering to the mentioned techniques, the study of Ridi is the one, using Plug-based Smart Meters, which facilitates its applicability. They combine KNN and Gaussian Mixture Models (GMM) techniques. The main disadvantage is the limitations to scalability, as they store the row data in xml files [21].

Summarizing, although a great deal of progress has been made, the process of automatic identification still needs to be upgraded. Firstly, most studies are focused on the disaggregation of the total measurement, since they do not have individual meters for each plug. In addition, the majority of them need a historical load database of different electrical appliances, so they fail when a new device is introduced into the environment. The storage of that information can also be a handicap, since time-series records are often extremely large. This is translated into limited scalability. Finally, some aspects are still unresolved, such as the full automation of the identification process, and the recognition of low consumption devices, which are usually not taken into account when the total consumption is large.

3 System overview

The system represents an integrated solution to identify household appliances from the consumption data gathered by Smart Meters, installed in an existing real-world environment. The components involved in the system, whose graphical description is shown in Fig. 1, are grouped according to their function:

- The Data Collection hardware and software components are placed in each user's smart home. They obtain the consumption-related data from all the appliances and service robots and send them to the cloud at a predefined rate, in order to be used by the Recognition Module.
- The Recognition Module function takes place in the cloud, where the consumption Big Data, arriving in real-time, are used by the classifier element, which follows a client/server structure to perform the online

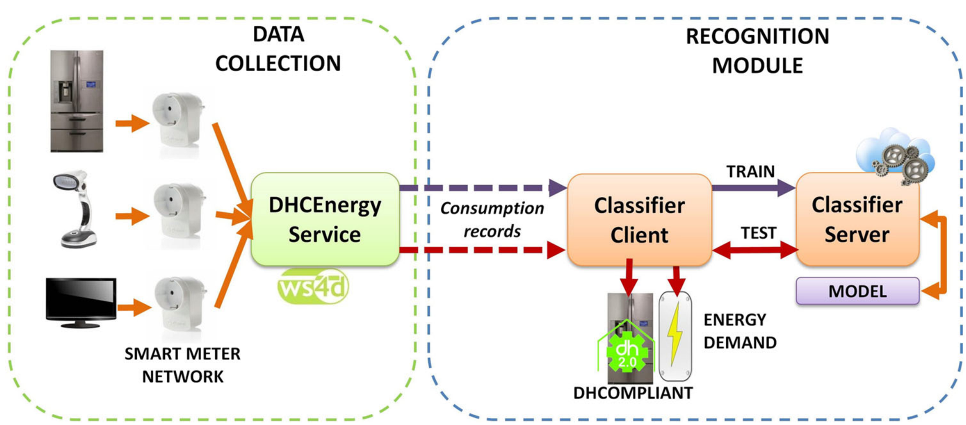

Fig. 1 Components of the proposed system

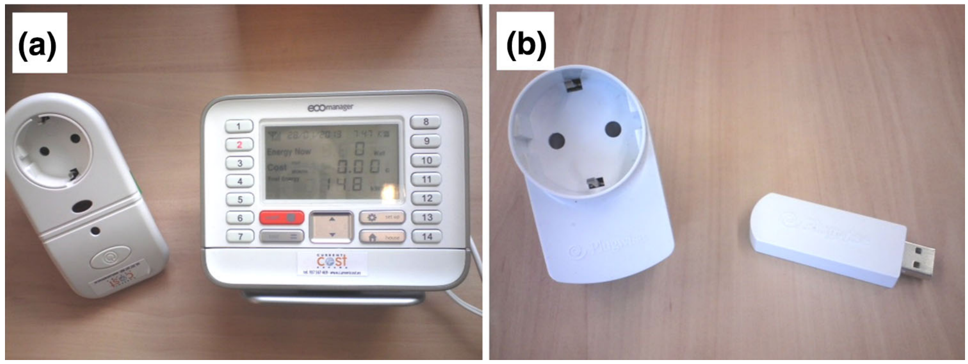

Fig. 2 **a** EcoManager Smart Meter (Current Cost). **b** Plugwise SmartMeter

learning. Once the device has been recognized, we can anticipate demand and deploy the corresponding DHC2.0 adapter.

These parts—Sects. 3.1 and 3.2—are described in detail in the next subsections.

3.1 Data collection

In order to set up interoperability in a Digital Home environment and allow cooperation between devices designed by different manufactures, a standard communication protocol is needed. DHC2.0, which is based on the Web Service for Device (WS4D) technology [22], is used in this work. Several sub-modules, each delivering specific services, make up the DHC2.0 architecture. Specifically, the DHC Energy module handles those aspects related to the energy efficiency of the devices integrating the Digital Home environment.

Regarding the hardware requirements, intelligent measuring devices (Smart Meters) are able to report information about the consumed power at a predefined rate. For instance, the plug-based Smart Meters, shown in Fig. 2, obtain the consumption value (in watts) of each appliance connected to them and send it to the plugs–control unit by means of radio-frequency and ZigBee protocols, respectively. This proposal, as with the DHC protocol, aims to be applicable to any meter device, regardless of brand or model. In addition, selecting different meters to test the same experiment ensures that the possible noise introduced by them has no influence on the classification process.

From the analysis of the measured data, it can be deduced that the loading phase pattern remains constant for all of them. As an example, Fig. 3 shows how the consumption pattern of the fridge (a) and the monitor (b) is repeated over 24 h.

The consumption values can be considered as a time-series sequence. This type of data, characterized by being composed of an ordered list of real numbers, where each number represents a value at a point in time, is present in fields such as medicine [23], document analysis [24], speech recognition [25], or the economy [26]. Although these research areas go beyond the scope of this article, taking their identification methods into account was considered useful, as the processed data have several characteristics in common.

The consumption records have some intrinsic characteristics, due to the continuous creation over time, such as serial correlation, stationary, noise, or missing values. This can affect their correct classification [27], since the majority of algorithms do not take such temporality into account. These peculiarities make some weighted algorithms more suitable than others, as for example, Dynamic Time Warping [28], which is one of the tested algorithms, as will be seen in the Experiment Section.

Finally, acting as an intermediary between the Smart Meter network and the Recognition Module, the DHC Energy Adapter software collects the real-time consumption values and makes them available. It is also responsible for sending this information to the cloud. Cloud technology does not require a large infrastructure at home and, moreover, provides facilities to manage and maintain the integrity, security, and availability of data. Concerning the possible growth of data (increment of the number of homes, as well as the devices per home), the other key technology is Big Data, as it facilitates its scalability. Furthermore, it offers near to real-time monitoring and other information analysis and processing possibilities that fit perfectly with the proposed system, such as the support for ML algorithms, which will be used by the Recognition Module.

3.2 Recognition module

The purpose of this module was to identify which device has the highest probability of having generated an unlabeled consumption record. To do so, this module trains an electrical device classifier using supervised Machine Learning (ML) techniques.

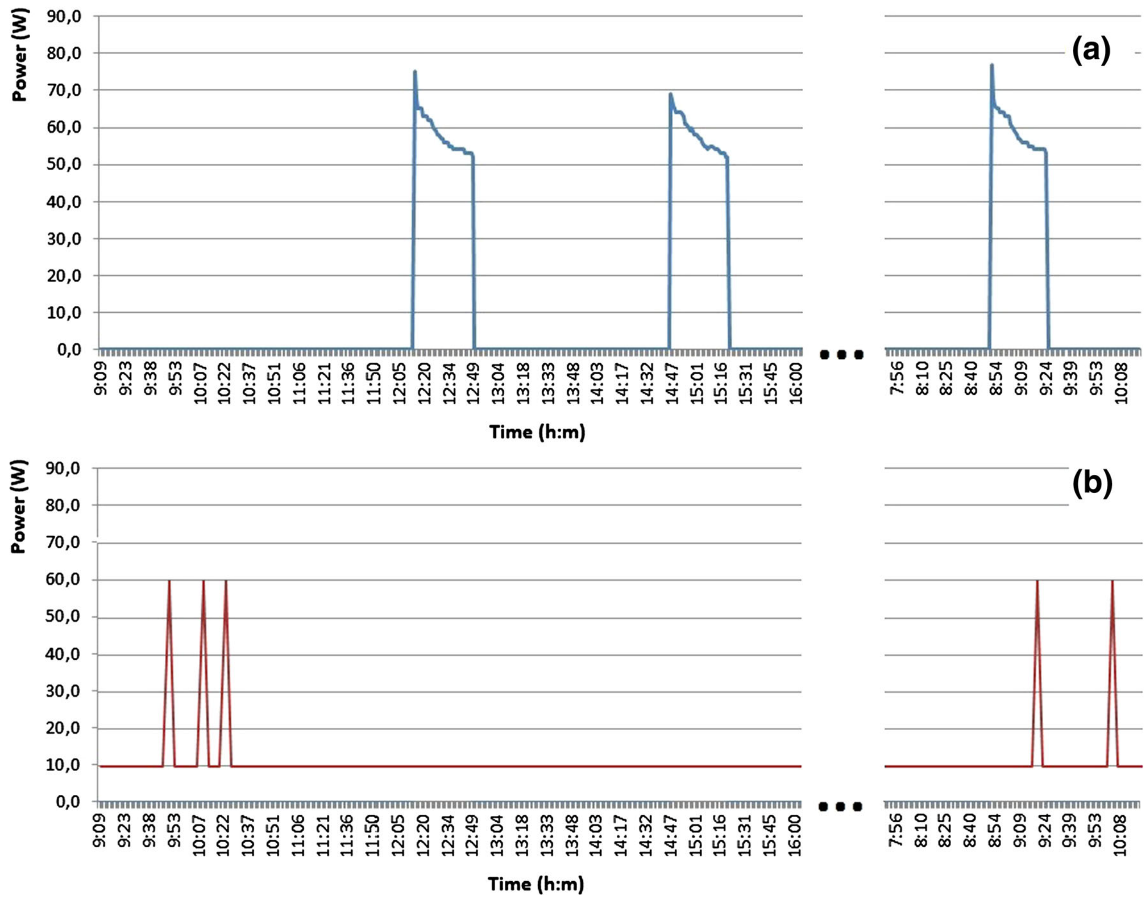

Fig. 3 Example of the power consumption measured for the fridge (**a**) and the monitor (**b**) during 24 h

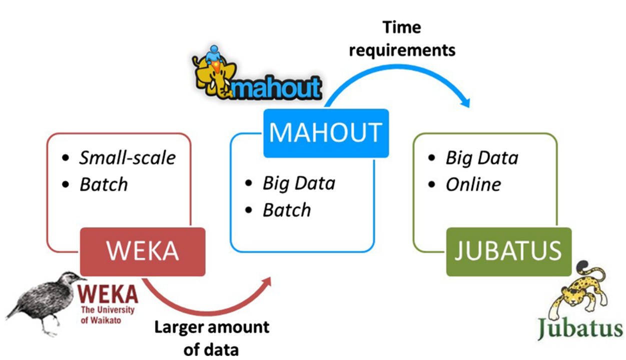

Fig. 4 Analyzed machine learning tools

With the final aim of choosing the ML technique that best suits the environment described at the beginning of the section, as well as the type of input data, several available approaches were analyzed (see Fig. 4). Firstly, Weka [29] is a matured software that has the advantage of incorporating large numbers of training algorithms. It was used in the preparatory phase of this research for exploring and characterizing the data and can easily test the suitability of different learning methods. Nevertheless, for larger amounts of data, the tool did not work as expected, so specific big data tools were studied. Mahout [30] is an Apache project that aims to produce a free implementation package that includes the main ML algorithms. The project is very active, but there are still algorithms to be incorporated, especially for time-series classifications. Its main advantage over other stand-alone implementations is the scalability offered when running on Hadoop [31]. Taking into account the fact that power consumption data are an infinite time series, the online learning approach was considered a suitable option, offering a simple, fast solution requiring less memory, and which avoids re-training when adding new data, since the model is updated at the end of each iteration. In particular, the Jubatus online learning framework is a tool which maintains the scalability characteristics of Mahout and, in addition, allows a real-time response to be obtained. It incorporates some weighted algorithms which are the most appropriate for time-series classifications and has been successfully tested in other fields such as computer vision [32] or detection of malicious web sites [33].

Regarding scalability, the throughput of a Jubatus classifier increases almost linearly with the number of servers

[34]. Besides, Jubatus has been evaluated by classifying Twitter tweets on a global scale (8000 per s) with two servers. An accuracy rate of 90 % in batch processing was achieved with data obtained within 10 s [35].

In our particular case, considering that each home submits consumption information every minute, it means 525,600 samples per year. Each sample causes the transmission of 1 kilobyte; therefore, each home generates 538,214,400 bytes of information per year. Considering a population of ten million homes, a system able to process 5 Petabytes of information per year is needed. Additionally, it would be necessary to support the execution of the operations to be performed with all this information, i.e., the learning process and the model synchronization among servers, which could greatly increase the needs (Fig. 5 shows the architecture of the described scenario).

Jubatus is based on a client/server structure, where the Classifier Server performs the main role in the learning process using the consumption data provided by the classifier client as a basis. As the training is done online, the Classifier Server obtains and saves a new version of the model in each interaction.

The classification process involves two main operations that can be performed in parallel:

- *Training the model:* the train function of the Classifier Server receives the labeled record (list of tuple of datum and its label, following the Jubatus nomenclature) and returns the number of trained datum.
- *Evaluation and adjustment of the model:* The model is tested with unlabeled data by means of the classify function. It receives the list of datum to classify and returns a list of estimated results, specifically, for each label, the probability of having generated the input record. The score, which represents the possibility of belonging to each class, is calculated as the inner product of the model coefficients and the feature vector.

In this step, it is possible to adjust the input variables contained in the Training Datum and to determine and configure the learning algorithm in order to improve the accuracy of the classifier. The results of several different tested configurations are listed in the next section.

4 The experiment

In a context such as the one described in the previous section, the following hypothesis is posed: it is possible to identify electrical devices based on their consumption data, using an online classifier. This will involve an experiment to test it. Firstly, the design of the experiment is described, followed by the process of obtaining the data and using them for classifying the appliances with Jubatus. Finally, the obtained results are presented.

4.1 Design of the experiment

The SysML block diagram in Fig. 5 shows the structure of the experiment. On the one hand, the DHC Adapter obtains the consumption data through a network of Smart Meters, which are connected to the devices under study, and makes them available. As can be seen in Fig. 6, the electricity consumption values of seven appliances (CRT monitor, LCD monitor, heater, lamp, fridge, printer, and smart TV) are measured in the experiment. On the other hand, the Recognition Module is represented by the Classifier Server, which is continuously running and waiting for the Classifier Client, which sends the labeled and unlabeled records to do the training and testing, respectively. In each iteration of the experiment, the Classifier Server receives the data, learns online, and updates the model.

The Classifier Tester element is introduced to launch the experiment, thereby obtaining and configuring the necessary elements. It consumes the DPWS service offered by the adapter to collect the consumption values and uses them to compose the Training Datum. The classifier handles the missing values by taking the last read value. If it is the first reading, it is ignored.

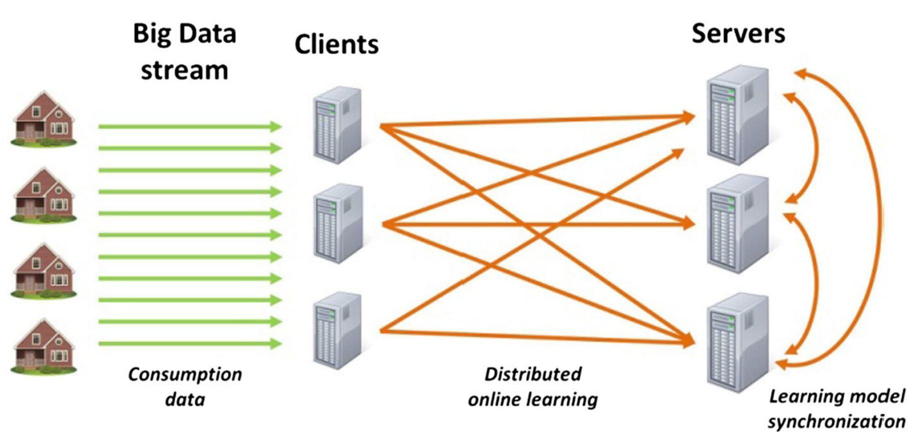

Fig. 5 Future application scenario

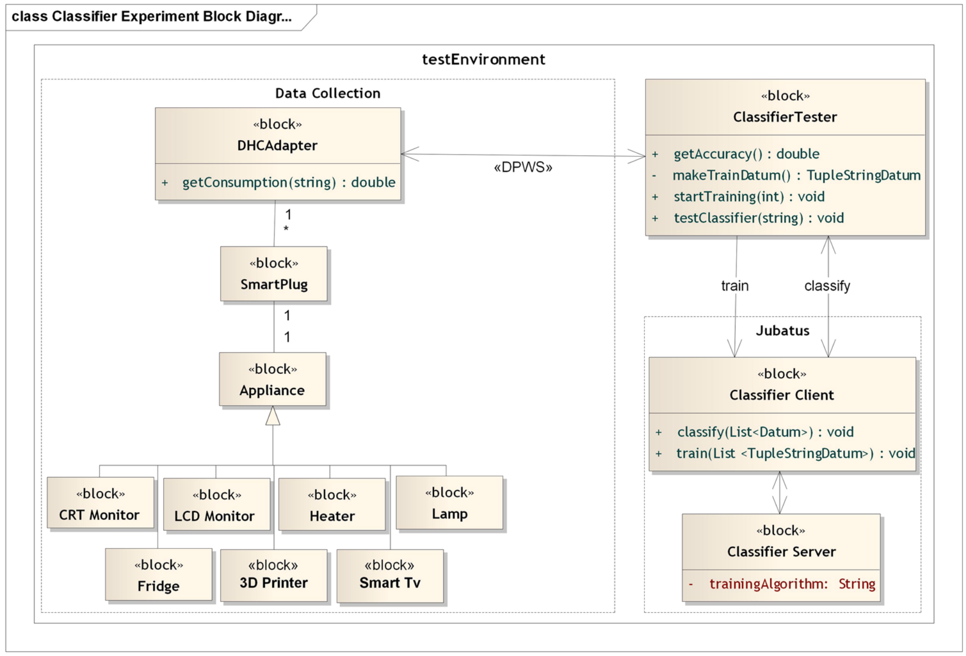

Fig. 6 SysML block diagram of the experiment

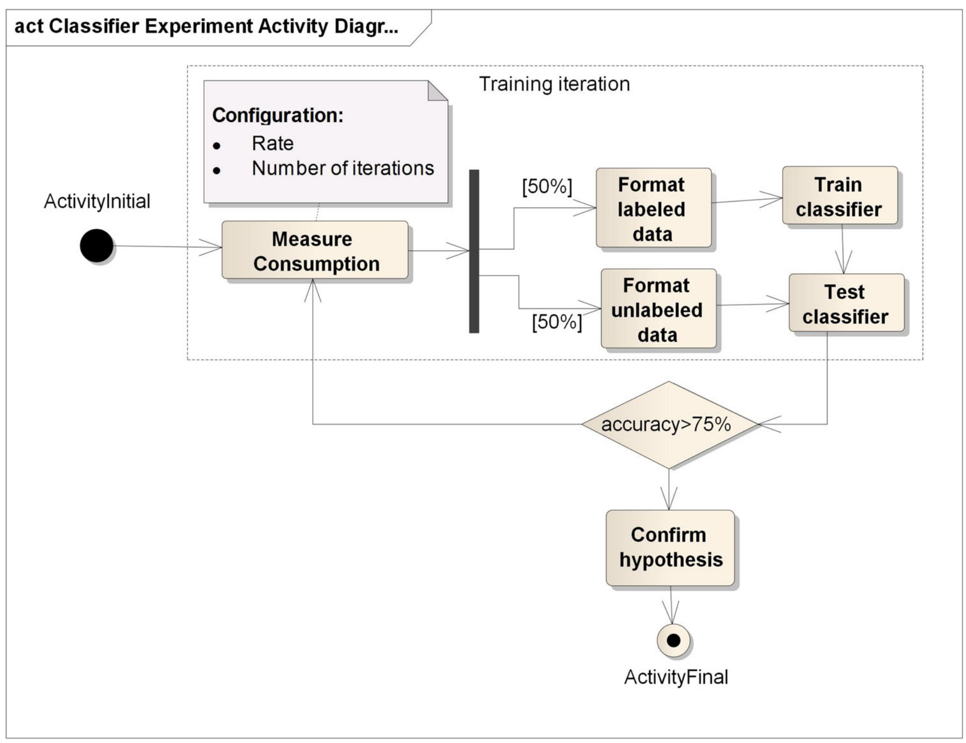

Fig. 7 SysML Activity diagram of the experiment

The process carried out for testing each algorithm is shown in the activity diagram of Fig. 7. At the beginning of the experiment, the specific configuration is defined. On the one hand, the measuring rate and consequently the window size are set. On the other hand, the number of iterations, to determine the training time, is also fixed. Specifically, three different rates were tested for each algorithm (10 s, 1 min, and 3.75 min), analyzing the results for four training times (1, 2, 4, and 8 h).

In each iteration, fifty percent of the measured data are used for training the classifier (updating the model), while the remaining fifty percent is used for testing it. If the accuracy is 75 % or higher, the hypothesis can be confirmed, and hence the classifier works as expected.

Fig. 8 Code fragment illustrating the creation of training records

```
private static TupleStringDatum makeTrainDatum(String label, double[] consumption) {
    TupleStringDatum t = new TupleStringDatum();
    t.first = label;
    t.second = makeDatum(consumption);
    return t;
}

private static Datum makeDatum(double[] consumption ) {
    Datum d = new Datum();
    d.string_values = new ArrayList<TupleStringString>();
    d.num_values = new ArrayList<TupleStringDouble>();
    ...
    d.num_values.add(makeTupleStringDouble("min",min));
    d.num_values.add(makeTupleStringDouble("max",max));
    d.num_values.add(makeTupleStringDouble("mean",mean));
    d.num_values.add(makeTupleStringDouble("sum",sum));
    d.num_values.add(makeTupleStringDouble("deviation",deviation));
    d.num_values.add(makeTupleStringDouble("variance",variance));
    d.num_values.addAll(fourier(consumption));

    return d;
}
```

The accuracy of the classifier is calculated as the number of times an unlabeled record is classified in the correct class, in relation to the total number of tests carried out. Both the first and second choices were taken into account, considering the weight of the second as half [41].

4.2 Jubatus classification

Once a record of sixteen correct consumption measures is obtained, the Jubatus Datum object—used by the Classifier Client—has to be composed. An example of the Java code is shown in Fig. 8. It is made up of the minimum, maximum, mean, sum, deviation, and variance of the consumption values record. Finally, the Fast Fourier Transform (FFT) was used to introduce the frequency aspect.

The output of the FFT is an array of 16 complex numbers, corresponding to the number of consumption measures per iteration—using a multiple of two is appropriate for the FFT. It is possible to use both the real and imaginary part to get very accurate frequency information, by simply looking at the magnitude, which is calculated using the distance Eq. (1).

$$\text{Magnitude}(i) = \sqrt{\text{real}(i)^2 + \text{imaginary}(i)^2} \qquad (1)$$

The makeTrainDatum function is used to label the 22-element records created by the makeDatum function, which is also used in the testing phase (since the record is not labeled in that case).

Jubatus only supports linear models for classification. A model includes a list of coefficients and their deviations if needed. The experiment has tested all the training algorithms implemented in Jubatus. The only differences between them are their equations for updating the coefficients of the linear model [34]. They can be classified in three families according to their basis:

- Perceptron [36], the classical online learning algorithm, performs a multiclass classification based on a set of weight vectors (one for each class), which are updated according to the prediction results, leading to the segmentation of the data space. Based on this, passive aggressive (PA) [37] and two improved versions with a better ability to cope with noise are offered by the tool, but they do not offer optimum results in multi-class classification.
- Confidence Weighted (CW) [38] is based on the notion of parameter confidence measurement, as an improvement over the abovementioned methods. Maintaining that idea, Adaptive Regularization of weights (AROW) [39] also offers large margin training and the capacity to handle non-separable data. Normal Gaussian herding (NHERD) [40] is an attempt to improve learning when some noise is present.

For launching the experiments, three parameters need to be set in a json configuration file. Firstly, the method (e.g., "AROW"), secondly, the converter (which decides how to extract each feature vector from input data), and finally, the *regularization_weight* parameter (when this parameter becomes bigger, the learning speed will increase, while the noise will decrease).

5 Results

Using a fast measuring rate, and therefore a small window (since a training record is made up of sixteen consumption measures), will enable the learner to adapt more rapidly. A

Table 2 Accuracy of the classification tests over time for each considered algorithm with configuration 1 (10 s rate, 2.66 min for each iteration)

Training time (h)	No iterations	Perceptron (%)	PA (%)	PA1 (%)	PA2 (%)	CW (%)	AROW (%)	NHERD (%)
1	23	37.5	37.5	37.5	12.5	87.5	75.0	50.0
2	45	37.5	37.5	37.5	37.5	50.0	75.0	37.5
4	90	37.5	37.5	37.5	37.5	87.5	87.5	37.5
8	180	37.5	50.0	50.0	50.0	75.0	75.0	37.5

Table 3 Accuracy of the classification tests over time for each considered algorithm with configuration 2 (1 min rate, 16 min for each iteration)

Training time (h)	No iterations	Perceptron (%)	PA (%)	PA1 (%)	PA2 (%)	CW (%)	AROW (%)	NHERD (%)
1	4	37.5	37.5	37.5	62.5	50.0	62.5	37.5
2	8	50.0	37.5	37.5	37.5	62.5	75.0	37.5
4	15	37.5	37.5	37.5	50.0	75.0	75.0	50.0
8	30	62.5	50.0	37.5	37.5	100	87.5	37.5

Table 4 Accuracy of the classification tests over time for each considered algorithm with configuration 3 (3.75 min rate, 1 h for each iteration)

Training time (h)	No iterations	Perceptron (%)	PA (%)	PA1 (%)	PA2 (%)	CW (%)	AROW (%)	NHERD (%)
1	1	62.5	37.5	37.5	50.0	87.5	37.5	37.5
2	2	62.5	50.0	50.0	37.5	75.0	50.0	37.5
4	4	50.0	50.0	46.8	37.5	75.0	37.5	37.5
8	8	37.5	62.0	43.7	50.0	75.0	50.0	37.5

larger window will lend more stability to the overall process. For the first configuration, a rate of 10 s was used (2 min and 40 s for each iteration), and the results are listed in Table 2. In the second, a 1-min rate was chosen (16 min for each iteration), and the results are shown in Table 3. Finally, in the third configuration (see Table 4), measurements were obtained each 4 min (1 h for each iteration).

As can be seen, the algorithms belonging to the first family (perceptron, PA, PA1, and PA2) show a similar behavior, with medium recognition rates, which are lowest with the first configuration. The weighted algorithms (CW and AROW) offer the best performance of all the studied configurations. Specifically, CW has achieved 100 % correct recognition rates after 8 h of training using the second configuration. Finally, NHERD did not obtain the expected results, offering the worst results, since the classifier seemed not to learn, showing a nearly constant rate of success.

According to the results shown in tables, the most suitable window size is the one used in the second configuration. The evolution learning rate of the classifier in that configuration, for each algorithm, can be seen in Fig. 9, where the accumulated accuracy in the first 15 iterations (4 h of training) is shown. At the beginning of the training, AROW shows a better accuracy, but from the thirteenth iteration, its accuracy remains constant, while CW continues to grow, achieving 75.83 % of accumulated accuracy rate.

6 Conclusions and future work

In this paper, we propose a novel solution for the identification of home appliances based on the collection and analysis of their power consumption values by a network of plug-based Smart Meters, which permits a brand independent, cost-effective, and easy-to-install architecture.

The identification process is based on Machine Learning techniques, training a supervised classifier to recognize which device has the highest probability of having generated an unlabeled consumption record. The online learning approach avoids the problem of storing the large amount of data generated by the meters. Besides, it is a fact that this type of infrastructure is becoming more widespread, so the number of homes adopting this proposal would be in the order of millions. In that case, Big Data technology will be the key to process such amounts of data. In addition, it

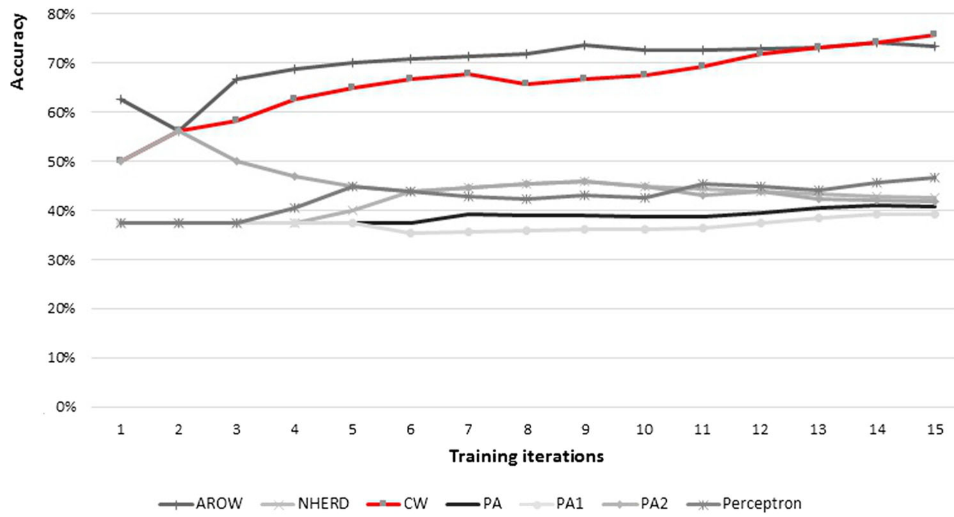

Fig. 9 Evolution of the accumulated accuracy of the classifier for each training algorithm using the second configuration

presents other advantages such as scalability and minimum required infrastructure.

An experiment was carried out to test the system. The classifier was successfully trained using consumption data from seven devices. Seven different learning algorithms were tested under three different experimental configurations, and an accumulated accuracy of 75.83 % after 4 h of training was obtained with the CW algorithm, followed closely by the other weighted algorithm, AROW.

In addition to the advantages that this identification system could provide to the efficiency of the energy sector in the medium-long term, its functionality could also be applied in the short term to improve the DHC protocol. When a new device has to be incorporated to the DHC network, the proposed identification mechanism would enable us to know which specific DHC adapter has to be deployed. This would mean that, instead of doing this action manually, as it is currently done, it would be done automatically; hence, the interoperability of the system would be enhanced.

A potential improvement could be to use clustering techniques in a previous phase in order to find out which category the appliance belongs to and therefore reduces the number of candidates that the classifier would need to screen it with.

As far as possible fields of application goes, the proposed system presents promising characteristics that would contribute to reaching a future energy scenario where the supply and demand curve will always be accurately matched.

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Artículo 3: *Review of Display Technologies Focusing on Power Consumption*

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Review

Review of Display Technologies Focusing on Power Consumption

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Abstract: This paper provides an overview of the main manufacturing technologies of displays, focusing on those with low and ultra-low levels of power consumption, which make them suitable for current societal needs. Considering the typified value obtained from the manufacturer's specifications, four technologies—Liquid Crystal Displays, electronic paper, Organic Light-Emitting Display and Electroluminescent Displays—were selected in a first iteration. For each of them, several features, including size and brightness, were assessed in order to ascertain possible proportional relationships with the rate of consumption. To normalize the comparison between different display types, relative units such as the surface power density and the display frontal intensity efficiency were proposed. Organic light-emitting display had the best results in terms of power density for small display sizes. For larger sizes, it performs less satisfactorily than Liquid Crystal Displays in terms of energy efficiency.

Keywords: energy efficiency; power consumption; Liquid Crystal Display; Organic Light-Emitting Display; Electroluminescent Display; electronic paper

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1. Introduction

The world as a whole is currently in an overshoot condition. Population size and economic growth contribute significantly to this situation [1]. Specifically, the steady growth in the use of personal portable devices during the past decade—driven by the development of mobile telecommunications and the incorporation of personal digital assistant devices and electronic books into the market—has considerably increased the per person carbon footprint [2]. The International Energy Agency (IEA), which monitors the demand and supply of energy worldwide, aims to reduce the global consumption level to an acceptable limit. In order to do so, the IEA is calling for more efficient technologies for the aforementioned devices to be manufactured. In the *Energy Technology Perspectives Study*, the IEA points out that technologies can and must play an integral role in transforming the energy system to reduce greenhouse gases [3].

Leaving aside the environmental reasons to reduce power consumption, the demand for power in electronic devices has also increased, especially those with limited battery lifespan that need to reduce their rates of power consumption for optimal performance. According to several studies [4,5], one of the components with the highest percentage of total energy consumption, and therefore a suitable candidate for improvement, is the display. Traditionally, the reduction of t display energy consumption in electronic devices was done through methods that often relied on shutting off the display during inactive periods [6] or adjusting the luminance of the screens with light-based automatic brightness control (LABC) [7] methods. Due to current market conditions, the focus on improvement needs to shift to make the device itself more power efficient, through the use of display technologies with higher levels of energy efficiency.

The aim of this review is to identify which display technologies are most appropriate in terms of power consumption. The displays can be classified according to different approaches, for instance regarding the way they create the image, their size, the maturity of the technology, *etc.* [8], but to the best of our knowledge, the power consumption is rarely taken into account in any of them as a parameter to make a difference between display technologies.

Firstly, in the next section, the scope of the study is outlined. In Section 3, the main features influencing in the consumption of a display are explained in order to be understandable in Section 4, where the specific advantages of those features for some specific display modules are listed. Section 5 includes the analysis, comparison and discussion of the mentioned data. Applications and trends are detailed in Section 6. Finally, conclusions will be drawn and future work suggested.

2. Scope of the Study

Many display modules of different technologies coexist and compete for their share in the market. Due to the diversity in sizes and brands, the establishment of a standardized method that enables a reliable power consumption comparison between them has been considered relevant.

The International Committee for Display Metrology aims to solve the need of the display industry and research institutions for having a single reference standard on how to measure and characterize displays. As a result, the Information Display Measurements Standard (IDMS) [9] has been published by the Society for Information Display [10], replacing the previous Flat Panel Measurements (FPDM) standard.

Power consumption is defined by the IDMS as the power needed by the Device under Test (DuT) to reach its full operation. The components to be measured depend on the technology used to develop the display. For example, the power required for the backlight in LCD is part of the display power, since the DuT is not functional without it. As the power is additive, the total power of the device is the sum of all individual powers, including the backlight with inverter where applicable, the panel and any other incidental power from the elements needed to run the display.

In order to give a relative value to the power consumed by a display, different metrics can be used, such as the Environment Cost of Ownership (ECO) [11] for the Life Cycle Assessment (LCA) [12], that each look at the environmental impact of the technology. According to Vaclav Smil, the power density, which will be used in this work, is one of the most revealing variables in energetics for assessing consumption [13]. Following this approach, displays can be divided into high, medium, low and ultra-low power consumption items (the proposed range values for each category are listed in Table 1).

A complete classification of the technologies is shown in the Graphical Abstract. For each one, the power consumption density of ten different commercialized display modules was analyzed, extracting their technical specifications from the manufacturer's datasheet. The results revealed that some displays show a remarkable increase in power consumption with size. Therefore, it was concluded that the size could be a second criterion for assessing display technologies.

In the field of display development, which is strongly linked to the path set by manufacturers, the Japan Displays Inc. consortium [14], founded in 2012 (Sony Mobile, Toshiba Mobile and Hitachi displays) is a reference in the industry. There are also other interesting initiatives, such as the German Flat Panel Display Forum (DFF) platform [15], founded in 2000 and composed of more than 65 companies and institutions of the display community. They deal with relevant matters to the field, like future technology trends or market monopolies. According to market research [16], the market share of displays with reduced dimensions has been duplicated in the last five years and it is expected to continue growing over the next seven years, especially due to head-mounted displays. This, and the fact that power consumption increases with the size, were the main drivers in reducing the scope of this article. Additionally, not all the display technologies are manufactured in all sizes, due to intrinsic restrictions or market directions.

The Cathode Ray Tube (CRT), although it has been used for decades, requires at least twice the power of a Liquid Crystal Display (LCD) [17], and only remains present in specific graphic-related fields, due to its higher color fidelity, contrast, and wide viewing angle. Field Emission Displays (FED) follows the idea of CRT, but uses millions of electron guns instead of only one [18]. Different field-emission electron sources can be used, including carbon nanotube Field Emission Displays (CNT-FED) [19] and Ballistic Electron Surface Emitting Display (BSD) [20], which are now being actively developed. This technology could offer slim, high quality for all sizes of display. Therefore, they are expected to be low-power displays, as little or no power is consumed in generating electrons. Motorola and Samsung, among others, are supporting this technology and they have already created some successful prototypes, producing high resolution images like CRT without the bulky appearance. Another closely related technology is Surface-conduction Electron-emitter (SED) [21], differing primarily in the details of the electron emitters.

Plasma Display Panel (PDP) is not economically profitable to be manufactured in small sizes [22] and nor is its subtype Alternate Lighting of Surfaces (ALiS). Digital Light Processing (DLP) is a system that uses an optical semiconductor device developed by Texas Instruments in 1987. The device, known as the Digital Mirror Device (DMD chip) is essentially a very precise light switch made up of millions of microscopic mirrors that, combined with a digital video or graphic signal, a light source, and a projection lens, can reflect an all-digital image onto any surface. DLP technology can generate large, bright projections with high contrast ratios on screens with up to 35 trillion colors. Other promising technology is Laser Phosphor Display (LPD), still in the development phase, hence numeric values cannot be provided due to the lack of available information on existing products. Thus, the comparison carried out in this study will be more reliable if the aforementioned categories and subcategories are left out.

In summation, the final chosen parameters for module classification are size and power consumption density. The size categories into which the modules can be classified are: microdisplays, typically not more than 25 mm (1 inch) image diagonal [23], small-sized (diagonal less than 7 inches), medium-sized (from 7 inches to 20) and large (more than 20 inches). The power consumption density categories are established in Table 1.

Table 1. Considered power density consumption ranges.

Power Consumption Level	Power density (mW/cm^2)
High	>250
Medium	100–250
Low	10–100
Ultra-low	0–10

Recalling the objectives set out in the introduction section, the scope of this work will cover the low-power and ultra-low power small-sized displays. The dotted line of Figure 1 limits the technologies that fulfill these requirements and will be analyzed further.

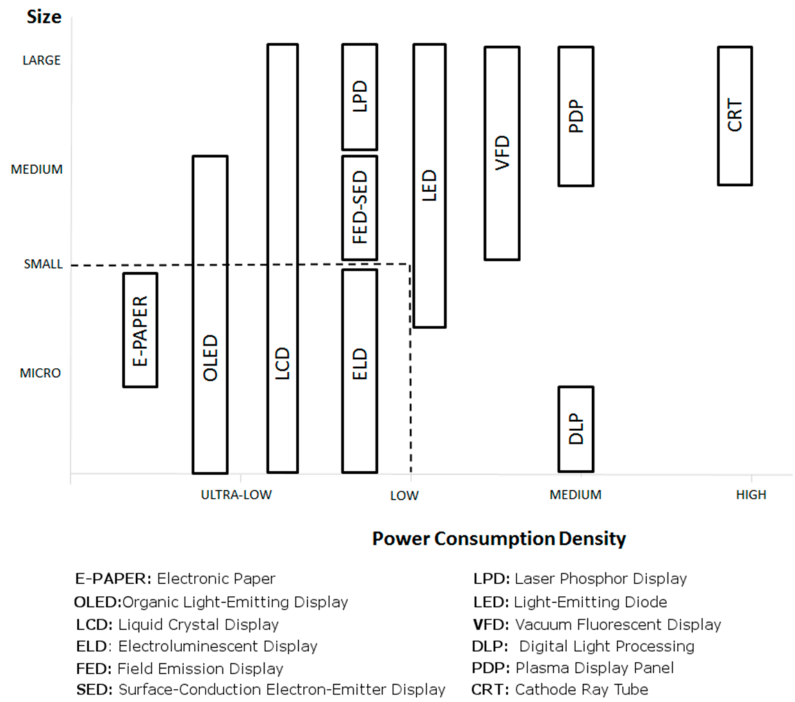

Figure 1. Relation between size and power consumption density in the studied display technologies.

3. Characterization of Displays

According to the technology family, a display can be *non-emissive*, with a backlight in its design, or *emissive*, if it acts as a light source itself. Regarding the calculation of the power consumption, in the non-emissive family, the backlight is necessary for its full operation, so the power consumed by it must be included in the total power consumption (Pdisplay), as shown in Equation (1):

$$P_{display} = P_{panel} + P_{backlight} \tag{1}$$

Emissive displays show a remarkable increase in power consumption with size, while in reflective, the value remained almost proportional. Furthermore, the power consumption could be influenced by other features, such as human factors or technical specifications. The following display characteristics were taken into consideration in this study:

- The brightness, which is defined as the level of light intensity perceived by the viewer. It is estimated by the luminance or the amount of light emitted from a source in a given direction and it is measured in candela per square meter or nits. The contrast is also considered, determined as the ratio (CR) between the luminance of the brightness and the darkest color that the display is capable of producing.
- The information content of a display, which is established as the total number of pixels, the size of them (resolution) and the size of the display (typically given by the diagonal length in inches). It is also common to provide the aspect ratio—proportion between the width and the height of the screen—and the screen area (normally measured in square centimeters).
- Other characteristics that can be influential in the consumption are the number of colors that the display can show and the angle of view (VA)—formally defined as the angle at which the viewer has to be positioned in relation to the screen in order to clearly see the image on a display.

4. Low and Ultra-Low Power Consumption Microdisplay Technologies

This section is organized regarding the specific technology used by the display subjects under study. For each technology, all the studied modules were grouped in categories with minimal dispersion of power consumption density. Within each group, the element with values closest to the mean, was selected as the most representative. For those selected modules, information about diagonal size (inches), weight (g), brightness (cd/m^2), contrast ratio (CR), degrees of viewing angle (VA) and absolute power consumption (mW), obtained from the manufacturer is given in this section.

4.1. Liquid Crystal Display (LCD)

The term liquid crystal is used to describe a substance which is in a state between liquid and solid but exhibits the properties of both. The first observations of liquid crystalline behavior were made towards the end of the 19th century by Reinitzer and Lehmann [24], and since then, LCD technology has enjoyed significant advances and it currently occupies the largest proportion of the entire display market share [25].

LCD belongs to a non-emissive display category and can be classified in two broad categories, Passive Matrix (PMLCD) and Active Matrix (AMLCD). The basic difference between the two categories is the way the pixel is addressed to produce the different luminance components of an image.

Generally, the power consumption of any LCD is related to the drive frequency (the lower the frame rate becomes, the less power consumed) and the displayed image.

In PMLCD, pixels are addressed directly and they must retain their state between screen refreshes without the benefit of a steady electrical charge. It is used in devices where less content of information needs to be displayed and when the power consumption has to be reduced, since less backlight is needed.

In AMLCD, a switch is placed at each pixel which decouples the pixel-selection function. Thin Film Transistor (TFT), the main technology of the AMLCD subgroup, can also be divided regarding the material used for its elaboration, into amorphous silicon (a-Si), continuous grain silicon (CGS) and low temperature polycrystalline silicon (LTPS TFT). A new approach is the indium-gallium-zinc-oxide (IGZO) technology [26] developed by Sharp.

In addition, cholesteric LCD displays (ChLCD) is a novel LCD technology that only consumes power if the image is updated [27]. Due to its particular characteristics, this type of display will be studied in the e-paper section.

Table 2 provides technical data about the six selected LCD displays. The first row represents the PMLCD category, which having a power consumption close to average, offers a monochrome graphic display, in contrast to the AMLCD modules. The greater the number of pixels on a screen, the better the quality of the image produced, but as the number of pixels (and, correspondingly, columns and rows) increases, this type of display becomes less feasible, since under those conditions, it shows slow response times and poor contrast outcomes. Another issue to take into account is the liquid crystal alignment mode, where Twisted Nematic (TN) and Super-Twisted Nematic (STN) types are the simplest and least expensive, but offering a poor viewing angle (of approx. 45 degrees). Vertical Alignment (VA) technology generally appears under various trade names (ASV by Sharp, PVA by Samsung, *etc.*) and tries to improve the viewing angle of the device (for instance, Ampire VA device offers 160 degrees *versus* the 45 of the TN device by AUO). In-plane switching (IPS TFT), as the Hitachi module from the table shows, also has a better viewing angle than TN and the color and contrast is also improved. However, the power consumption required to make the molecules switch is higher.

Table 2. Features of specific Liquid Crystal Displays.

Type	*Model*	*Diag. Size (in)*	*Weight (g)*	*Brightness (cd/m^2)*	*CR*	*VA*	*Power (mW)*
PMLCD (STN)	**F-55471GNFJ** [28]	5.2	75.1	72	5:1	90	615
a-Si TFT (TN)	**A015AN04** [29]	1.5	6	170	150:1	80	197
a-Si TFT (VA)	**AM-240320LFTZQW-00H** [30]	2.4	TBD	400	450:1	160	272
a-Si TFT (IPS)	**TX15D02VM0CAA** [31]	5.8	175	450	800:1	170	4900
CG-S TFT	**LS037V7DD06** [32]	3.7	39	100	100:1	80	490
LTPS TFT	**ANDpSi025TH** [33,34]	2.5	15	250	300:1	80	216

LCDs are used in a wide range of applications including televisions, monitors, instrument panels, video players, gaming devices, clocks, calculators or phones. For instance, LTPS LCD (Retina HD display) technology is the one used in the iPhone 6. In Figure 2, an example of this type of module can be seen.

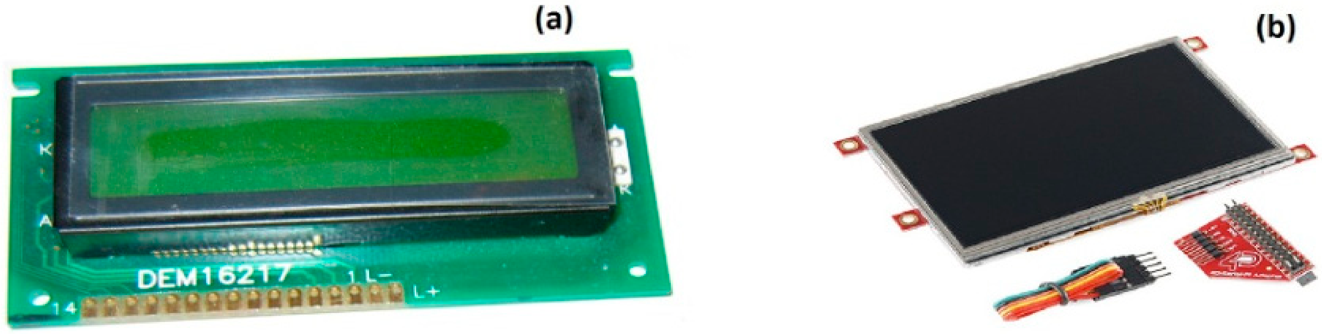

Figure 2. (**a**) Passive and (**b**) active matrix LCD modules (by SparkFun Electronics).

4.2. Electronic Paper (E-Paper)

Electronic paper, popularly known as e-paper, can be defined as a dynamic display technology that emulates traditional paper. As LCD, e-paper belongs to the non-emissive display category but, in this case, no backlight is needed since the ambient light from the environment is enough.

The display is composed of millions of microcapsules containing positively charged white and negatively charged black particles suspended in a clear liquid, which are capable of producing the resolution only found in print. As they are bi-stable, they only consume power while the display is being updated. The power required for the update process depends on the size of the display.

The first commercial success of monochrome e-paper devices was due to the Electrophoretics technology, wrongly referred to as electronic paper displays (EPD), whose main exponent is microencapsulated electrophoretic displays, also known as e-ink [35]. Another similar approach, microcellular electrophoretic display films (SiPix), was bought by e-ink. There are other proprietary electrophoretic displays, which include Quick-Response Liquid Powder Display (QR-LPD) by Bridgestone [36], bichromal beads [37] by Xerox (Gyricon), or reverse emulsion electrophoretic display (REED) used by Zikon Corp.

Cholesteric liquid crystal (ChLCD), already mentioned as a subgroup of LCD, is generally classified as e-paper because of its zero consumption when it is not receiving screen updates. Figure 3a, below, shows a cholesteric display powered by solar panels.

A next generation of flexible, color and video e-paper is currently emerging. The most promising seems to be the electro-wetting approach (EWD) [38]. Its main component, liquavista (see Figure 3b), was developed by Philips but currently belongs to Amazon. Another interesting technology based on Interferometric Modulation (IMOD) is microelectromechanical sytems (MEMS) [39], whose potential has been demonstrated through several prototypes (trademarked Mirasol [40]) developed by Qualcomm.

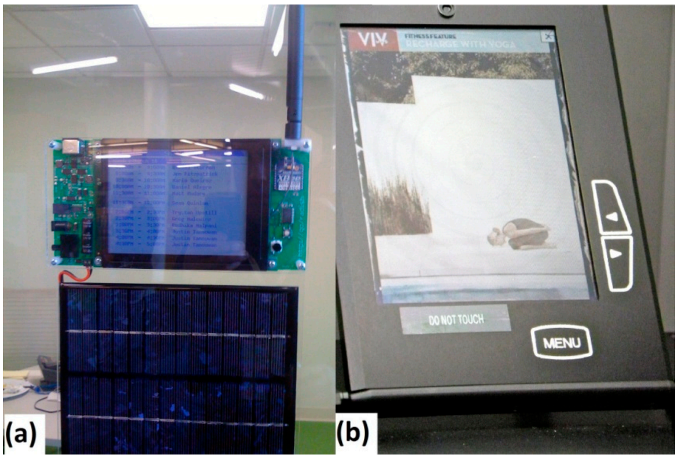

Figure 3. (**a**) Google Radish project using solar panels and a cholesteric display (by Niall Kennedy) and (**b**) Liquavista prototype.

Some other remarkable developments are the in-plane electrophoretics (IPE) patented by Canon [41] and HP's Electrokinetic (EKD) [42], although they are at least several years away from a general market uptake [43].

Another less matured technology is electrofluidic [44], which presents the main novelty of using a three-dimensional microfluidic device structure and offering brilliantly colored aqueous pigment dispersions. Recently, other lines of investigation have aimed to simulate traditional paper through electronic paper made from microbial cellulose [45].

Generally, the main characteristics of electronic paper are flexibility, readability, multi-functionality and ultra-low power consumption—zero power consumption during the non-updating period [46]. It is common to find this kind of technology in small sizes, although there are approaches with A5 size [47]. The majority are monochrome but there are also color options such as e-ink [48] or electrochromic (EC) technologies [49]. Liquavista, the recent acquisition of Amazon, also allows colors to be incorporated into the display. In addition, the best contribution of liquavista is that its low consumption remains almost constant in all modes of operation, while e-ink offers good levels for e-books, but rises a lot in operations requiring interaction with the user, such as web browsing.

Table 3, below, lists e-paper displays with their technical data.

Table 3. Features of specific electronic paper displays.

Type	*Model*	*Diag. Size (in)*	*Weight (g)*	*CR*	*VA*	*Power (mW)*
EPD	**GDE021A1** [50]	2.1	4	7:1	180	24
Pearl EPD	**ED060SCE** [51]	6	34	12:1	180	240
ChLCD	**LCD-09559** [52]	5.5	105	25:1	180	150
EWD	**Liquavista prototype (Amazon)** [53]	2.5	TBD	18:1	180	87

The most common applications of e-paper are eReaders, eLabels, USB sticks, clocks, billboards, *etc.* A good commercial example is the Kindle by Amazon that uses e-ink technology.

4.3. Organic Light-Emitting Display (OLED)

The Organic Light-Emitting Diode (OLED) is a light-emitting technology made by placing a series of thin organic films (made from carbon and hydrogen) between two conductors. When electrical current is applied, a bright light is emitted.

There are several development trends in the field of organic diodes and the most representative classification, based on the driving circuitry, is the active matrix OLED (AMOLED) [54–56] and the passive matrix OLED (PMOLED) [57].

Depending on the light type, different types can be distinguished, such as phosphorescent Organic Light-Emitting Diode (PhOLED), Transparent Organic Light-Emitting Diode (TOLED), or White Organic Light-Emitting Diode (WOLED).

Because of its nature, it is possible to create flexible and transparent interfaces [58]. When an OLED screen is marked with a flexible plastic substrate, such as a Polymer Light-Emitting Diode (PLED), it is called a Flexible Organic Light-Emitting Diode (FOLED). Other OLED advances have been achieved by using molecules in its composition, but they are still in the development process; some examples might be the Molecule Organic Light-Emitting Diode (MOLED) [59] and the Small Molecule Organic Light-Emitting Diode (SmOLED) [60].

All the OLED displays have some characteristics in common: high brightness and contrast, fast response time and excellent color definition. They offer a wide viewing angle (at around 160 degrees) as a result of the self-luminous effect. The main advantage, however, is their low power consumption (proportional to the number of pixels that are turned on—black dots do not need power), which depends only on the present content due to the fact that they do not require a backlight. This also makes them thinner and more efficient [61]. The handicap is still the price; since they are manufactured on a small scale, they have a high price on the market [60].

Some studies [62] have concluded that when using this technology, the power consumption of displays increases very strongly with size. Displays of different sizes within the studied range have therefore been analyzed and their features are listed in Table 4. Such increase is especially remarkable in the case of PMOLED (a module twice as large consumes six times more).

Table 4. Features of specific Organic Light-Emitting Displays.

Type	*Model*	*Diag. Size (in)*	*Weight (g)*	*Brightness (cd/m^2)*	*CR*	*VA*	*Power (mW)*
AM-OLED	**C0201QILK-C** [63]	2	6	190	10000:1	170	170
AM-OLED	**USMP-A34480TP** (Chi Mei El. Corp) [64]	3.4	30.1	160	10000:1	170	500
PM-OLED	**microOLED-160-G2** [65]	1.7	13	100	5000:1	160	100
PM-OLED	**RGS32256064WH002** [66]	3.2	11	70	2000:1	160	616

OLED technology is being conducted in the main companies and universities, such as Kodak, Sharp or eMagin. Although it started being used mainly in cameras, A/V players, car audio systems or other small devices such as the smart watch shown in Figure 4, the market share in mobile screens is increasing. For instance, Super AMOLED is the technology chosen by Samsung for its Galaxy S6.

Figure 4. Sony SmartWatch with an OLED display (by Bim imGarten).

4.4. Electroluminescent Display (ELD)

Electroluminescent Displays (ELD) have their origins in the first decade of the twentieth century, but they did not become commercially viable products until the 1980s.

Electroluminescent display technology takes advantage of the light-emission phenomenon due to a strong electric field. It consists of a solid state thin phosphor film and insulator stack deposited on a glass substrate and driven by high voltage electronics which generate alternating positive and negative pulses [67]. This is a very cost efficient light source, which results in low power consumption.

ELD displays belong to the emissive category and besides, they can be classified into two main groups. The first, thick-film dielectric electroluminescent (TDEL), is a phosphor-based flat panel display technology. TDEL is based on inorganic electroluminescent (IEL) technology and has a novel structure that combines both thick and thin-film processes. In the case that it incorporates a black thick film dielectric layer, it is called black thick-dielectric EL (BDEL). Thin-film electroluminescent (TFEL) [68] consists of a self-healing metal row electrode, two dielectrics sandwiching a light-emitting phosphor, which emits light via hot-electron impact excitation of luminescent dopants, and a transparent indium tin oxide (ITO) column electrode.

Color ELD technology has advanced significantly in recent years, especially for microdisplays. Other remarkable research still in progress in the electroluminescent field includes the Active Matrix Electroluminescence (AMEL) and the Transparent Electroluminescent Displays (TASEL) [69], such as the one shown in Figure 5.

Figure 5. Fully transparent TFEL Display (by Beneq Oy, Finland).

Electroluminescent technology is characterized by having low power consumption and low contrast ratios. Attention should also be paid to the viewing angle values which are around 180 degrees, achieving 360 in the case of transparent TASEL displays [70]. Table 5 contains the studied feature values for four representative ELD displays. In the case of TDEL and AMEL, the values for a prototype are given since they have not yet been commercialized. The two main firms that have developed and commercialized this technology are Sharp and Planar Systems.

Table 5. Features of specific Electroluminescent Displays.

Type	*Model*	*Diag. Size (in)*	*Weight (g)*	*Brightness (cd/m²)*	*CR*	*VA*	*Power (mW)*
AMEL	**VGA prototype** (Planar) [67]	0.758	2.1	342	100:1	160	400
TDEL	**TDEL prototype** (TDK Corp) [71]	4.25	284	200	3:1	180	10,000
TFEL	**EL320.240.36 HB** [72]	5.7	180	150	90:1	160	3500
TFEL	**LJ32H028** [73]	4.7	270	200	300:1	160	5000

5. Results and Discussion

In order to facilitate the drawing of conclusions from the technical data presented in the previous section, the main features are graphically shown in Figure 6. The radar charts allow comparing the relative weight, brightness, viewing angle and contrast ratio values between the different display technology groups. For those categories in which more than one element has been studied, the mentioned features presented uniform outcomes; hence the average value was taken as a reference to make comparisons with other technologies.

To compare weights, the relative value (weight to active area) was calculated. All technologies offer a value close to 1 g/cm^2, with the exception of TFEL that stands with mean values of 2.9 g/cm^2, reaching highs of up to 4 g/cm^2.

Two technologies are presented at the ends when the brightness values are analyzed: on one side, e-paper where, lacking light emission, the brightness can be considered zero; and second, AMLCD, where the average brightness of some modules reaches values of 450 cd/m^2.

Regarding the viewing angle, LCD is the technology that provides the worst average results, but that can be improved by using new methods of alignment, as is the case of VA or IPS, which allows viewing angles up to 170 degrees. In this aspect, EL displays highlights with values from 160 up to 360 degrees in the innovative TASEL transparent display.

Finally, the contrast ratio is considerably lower in PMLCD and e-paper, but enough for the kind of applications that these technologies are designed for.

Focusing on the characteristics concerning power consumption, Table 6 shows a comparison of the main parameters for each of the studied display technologies.

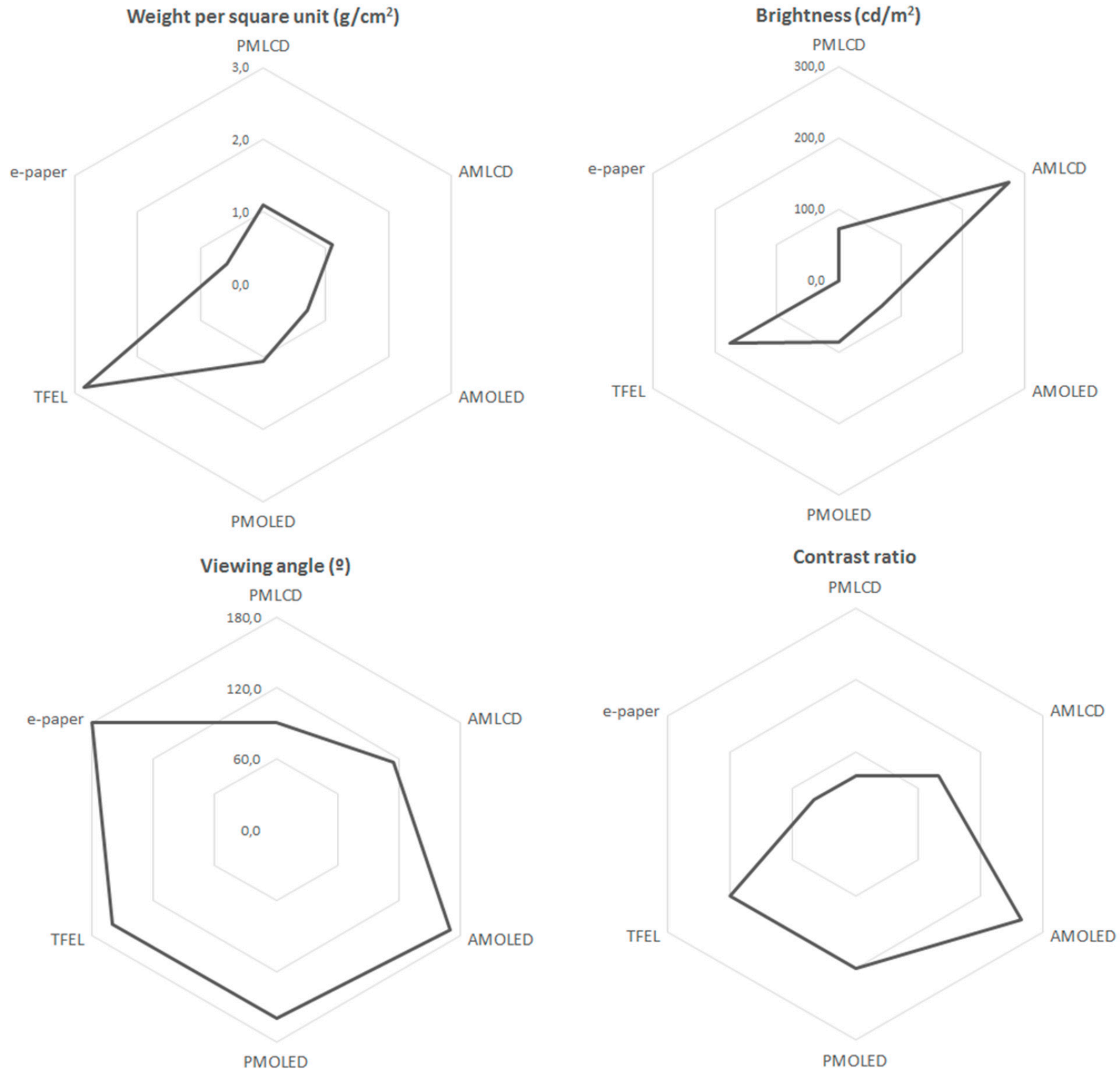

Figure 6. Radar charts of relative weight, brightness, viewing angle and contrast of studied technologies.

Table 6. Power consumption-related features comparison.

	Parameter	STN-LCD	TFT-LCD	EPD	OLED	ELD
Power Consumption	Typ. (mW) *	100–200	200–300	25–50	150–200	1500–2000
	Max. (mW) *	1000	300	100	1000	5000
	Proportional to size	NO	NO	YES	YES	YES
	Stable state	YES	YES	NO	YES	YES
	Black image	YES	YES	NO	NO	NO
	Backlight	YES	YES	NO	NO	NO
	Power saving mode	NO	YES	NO	YES	YES
	Unit cost	Low	Medium	Medium/high	Medium/high	High
	Main applications	Cheap electronics, toys	Wide range applications	E-book, watches	Mobile	Embedded devices
	Weak points	Resolution	Visual quality	Color, response time	Lifespan	Size, consumption

* Range values for 1.5–2.5 inches displays.

The results exposed until now, offer a first characterization of each type of display, but relative measures related with the power consumption are needed to make accurate and reliable comparisons between displays of different natures.

The amount of power per unit area or surface power density P_d (measured in mW per square centimeter of active screen area) can be used (see Equation (2)).

$$P_d = \frac{P}{S} \quad (2)$$

A comparison of the power density of the studied displays is shown in Figure 7.

As the chart stands out, on the one hand, electronic paper modules (EPD, EWD and ChLCD) offer the lowest power consumption values, but it is necessary to take into account the fact that this technology is used for the development of very specific displays (typically monochrome, focused to display text, allowing sunlight readability, *etc.*). The shortcoming is that e-papers are not viewable without ambient light. Additionally and more importantly, it uses little to no power to preserve a static image on the screen.

Close to the same power density value but even higher is LCD technology. The passive matrix PMLCD and the active matrix, a-Si TFT (with Vertical Alignment mode) obtain the best results, although there is a subtype of LCD with high consumption, a- Si TFT IPS, because of the high power required to make the molecules switch.

Finally, within the range defined as low power consumption, electroluminescent devices are the most power-consuming ones.

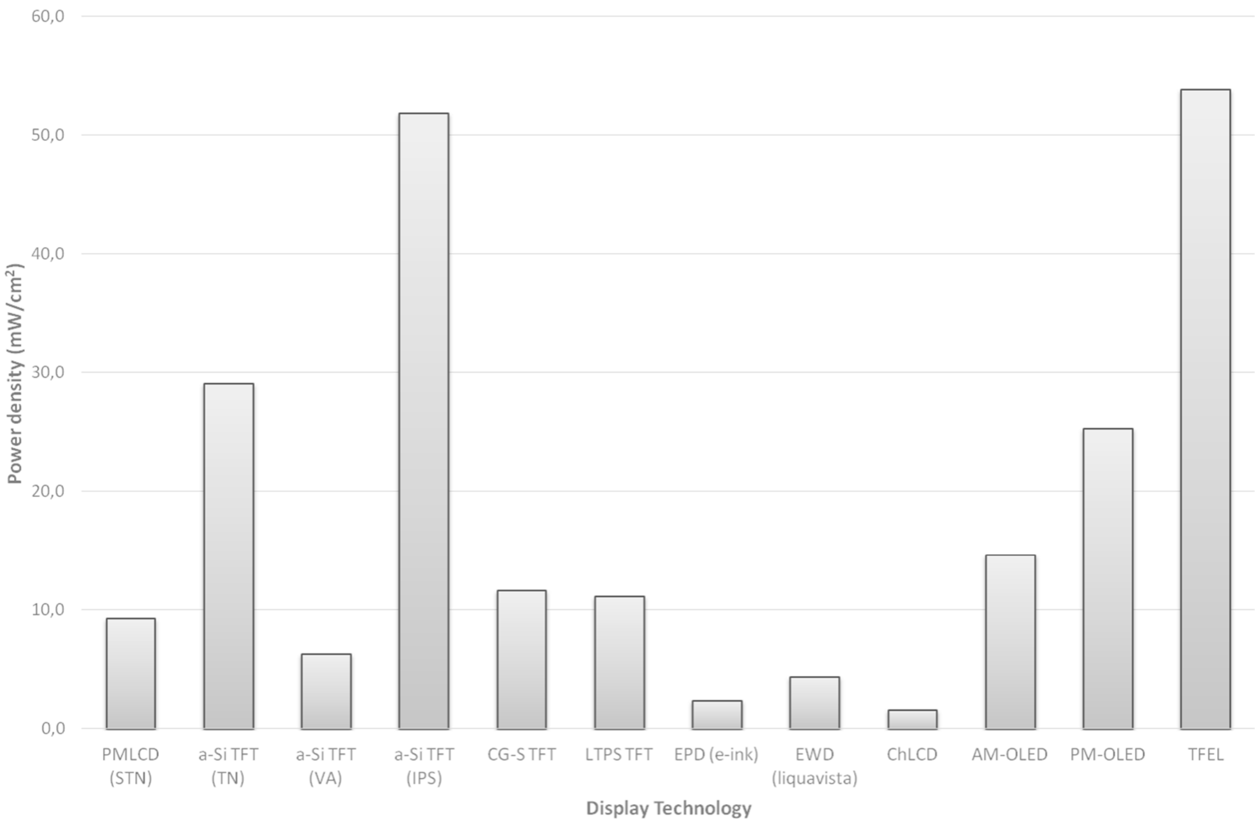

Figure 7. Power density of studied display technologies.

Due to the influence of what is being displayed on the screen in the consumption of some displays, it seems appropriate to perform a comparison while keeping constant that pattern. The display intensity efficiency or the energy efficiency of a display has been used. It is defined by the IDMS as the ratio of the luminous intensity I (defined as the product of the frontal luminance L_W of the white full screen and the active area S of the display, as is shown in Equation (3)) to the power consumption P (see Equation (4)). It is measured in candle per watt.

$$I = L_W S \tag{3}$$

$$\xi = \frac{I}{P} \tag{4}$$

After analyzing the energy efficiency values for the studied modules (electronic paper displays have not being taken into account because the frontal luminance efficiency is not valuable as a figure of merit), significant differences depending on whether the type of display is emissive or non-emissive have been detected. A comparison between LCD and OLED modules (differencing between active and passive technologies) is shown in Figure 8. Although outside the scope of the study, for larger sizes, OLED will perform worse than LCD in terms of energy efficiency.

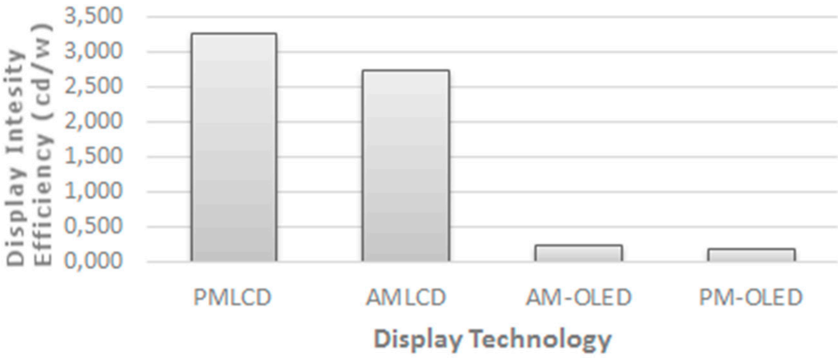

Figure 8. Comparison of display intensity efficiency of LCD and OLED in their active and passive versions.

6. Applications and Trends

Novelty lines of research are exploring new fields of application. Since there are no commercial devices until the technology reaches a mature stage, an accurate idea of the current trends can be obtained through an analysis of the patent networks as proposed by Chang [74].

Microdisplays are the basis that enables projection displays to screen large images from small dimension devices, thereby offering lower power consumption rates at reduced cost and under extremely portable conditions. An extension would be near-to-eye (NTE) systems that require the user to place the display close to their eyes with a head-mounted display, offering the same mentioned advantages. An emerging field of study of this see-through display is the occlusion capability, which enhances user's perception, visibility and realism [75].

Another new trend of research during the last few years has been focused on developing flexible displays in curved, conformal, bendable and even rollable shapes. This opens up the possibility of incorporating new applications and products into the market. The key of this approach is the material employed. The use of polymers [76], as well as graphene [77], seems very promising in terms of consumption. There are prototypes of different technologies and sizes, from a large plasma display [78] to a small AMOLED module [79] passing through the Mobius Display by E-ink [80], which maintains the power consumption levels of other e-ink displays.

3D displays are one of the most futuristic approaches but they are already a reality. The first attempts used 2D technologies, such as LCD or DLP [81], and a special device, commonly glasses, for offering the stereoscopic effect (a different picture to each eye). One step further, the autostereoscopic technology [82] is based on the previous and displays multiple different images on one display screen, each visible from particular places in front of the screen [83]. A widespread commercial device is Nintendo 3DS.

Besides the evolution of the technology, another complementary field of action to reduce the display consumption waste is the improvement in user interaction and usability of the interface itself [84]. Other research includes working on the adaptation of the software to conserve energy [85]. Display power management (DPM) policies can reduce the energy used for the display integrated in a system turning off and on the display depending on the attention of the user. As this action can result in unacceptable quality degradation, the need of new energy reduction and optimization techniques arises [86].

The main ones—LCD displays—are covered in the survey of Anggorosesar [87], which classifies the low-power techniques in four categories: backlight dimming, dynamic voltage scaling, software-based and hardware-based. They can achieve power saving ratios by up to 90% of the total system power with a small distortion level. Each of the techniques saves the power consumption of the display system by reducing the activity of the corresponding components such as the color depth [88], the refresh duty ratio [89], the frame buffer [90] or the backlight luminance. In the last approach, dynamic luminance scaling (DLS) of the backlight, with appropriate image compensation, stands out. Its extended version, EDLS, compensates for loss of brightness when the number of saturated pixels is small, and for loss of contrast when there are too many saturated pixels in the image [91].

Regarding emissive displays, especially OLED, although the previously described techniques can also be applied, there are more specific studies based on the idea that the relationship between intensity levels of color components and power consumption is not linear. For example, Dong *et al.* present three different models to provide power estimation for the system to manage and optimize energy consumption [92]. For its part, Chen *et al.*, use dynamic voltage scaling (DVS) for the power management of the display on mobile devices in video streaming applications [93]. Other approaches propose using a more efficient code such as RGBW, obtaining less color distortion with less power consumed [94].

The possibility of combining the advantages of each technique into one collaboration to improve the whole power system is research for the future [87].

7. Conclusions and Future Directions

The small-sized low-power displays are usually geared in the household context to phones, multimedia devices, navigators, *etc.*; while in the professional world, the automotive sector and industrial applications and appliances are the main users. Going beyond, in energy harvesting environments [95], where devices present extreme low-power consumption needs, high energy efficient displays could play an essential role.

Although great strides have already been made to reduce the consumption of the interfaces, it is still a main objective of industrial strategic agendas and research groups' lines of investigation.

This review has compiled relevant data related with the energy consumption of the main low-power display technologies, from the manufacturers' datasheets. The use of relative units has allowed comparing them accurately.

Some display technologies, such as OLED—reflective display with no backlight—or EPD—which retains the shown information—have intrinsically low power characteristics in small form factors. Several market reports place also OLED as a key technology up to 2020 [96]. It has the best contrast ratios and viewing angles, and good values for brightness and weight. The strong relationship between the number of active pixels and the power consumed makes it suitable for many specific applications.

Electronic paper is also a promising technology for applications that need ultra-low-power displays. Especially for those that require infrequent updating of images, this display consumes an extremely low amount of power.

Other more mature technologies are also concentrating on low-power small-sized display development, such as LCD. Even though it is making progress, it must continue to improve if it wants to remain competitive against other emerging display technologies.

Although ELD displays perform poorly in terms of energy, they present usage advantages under circumstances where full color is not required but where ruggedness, speed, brightness, high contrast, and a wide angle of vision is needed.

Display technologies must evolve fast enough to keep pace with advances in other areas. Each day new ways are devised with the aim of improving the brightness, contrast, and overall picture quality of the displays, but the demand for low energy-consuming displays is one of the main milestones that will drive technology evolution; this evolution will require new approaches and innovative ideas. New lines of research are thus exploring new fields of application to meet the changing needs of society.

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Author Contributions

All authors contributed extensively to the work presented in this paper. Ignacio Gonzalez Alonso and Eduardo Zalama Casanova designed and structured the contents. María Rodríguez Fernández gathered the information, analyzed the data and wrote the paper. All authors discussed the results and implications and commented on the manuscript at all stages.

Conflicts of Interest

The authors declare no conflict of interest.

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Capítulo III:

Publicaciones relacionadas

1. Congresos

Durante la investigación, la doctoranda ha participado en los siguientes congresos, siendo ponente en los dos primeros:

I. ICSEA *(International Conference on Software Engineering Advances)*. **Lisboa, Noviembre 2012.** Actas publicadas en:

> I. González, M. Rodríguez Fernández, J. J. Peralta, and A. Cortés, "***A Holistic Approach to Energy Efficiency Management Systems***," in *ICSEA 2012, The Seventh International Conference on Software Engineering Advances*, 2012, pp. 415–420.

*Este artículo fue elegido como **Best Award Paper**.*

II. **INTERA (**International *Technology Robotics Applications*). **Oviedo, Marzo 2013**. Actas publicadas en:

> M. Rodriguez, I. González, and E. Zalama, "***Identification of Electrical Devices Applying Big Data and Machine Learning Techniques to Power Consumption Data***," in INTERA 2013, *International Technology Robotics Applications*, Springer, 2014, pp. 37–46.

III. **Greencities** (*Salón de la Inteligencia Aplicada a la Sostenibilidad Urbana*)**. Málaga, Septiembre 2013**. Actas publicadas en:

> I. G. Alonso, M. R. Fernández, J. J. Peralta, A. C. García, and J. M. O. Quintana, "***Técnicas de aprendizaje automático al servicio de la eficiencia energética en el hogar digital."*** ISBN-13: 978-84-695-8430-9.

2. Artículos

Los siguientes artículos también son fruto de la investigación realizada durante el desarrollo de este trabajo, siendo la doctoranda coautora de los mismos:

I. I. González Alonso, M. Rodríguez Fernández, J. Jacobo Peralta, and A. Cortés García, “***A Holistic Approach to Energy Efficiency Systems through Consumption Management and Big Data Analytics***,” *Int. J. Adv. Softw.*, vol. 6, no. 3 and 4, pp. 261–271, 2013.

II. A. P. Otero, R. Suárez, J.M. R. Varas, M. Suárez, M.P. A. G.Fuente, R. Fernández, M. R. Fernández, and I. G. Alonso, ***“Integration of Digital Home, Smart appliances and Service Robots Using DHCompliant 2.0”,*** *Int. J. Robot. Autom., vol. 30, no. 4, 2015.*

Por último, aunque por su relación directa con la temática de la tesis, deberían formar parte de la misma, cabe resaltar los siguientes artículos, que actualmente se encuentran aceptados con cambios:

III. M. Rodriguez, E. Zalama and I. González, ***“Improving the interoperability in the Digital Home through the automatic generation of software adapters from a SysML model”.*** Aceptado y pendiente de publicación en *Journal of Intelligent and Robotic Systems.*

IV. M. Rodriguez, E. Zalama and I. González, ***“Mejora de la interoperabilidad en el Hogar Digital a través de la generación automática de adaptadores”.*** Aceptado y pendiente de publicación en *Revista Iberoamericana de Automática e Informática Industrial.*

El uso eficiente de los recursos es un reto de la sociedad actual como así se refleja en la Hoja de Ruta de la Comisión Europea. En la última década, han tenido lugar grandes avances en este campo que han potenciado los conceptos de Hogar Digital y *Smart Grid*.

La generalización del uso de medidores inteligentes y sensores de distinto tipo en el ámbito doméstico, permite extraer de forma fácil y asequible datos de consumo, luminosidad, etc. Se parte de la idea de aprender de dichos datos para extraer valor de los mismos. El conocimiento de los hábitos de consumo del usuario y de su entorno permitirá llevar a cabo acciones que ayudarán a mejorar la eficiencia energética. Teniendo en cuenta que toda solución planteada ha de ser escalable, ya que los datos utilizados se generan de forma creciente a lo largo del tiempo, y el número de hogares que integran este tipo de dispositivos va en aumento, el uso de técnicas Big Data será crucial.

Por otro lado, con la intención de dar un primer paso en la reducción del consumo de los propios dispositivos, se presenta un estudio de las principales técnicas de fabricación de *displays* desde el punto de vista de la eficiencia energética.

Este documento se presenta como un compendio de tres trabajos publicados en revistas con factor de impacto internacional.

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