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Keywords: Deep Learning, AMR, Smart-Meter, Smart-Socket, HEMS, Smart-Cities, ILM.

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Article

Model for Identification of Electrical Appliance and Determination of Patterns Using High-Resolution WSN for the Efficient Home Energy Consumption Based on Deep Learning

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Summary: The introduction of non-conventional renewable energies (photovoltaic and wind, in the residential case) demand new proposals and opportunities to obtain a domestic energy management system (HEMS), which allows reducing the use of electrical energy. The HEMS incorporates artificial intelligence (AI) techniques to respond to energy demand (DR), which can control, switch, turn on and off, modifying the consumption profile, reducing monthly billing, which as a consequence brings improvement. of the quality of life at home. Based on what has been described, a model for identifying electrical appliances and determining consumption patterns for the home is proposed, using intrusive measurement/actuator equipment called Smart Socket. The Smart Socket measures the electrical variables of voltage and current in real time, calculating the powers and active-reactive-apparent energies of each household appliance (or the most relevant ones). The information provided by the Smart Socket is used as a basis to configure the HEMS, with the aim of optimizing energy use using artificial intelligence techniques and tools, thus reducing energy consumption, CO2 emissions and the user's monthly billing. residential.

Keywords: deep learning; AMR; smart-meter; smart-socket; HEMS; smart-cities; ILM

1. Introduction

Electronic management systemsHome Energy Management System (HEMS) plays a crucial role in measuring, controlling and optimizing the energy consumption of appliances and appliances belonging to a residential user's home. For the electricity distribution company, knowing the behavior profile allows the use of the capacity of its infrastructure to be maximized, obtaining a reduction in emissions and contributing to sustainable development. For its part, for the residential consumer, it allows the responsible use of energy, obtaining a reduction in their monthly billing. As a whole, the technological advances of recent years in the communication and information sectors are allowing the current electricity supply service to be more modern and efficient, by improving control, monitoring, detection and automation capabilities, thanks to the use of artificial intelligence.

The proposal to face this new challenge is to achieve the development of a home energy demand management platform (HAN-HEMS) through the measurement and estimation of the energy consumption of a home, using agent nodes and an intelligent system based on the availability of non-conventional renewable energy, so that the platformallow consumption control and remote monitoring through the Internet. In order to identify the surplus of renewable energy harvested by

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the end user, it is necessary to obtain a real-time consumption profile, which is defined by their daily habits of using household appliances.

This article proposes an intrusive residential electrical energy management model, based on the availability of electrical energy with the use of IoT and artificial intelligence. In this way and through Smart-Sockets, which allow the measurement of the real demand used together with the estimation of the user's home consumption, the model based on deep learning, associated with the classification for time series, seeks greater energy efficiency in consumption by the end customer. The rest of the document is organized as follows: section two presents the works related to this research; Section three describes the methodology used and the development of the proposed system; Section four presents the experimental development and the results obtained; Section five shows the discussion of results; section six shows the conclusions of the article; and finally, section seven presents future work.

2. Literature Review

The massification of the meters of accountants, smart devices, low-cost sensors and smart home appliances over the last decade, have encouraged a favorable environment for the development of new management strategies of energy demand, which include communication, decision making and the interaction between users, devices and the electrical grid. AlthoughTherefore, there is a problem of interest in smart networks or smart-grids: obtaining, storing and analyzing hard data on the electrical consumption of residential users alone is not sufficient to provide root cause elements of energy demand and what it can do to reduce and/or optimize it [1]. Additionally, the more we want to delve into this last aspect, the higher resolution data is needed for a precise energy analysis, which implies, as a final consequence, overcoming these technological obstacles by automating the operations of the electrical network.

An important element that motivates the development of this work are the different alternatives that exist for measuring and/or estimating the energy consumption of a home, commonly called "pattern of consumption of electrical appliances".

HEMS use monitoring techniques that are generally classified into non-intrusive load monitoring (NILM) and intrusive load monitoring (ILM) [2]. The characteristics that differentiate these two techniques is that NILM only uses one monitoring point that is generally located at the main power input of the home's electrical system (known as Smart Meter), while ILM uses sensing devices in each of the sockets (Smart Socket SS; Smart-Plug SP) of all or main connected loads [3]. On the other hand, NILM systems have the advantage of not intervening in the home circuit with expensive monitoring devices [4]. On the other hand, ILM systems, by having sensors in different loads of the circuit, provide more precise details about the consumption and alarms referring to each appliance [5], making it possible to monitor very low power devices and differentiate between variable consumption and consumption between a set of devices [6]. Scientific publications on NILM-type approaches outnumber those on the ILM approach [7], as the NILM approach proves to be much older.

The climate change that the planet is experiencing rapidly has led each country to propose strategies that involve efficient use of energy resources [8]. Particularly, the Chilean state has established an energy policy for the year 2050, which establishes energy efficiency as one of its pillars [9]. In this context, the residential consumer has taken an active role to manage their use of electrical energy and thereby influence the behavior of their consumption pattern. These assertions inspire the development of new technologies and methodologies that allow the participation of consumers in the operation of the electrical network at the end-user level, an example of this being the Smart-Socket wireless sensor networks, which apart from measuring each appliance, they can turn it on or off.

A Smart-Sockets sensor network is designed for use under multiple operating states as a single device. This feature is particularly useful for work, industrial, building and domestic environments, since by identifying the appliances that are used in said space, based on the behavior of the current patterns consumed by the electrical appliance, it is possible to monitor, program and control the energy consumption efficiently [10]. Achieving the desired degree of coverage in space and time

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requires the use of appropriate communication protocols for each use case (Wi-Fi, PLC or ZigBee, among others). Seamless sensor network integration is important for success in telemetry and ubiquitous computing.

In [11,12] various hardware and software architectures of systems that analyze test devices are discussed and the current consumption patterns and profiles of home appliances are explained. In addition to this, the relevance of these architectures for the development and implementation of new infrastructures and applications for smart cities is explained. From this review, relevant background information is presented such as the use of classifier algorithms that do not need training, but do require a database that is updated periodically and automatically, thus generating the need for a dynamic, connected data storage. to each of the electronic devices and, consequently, take advantage of the benefits that the world of the public cloud offers [13]. From this point, it is relevant to mention that the identification of consumption patterns of electrical appliances focuses on energy disaggregation and device recognition.

The works [14–17] show the development of an intelligent system that analyzes the periodic use of electrical appliances in a home to extract and determine the behavioral patterns of residential users. under an IoT environment. Particularly, in [15,16], there is an additional objective within their research, which consists of reducing the excessive electricity consumption of appliances through an alert system. In [18–20] data obtained by Smart-Plug type smart meters are used to identify appliances, using an approach based on artificial neural networks. The results of [20] are considered acceptable, given that the score of the classification capacity estimator obtained with respect to the recognition of F1 appliances reaches 77.6%. In [21] they also use Smart Plugs for data collection, however, in this case the authors intelligently process the collected time series data and classify them using multi-layer feedback neural networks. The results of their experiment allow us to obtain the energy consumption pattern of various appliances, based on a daily cycle of use. A k-active neighbor-based appliance recognition approach is presented in [22] to learn from unlabeled data collected through Arduino-operated Smart-Plugs. In [23] the authors provide an affinity propagation clustering algorithm with NILM approach based on a vector graphical model and the theory of belief propagation. The experiment carried out demonstrates that it is possible to correctly recognize basic and combined classes of electrical devices. In [24,25] various unsupervised machine learning techniques are presented to identify electricity consumption patterns in home environments. The particularity of these articles is that additional data mining techniques are used to meet the aforementioned objective. In works [26–28] algorithms based on fuzzy logic are used that, by activating the calculation of parameters such as maximum power, average power and cycle duration, obtain a result for the membership function , thus achieving the identification of electrical devices through degrees of truth. The works [29,30] carry out data sampling in the order of 10 to 15 minutes, for the automatic recognition of electrical devices using fuzzy logic, since their objective is to determine the energy consumption associated with billing systems. .

In this work, a home electrical energy management model is proposed, based on the capture of electrical parameters through Smart-Sockets, allowing residential users to participate in the control of energy demand in real time, adapting consumption. in such a way as to allow the reduction of energy demand during peak hours, intelligently adapt consumption to off-peak hours, make responsible use of energy and, as a consequence, obtain a reduction in your monthly billing. The proposed model manages to achieve a sampling rate of the order of 10 seconds, higher than the works [31–35]. This resolution not only allows the differentiation of each electrical device, but also the activation of alarms and alerts. Finally, the Deep Learning algorithm used, based on a multi-layer neural network, manages to discriminate each of the devices with great efficiency (F1 score of 97%), sending information in real time to the user, determining the home's electrical consumption. and each of your appliances.

3. Methodology and system development

Figure 1 shows the schematic diagram that briefly describes each of the stages of the methodology implemented in this work.

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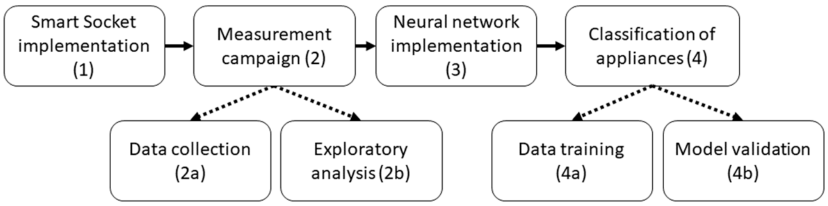

Figure 1. Description of the methodology used.

1. Phase (1).

A current/voltage measurement module with Internet Protocol (IP) wireless communication is designed. Ranges of maximum values are established for the voltage (< 230 Volts) and for the current (< 16 Amperes) and, finally, a protection system for overloads and automatic operation is configured based on the electrical parameters already defined.

2. Phase (2).

Data and measurements are recorded for a set of previously defined electrical appliances, which are part of a common home environment for a residential user in the Santiago Metropolitan Region.

a. Phase (2a).

Measurements of the 7 most common household appliances are recorded, measured in 10 different homes, with sampling times of 10 seconds and with work cycles that depend on the operation of each appliance. In this phase, particular care must be taken with some elements that correspond to recurring failures in data collection tasks: Failures in data integrity associated with data storage problems; Connection problems between the device and the public cloud services used for data analysis; Inconsistencies in data structuring (data type or column type).

b. Phase (2b).

This exploratory analysis phase seeks to optimally manage the data source generated from the collection phase, with the aim of facilitating the identification of patterns and/or possible anomalies. To this end, the review of the following elements is considered: Review of missing data and its possible imputation; Variable selection using statistical methods; Review of distributions and correlations; Variable engineering.

3. Phase (3).

It contemplates the implementation of a multi-layer artificial neural network, where the nodes of these layers are linked in a unidirectional manner to identify non-linear characteristics.

4. Phase (4).

The data is sent to the cloud with the objective of generating representative values of each of the appliances to be compared. The respective fingerprint of electrical consumption is identified for each of the appliances.

a. Phase (4a).

The implemented neural network learns through training. Examples with known results and the responses to compare with the results of the proposed model are continually presented to the neural network. For this phase to deliver correct performance, it is necessary to take into consideration the following: Definition of the method of dividing the data sets, in order to exercise correct balancing thereof; Definition of the model to be used to verify or refute the initially stated hypothesis, considering variables such as explanatory, scalability, speed and precision; Definition of model parameterization.

b. Phase (4b).

For the evaluation of the model, the following elements are considered: Definition of the set of tests to be compared, identifying the most precise metric to contrast the results obtained by the model; Definition of the acceptance threshold for performance metrics, in order to evaluate whether the performance or accuracy of the model is satisfactory or not.

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The developed system allows data collection through the use of a network of intelligent wireless sensors, called Smart Sockets. These single-phase devices are located in each outlet in the home, allowing the monitoring of electrical parameters of each appliance, such as voltage, current and power, in nominal 50 Hz and 220 VAC loads, considering 230 Volts as maximum operating values. and 16 Amps. Additionally, the proposed model has the flexibility of portability of the device to different power outlets within the deployed coverage environment, whose operation can be visible through a web platform or via a smartphone type device (Figure 2).

As Smart Sockets are fundamentally oriented to monitoring domestic electrical loads, with low-impact non-industrial consumption characteristics and dynamics, they are expected to operate under the following conditions:

- Loads with low presence or impact of transients or electrical impulses.
- Electrical network with good stability, voltage regulation and low presence of harmonics.

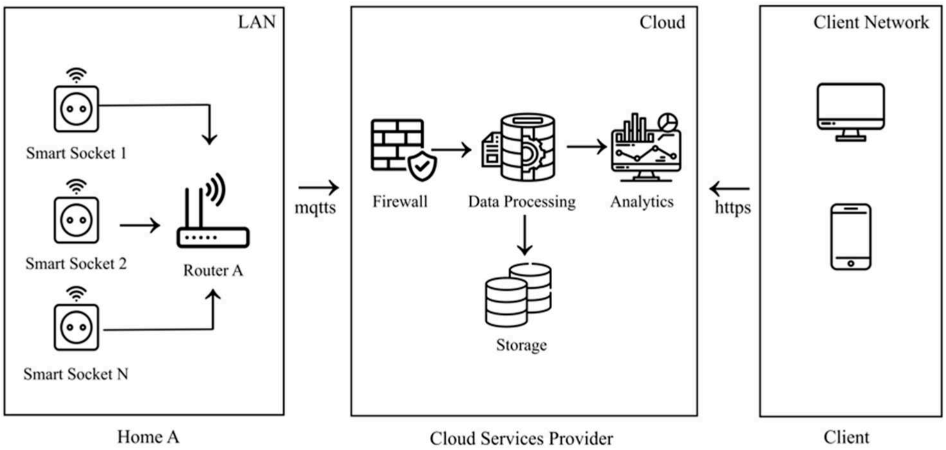

Figure 2. Smart Socket ILM system developed.

The proposed architecture for this Smart Socket considers the use of the IEEE 802.11 (Wi-Fi) standard as the communication protocol. The microprocessing unit considered for this device is the ESP8266 chip, which allows the processing of the measured data and its sending to a Gateway type device, which is responsible for transmitting data to public cloud services over the Internet. Voltage measurement is performed through a small power transformer and current measurement through a shunt resistor capable of measuring up to 16 Amps, allowing power calculation. (Figure 3). With all the parameters already described, it is possible to calculate the power and energy consumed by a certain electrical appliance. Based on the architecture described, the summary of Smart-Sockets functionalities are as follows:

- Measure the voltage and instantaneous current that are present in the appliance.
- Calculate the instantaneous power demanded by the connected appliance.
- Calculate the energy consumed by the connected appliance.
- Execute the communication request algorithm to transmit the power consumption and make the decision to turn on/off the Smart-Socket device by the coordinator.

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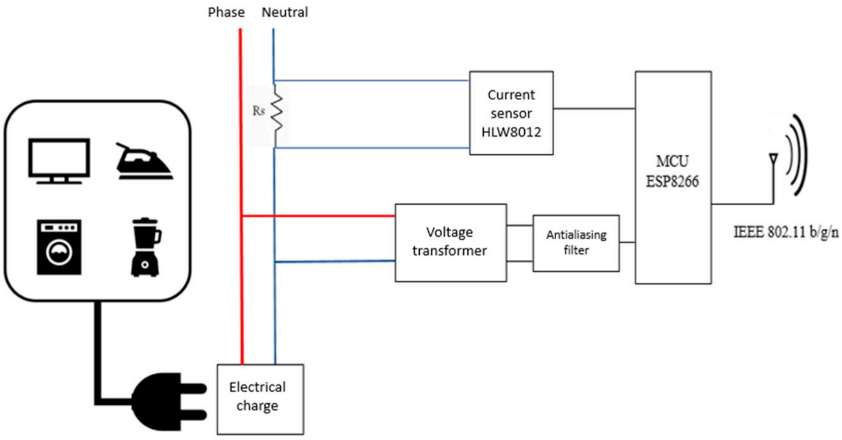

Figure 3. Architecture of a Smart Socket.

Given the need to generate a recognition model for electrical devices that is economical and easy to implement, with a low-power integrated circuit, it was therefore chosen to use a classification model based on time series. In this work, and since time series data cannot be used directly in a classification model, it was necessary to generate a representation that role models the characteristics of the series, generating a fixed input for the subsequent classification model. To carry out this task, the "Time Series Feature Extraction on Basis of Scalable Hypothesis test" method was used. After the representation of the time series, using the "Red Feed Forward"model based on Deep Learning and considering as an input value a curve vector of the electric charge and as an output the recognition of an appliance, it was possible to determine and classify each electrical appliance connected to the Smart-Socket device.

4. Experimental development

A The steps carried out for experimental development are highlighted below:

1. Data set.

For this study, a classification model for electrical appliances is designed and implemented based on time series analysis, with the objective of detecting and classifying appliances connected to the home electrical network. For this experiment, the proposed system was installed in 10 homes in Santiago de Chile, during the months of July, August and September, the middle of the winter season. Each residence has measurement equipment with an ILM (intrusive) approach, installed in each electrical outlet in the home,but more precise and reliable for on-off measurement and control. The different consumption patterns generated were constructed and analyzed from data that comes from multiple brands and models of household appliances present in the homes of the collaborators of this research.

To carry out the data collection process associated with the consumption of household appliances, the operation of the electrical parameters of each of them was measured through an intrusive charging system using an AMR.(Automatic Meter Reader) high resolution, which recorded the behavior of each electrical device in terms of electrical current consumed under multiple operating states. Between 360 and 400 samples were obtained per hour of consumption of each of the variables for each electrical appliance under study: washing machine, refrigerator, kettle, toaster, heater, router and electric stove. The intrusive charging system recorded a sample measurement of electrical consumption every 10 seconds and the behavior was measured for at least 24 hours of operation. Despite the large volume of data obtained, only 70% of them were used for training the model.

The initial results shown in this article were obtained after experimentation with only 7 appliances, given that they are the electrical devices of main use for a domestic human being (heating,

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cooking food, washing clothes and teleworking). Figure 4 shows the simultaneous behavior of the 7 devices depending on the electrical current demanded during 60 minutes of operation.

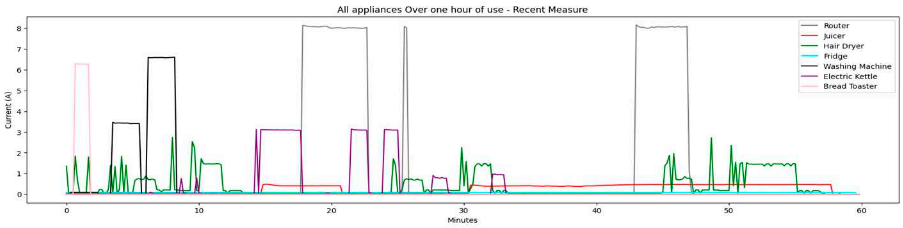

Figure 4. Simultaneous electrical current consumption profiles of appliances under study in one hour of consumption. The average arithmetic consumption is 675 [Kw/h].

Although the total household energy consumption behavior tends to be complex to visualize, if the curves are separated intuitively, it can be seen that some devices have similar behaviors in relation to the electrical current demanded (inductive, resistive elements and non-linear loads, example, data transmission). It is precisely this differentiation that we seek to replicate through artificial intelligence techniques, allowing the detection, prediction and classification of electrical devices according to their electrical behavior depending on time and conditions of use.

2. Appliance classification model.

Once the parameters and variables of the electrical energy consumption of each device under study were captured, a source of data and information was generated as a means of training the model. From this point, a household appliance classification model based on time series is developed.

Since time series data cannot be used directly in a classification model, it is necessary to generate a representation that allows modeling the characteristics of the series and generating a static input for the subsequent classification model. To carry out this task, the "Time Series Feature Extraction on Basis of Scalable Hypothesis Tests" method was used, which allows generating a large number of time series features, since it contains 63 series methods that contemplate a total of 794 attributes with their respective significance. After the representation of the time series, a Deep Learning model called "Feed Forward" was used, where the parameters used were the following:

Table 1. Parameters defined in the neural network model used.

Parameters	Values
Hidden layers	5
Neurons by layers	512, 256, 128, 64, 32
Optimizer	SGD
Learning rate	0,001
Iterations	250

The graphical detail of the network architecture used can be analyzed in Figure 5 and corresponds to a neural network with 5 hidden layers, where the defined input is a statistical representation of the behavior of the time series data and the result is the classification of the respective appliance.

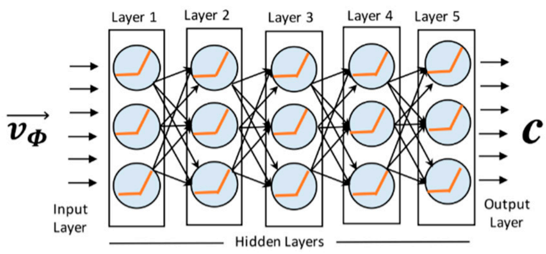

Figure 5. Graphical representation of the neural network architecture used.

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Finally, and for model validation purposes, the accuracy measure is used, given that the classes are represented in a balanced way with the number of measurements.

3. Results.

First campaign of measures: During the months of April, May and June 2020, autumn season in Santiago de Chile, measurements of electrical appliances were carried out using Smart Sockets ILM in 20 different homes, with sampling times of 20 seconds and with work cycles that depended on the operation. of each appliance. These results are presented below, where the measured electrical device is clearly indicated, along with its respective electrical current consumption pattern:

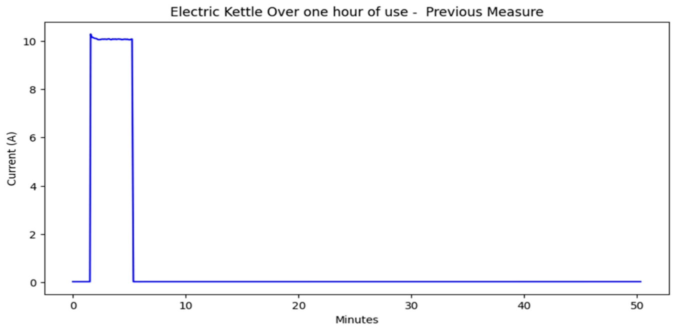

Figure 6. Electrical current consumption pattern of an Ursus Trotter 2000 brand kettle [watts]. Measurement interval of 60 minutes.

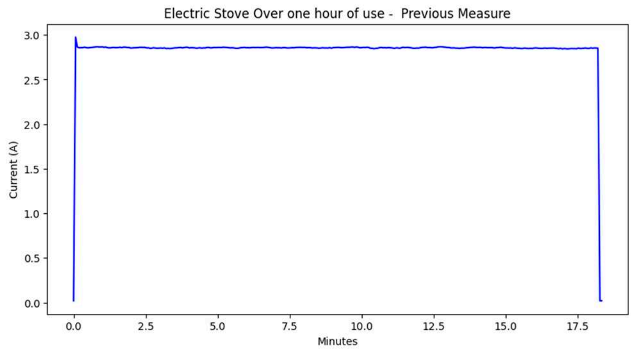

Figure 7. Electrical current consumption pattern of a generic 700 [watts] brand stove. 20 minute measurement interval.

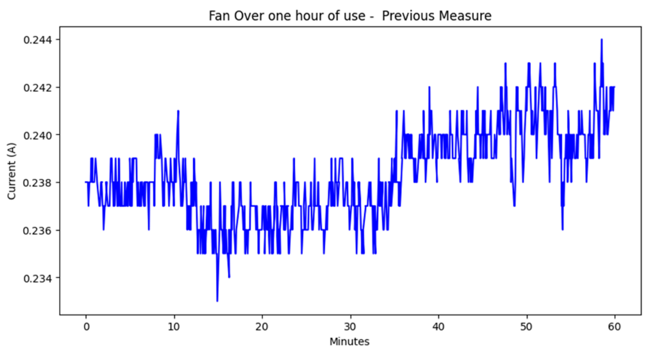

Figure 8. Electrical current consumption pattern of a Somela 55 [watts] fan. Measurement interval of 60 minutes.

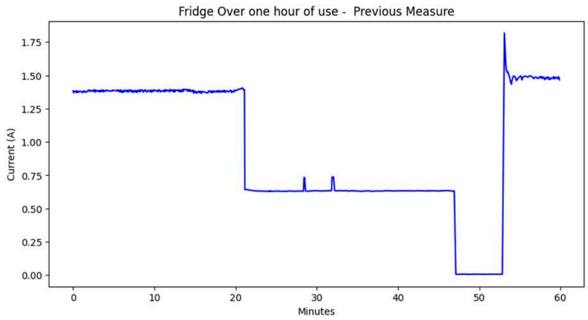

Figure 9. Electrical current consumption pattern of a Mademsa 200 [watts] refrigerator. Measurement interval of 60 minutes.

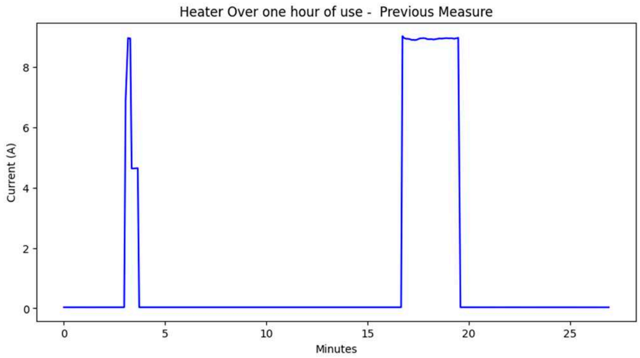

Figure 10. Electric current consumption pattern of a Nec 2000 brand heater [watts]. 30 minute measurement interval.

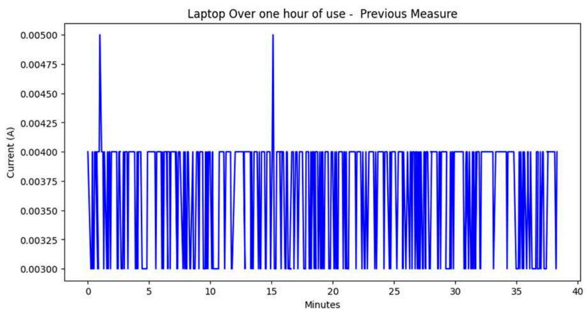

Figure 11. Electrical current consumption pattern of an HP 245 [watts] notebook. 40 minute measurement interval.

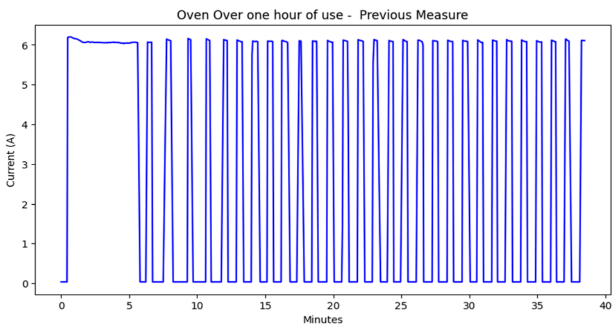

Figure 12. Electric current consumption pattern of a Thomas 1200 [watts] oven. 40 minute measurement interval.

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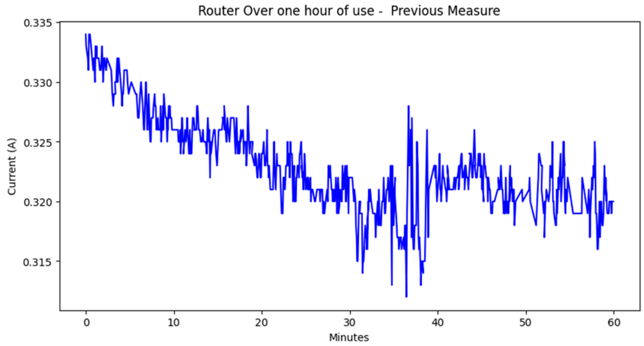

Figure 13. Electrical current consumption pattern of a Cisco brand Wi-Fi router 60 [watts]. Measurement interval of 60 minutes.

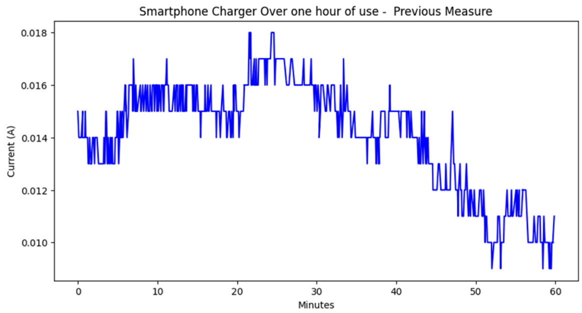

Figure 14. Electric current consumption pattern of a Samsung brand cell phone charger 5 [watts]. Measurement interval of 60 minutes.

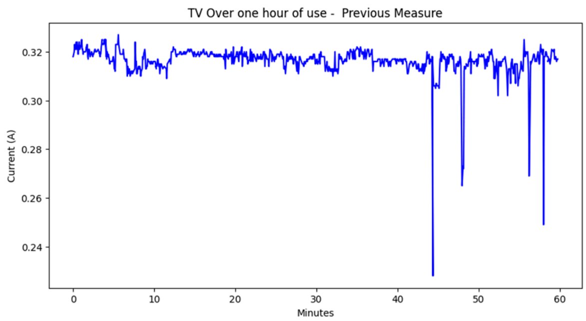

Figure 15. Electrical current consumption pattern of an LG 75 [watts] television. Measurement interval of 60 minutes.

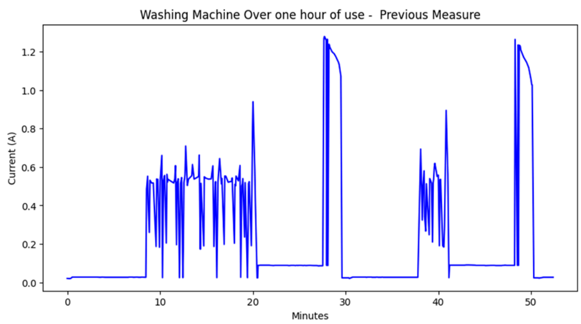

Figure 16. Electrical current consumption pattern of an Electrolux 200 [watts] washing machine. Measurement interval of 60 minutes.

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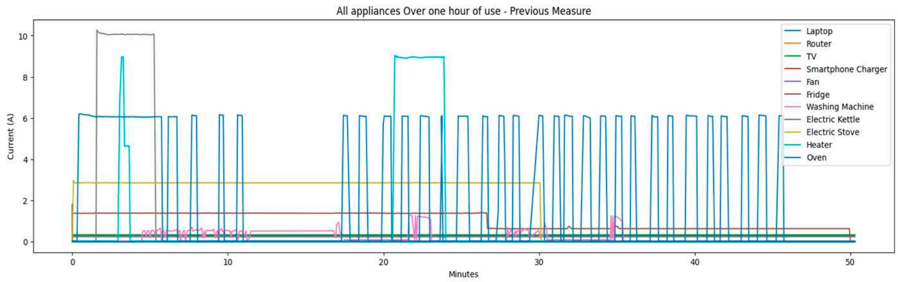

Figure 17. Simultaneous electrical current consumption profiles of appliances under study in one hour of consumption. The arithmetic average of consumption is 850 [Kw/h].

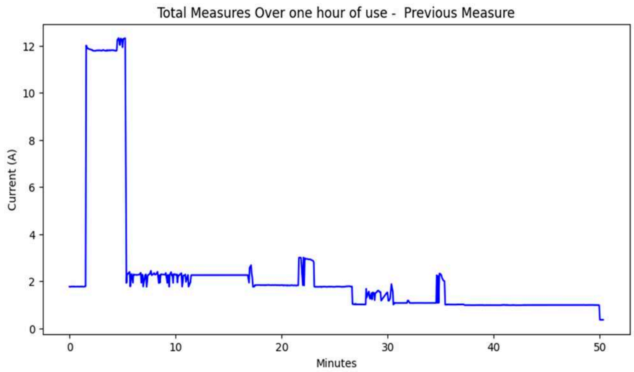

Figure 18. Energy consumed simultaneously by appliances under study in one hour of consumption, “Demand Energy Budget” in the first campaign. The arithmetic average of consumption is 675 [Kw/h].

Second campaign of measures: During the months of July, August and September 2023, the middle of the winter season in Santiago de Chile, measurements of electrical appliances were carried out using Smart Sockets ILM in 10 different homes, with sampling times of 10 seconds and with work cycles that depended on the operation of each appliance. The motivations for this new measurement campaign were the improvement in the sampling rate of the Smart Socket used, going from a sampling every 20 seconds to a sampling of 10 seconds per data obtained and the improvements implemented in the architecture and parameterization of the measurement model. neural networks used previously. These results are more precise than those previously obtained, and are presented below, where the electrical device measured is clearly indicated, along with its respective electrical current consumption pattern:

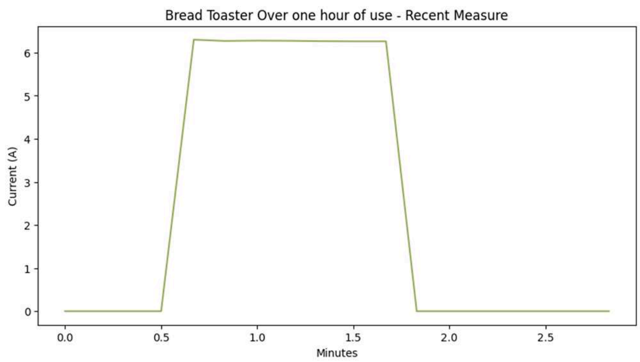

Figure 19. Electrical current consumption pattern of a Mademsa 1400 [watts] toaster. 3 minute measurement interval.

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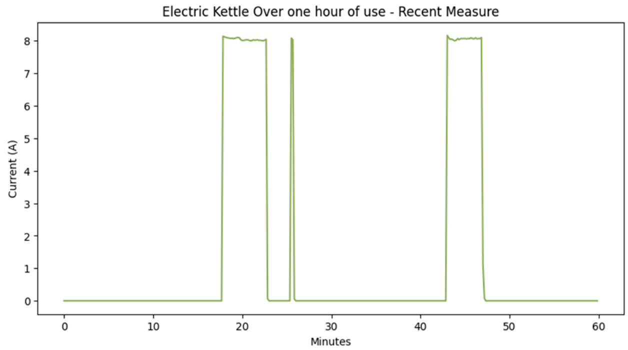

Figure 20. Electrical current consumption pattern of a Somela 1800 brand kettle [watts]. Measurement interval of 60 minutes.

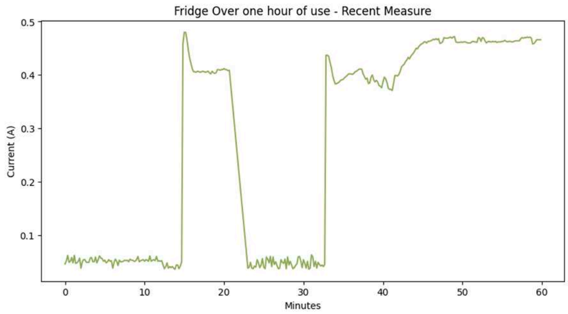

Figure 21. Electrical current consumption pattern of a Mademsa 110 [watts] refrigerator. Measurement interval of 60 minutes.

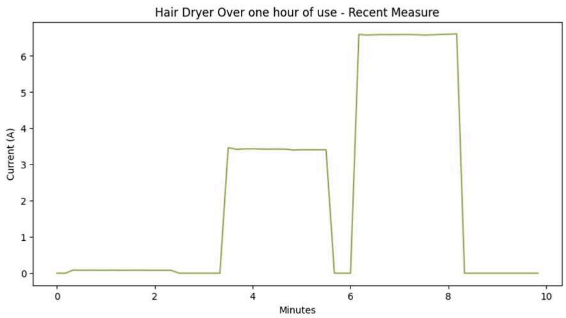

Figure 22. Electrical current consumption pattern of a generic GAMA 1600 [watts] hair dryer. 10 minute measurement interval.

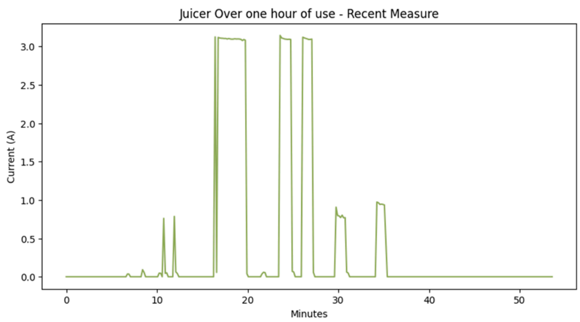

Figure 23. Electrical current consumption pattern of an Oster 700 brand juicer [watts]. Measurement interval of 60 minutes.

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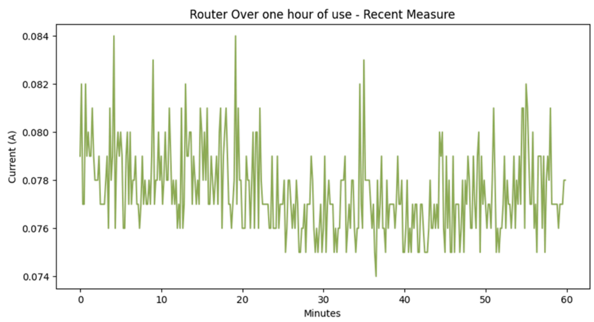

Figure 24. Electrical current consumption pattern of an Askey 20 [watts] router. Measurement interval of 60 minutes.

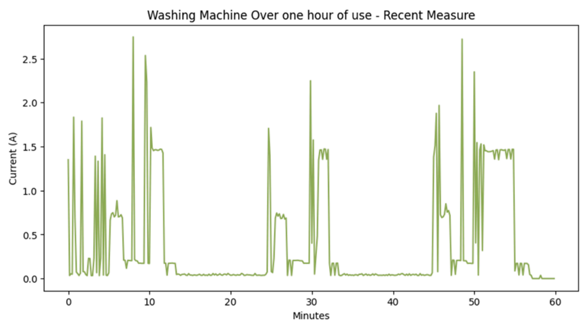

Figure 25. Electrical current consumption pattern of a Midea 600 [watts] washing machine. Measurement interval of 60 minutes.

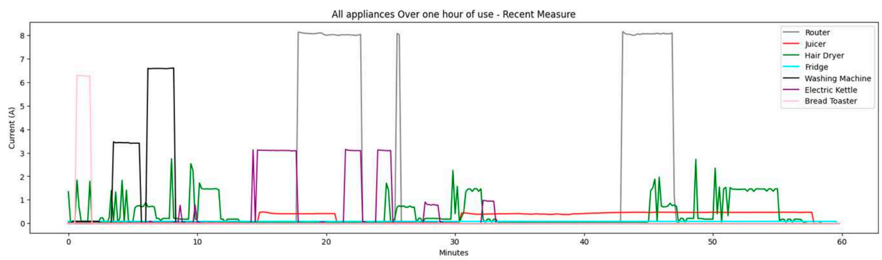

Figure 26. Simultaneous electrical current consumption profiles of appliances under study in one hour of consumption. The arithmetic average of consumption is 675 [Kw/h].

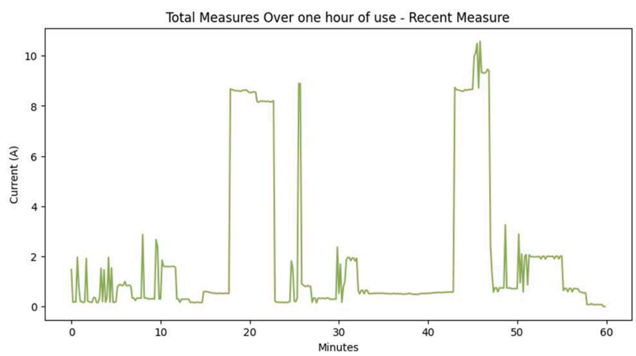

Figure 27. Energy consumed simultaneously by appliances under study in one hour of consumption, "Demand Energy Budget" in the second campaign. The arithmetic average of consumption is 675 [Kw/h].

5. Discussion of the results

The appliances that we consider "critical path" for modern human survival are: refrigerator, washing machine, dishwasher, television and the notebook. The standby function of some appliances is also incorporated, such as cell phone chargers, Wi-Fi routers, printers, scanners, among others. others.

A. Fridge.

At the top of the Ranking of which appliance consumes the most connection time and electricity is the refrigerator (it consumes 24 hours a day). The refrigerator represents 30.6% of the electricity consumption in our homes. It has approximately a consumption of 250-500 [watts/day] or 15 [kw/month].

B. TV.

In second place, of the appliances that consume the most electricity is the television with 10 hours of on. Television consumes 12.2% of total energy expenditure. You should avoid using stand-by and turn it off completely when not in use. Its consumption will depend on the type of screen, for example, a 32-inch LCD screen is 115 [watts/hour], while a plasma is around 300 [watts/hour].

C. Washing machine.

The washing machine represents 11.8% of the total electricity consumption, it is in third position in the ranking of which appliance consumes the most energy. If we use short programs and cold washes, electricity can be saved. Average consumption of approximately 255 [watts/hour].

D. Consumption "vampire" or Stand-by.

The consumption of cell phone chargers, Wi-Fi routers, music equipment turned off but connected, among others, is known as Stand-by. The well-known standby is not recommended as it seems, it consumes a total of 10.7% of electricity, much more than a stationary or laptop computer. Avoiding this would mean considerable savings on a residential user's monthly bill.

E. Electric oven.

The oven accounts for 8.3% of the energy expenditure. If it is kept clean of fat, avoiding opening it during cooking and turning it off beforehand to take advantage of the residual heat will help us reduce consumption. It consumes approximately between 1,800 and 2,200 [watts] per hour depending on the model and conditions of use and if it is used daily for cooking, it will occupy the first place on the list with an average consumption of 60 [kw/month].

F. Computer.

The computer occupies 6th place on the list of which appliance consumes the most energy. 7.7% is what the computer consumes in electricity. Energy consumption can be reduced if we lower the screen lighting, remove the screensaver and do not have the peripherals connected (wi-fi speakers, printer, scanner, to name a few).

G. Dishwasher.

It consumes 6.1% of electricity. Using short programs and at a lower temperature can save energy, as well as charging it to the maximum. Per hour, it consumes about 246 [watts].

H. Dryer.

Finally, we find the dryer, which according to this study on which appliances consume the most electricity, we know that it consumes 3.3% of electricity, although it could be an incorrect figure since only 28.3% of the population has one. dryer in your home (Chile, Undersecretary of Energy and Fuel 2022). The approximate consumption of the dryer during one hour is 2,700 [watts].

Although the above were the appliances that are most noticeable in our monthly bill, we must not forget about the rest of the appliances, which can consume more Watts in an hour, but of course, if we do the annual calculation, they are not the ones that consume the most , such as air conditioning or ceramic hob burners.

- Air conditioning: 690 [watts/hour].

- Vacuum cleaner: 675 [watts/hour].
- Blender: 200 [watts/hour].
- Mini music component: 75 [watts/hour].
- Juicer: 50 to 200 [watts/hour].
- Vitroceramic (one stove): 1,200-2,000 [watts/hour].
- Fryer: 1,000 [watts/hour].

On the other hand, the results of the validations of the Deep Learning model, used in the classification of household appliances, are shown in Figure 28. The results indicated in this article are better than those reported in [9,18–21]. , given that an average F1 score of 97% was achieved.

	precision	recall	f1-score	support
0	0.96	1.00	0.98	92
1	0.99	0.99	0.99	80
2	1.00	0.95	0.97	55
3	1.00	0.86	0.92	7
accuracy			0.98	234
macro avg	0.99	0.95	0.97	234
weighted avg	0.98	0.98	0.98	234

Figure 28. Results obtained from the validation of the Deep Learning model.

6. Conclusions

Based on the results of both campaigns as a whole presented in this article and considering the current profile or pattern in each device under study, it was possible to determine the average electrical energy consumption during one hour of operation. The use of several electrical appliances in simultaneous activity was also considered, thus determining the total value of the average energy consumed (area under the curve) and used by said appliances in that same time range. As a consequence of the above, the "Energy Budget"required for the operation of residential demand can be determined, on the one hand determining future billing, and on the other hand, it will allow knowing how much should be generated with Non-Conventional Renewable Energy systems. in the Photovoltaic-Wind Energy Harvest (Winter-Summer) for home supply. AlsoIt is possible to establish efficient administration of home electrical energy, as a result of precise knowledge of the average consumption per hour, a fact that allows the determination of the energy budget of a home for a day, a month or a year.

Considering the two measurement campaigns indicated in this document, together with the profile recognition current consumption of household appliances, which allows the separation of electrical appliances into three clusters (cluster 1 of appliances that transform electrical energy into heat, cluster 2 of appliances that transform energy into motor movement and cluster 3 of appliances that transform electrical energy in data), it is possible to make decisions in real time to turn on and off appliances, managing to correctly discriminate the appliances that should really be in use from those that should not (switched energy management).

Additionally, the use of public cloud services for the implementation of the artificial intelligence models described in this document is a significant improvement over previous works, given that their use allows obtaining data on the electrical current consumption of each device in real time. real, securely and with a high degree of availability (average SLAs of 99.9% availability). These benefits allow decisions to be made in real time with high levels of certainty (average F1 value of 97%), mainly because they help to have a better knowledge of energy (watt per hour concept).

7. Future work

Fault Detection: It is expected that as a result of the improvement in the sampling rate of the measurements, considering the behavior and long-time variability of the household appliances being measured, any difference in the current or voltage pattern, fundamentally of the resistive, inductive or Some non-linear behavior means an evident anomaly, which could be detected through a model and treated in predictive maintenance programs. In other words, any sudden change or change out of the current profile pattern would be detected as an electrical failure of the device, and the user could be informed to their mobile phone in real time. Along with this, if the measurement campaign were more extensive, for example, for 12 months, it would be possible to obtain the annual variability of each electrical device from the Deep Learning model generated.

Use and application in NCRE programs (Non-Conventional Renewable Energy): Electronic circuit improvements can be made to obtain greater resolution of the total energy consumption budget with all the necessary home appliances. This knowledge of the energy density of total-annual consumption in the home may allow determining how much energy should be obtained or generated through NCRE and/or stored in batteries, allowing intelligent and efficient energy management, carrying out billing. of the electrical distribution network to zero, and if there is a surplus, it can be injected into the network. Having a positive difference could lead to the sale of energy to the distribution company, satisfying the electrical consumption needs of a home and saving energy savings.

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References

1. Caldera, M.; Hussain, A.; Romano, S.; Re, V. Energy-Consumption Pattern-Detecting Technique for Household Appliances for Smart Home Platform. Energies 2023, 16, 824. https://doi.org/10.3390/en16020824.
2. Y.H. Lin, and M.-S. Tsai, “An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling,” IEEE Trans. Smart Grid, vol. 6, no. 4, pp. 1839-1851, 2015. DOI: 10.1109/TSG.2015.2388492.
3. T. Hasan, F. Javed, and N. Arshad, “An empirical investigation of V-I trajectory-based load signatures for non-intrusive load monitoring,” IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 870-878, 2013. DOI: 10.1109/TSG.2013.2271282.
4. A. Ridi, C. Gisler and J. Hennebert, "A Survey on Intrusive Load Monitoring for Appliance Recognition," 2014 22nd International Conference on Pattern Recognition, Stockholm, Sweden, 2014, pp. 3702-3707, doi: 10.1109/ICPR.2014.636.
5. Ulloa, F., García-Santander, L, Carrizo, D. and Hurtado, C.. "Towards a Home Energy Management Model Through a Coordinator of Smart Sockets" Latvian Journal of Physics and Technical Sciences, vol.55, no.4, 2018, pp.35-43. https://doi.org/10.2478/lpts-2018-0027.
6. P. Pawar and K. P. Vittal, "Design of smart socket for power optimization in home energy management system," 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 2017, pp. 1739-1744, doi: 10.1109/RTEICT.2017.8256897.
7. M. L. G. Villanueva, S. M. G. Dumlao and R. S. J. Reyes, "Appliance recognition system for ILM using AGILASx — Dataset of common appliances in the Philippines," 2016 Cloudification of the Internet of Things (CIoT), Paris, France, 2016, pp. 1-5, doi:10.1109/CIOT.2016.7872910.
8. Cannone, C.; Hoseinpoori, P.; Martindale, L.; Tennyson, E.M.; Gardumi, F.; Somavilla Croxatto, L.; Pye, S.; Mulugetta, Y.; Vrochidis, I.; Krishnamurthy, S.; et al. Addressing Challenges in Long-Term Strategic Energy Planning in LMICs: Learning Pathways in an Energy Planning Ecosystem. Energies 2023, 16, 7267. https://doi.org/10.3390/en16217267.
9. F. Ulloa-Vásquez, L. García-Santander, D. Carrizo and V. Heredia-Figueroa, "Intelligent electrical pattern recognition of appliances consumption for home energy management using high resolution measurement," in IEEE Latin America Transactions, vol. 20, no. 2, pp. 326-334, Feb. 2022, doi: 10.1109/TLA.2022.9661473.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 December 2023 doi:10.20944/preprints202312.1456.v1

10. Suryadevara, N.K.; Biswal, G.R. Smart Plugs: Paradigms and Applications in the Smart City-and-Smart Grid. Energies 2019, 12, 1957. https://doi.org/10.3390/en12101957.
11. Cruz, C.; Palomar, E.; Bravo, I.; Gardel, A. Towards Sustainable Energy-Efficient Communities Based on a Scheduling Algorithm. Sensors 2019, 19, 3973. https://doi.org/10.3390/s19183973.
12. Khalifeh, A.; Darabkh, K.A.; Khasawneh, A.M.; Alqaisieh, I.; Salameh, M.; AlAbdala, A.; Alrubaye, S.; Alassaf, A.; Al-HajAli, S.; Al-Wardat, R.; et al. Wireless Sensor Networks for Smart Cities: Network Design, Implementation and Performance Evaluation. Electronics 2021, 10, 218. https://doi.org/10.3390/electronics10020218.
13. Alam, T. Cloud-Based IoT Applications and Their Roles in Smart Cities. Smart Cities 2021, 4, 1196-1219. https://doi.org/10.3390/smartcities4030064.
14. Jaradat, A.; Lutfiyya, H.; Haque, A. Appliance Operation Modes Identification Using Cycles Clustering. arXiv 2021, arXiv:2101.10472.
15. A. Obushevs, I. Oleinikova and A. Mutule, "Demand side management platform for HAN flexibility estimation with agent control," 2016 13th International Conference on the European Energy Market (EEM), Porto, Portugal, 2016, pp. 1-5, doi: 10.1109/EEM.2016.7521185.
16. M. N. Ullah, N. Javaid, I. Khan, A. Mahmood and M. U. Farooq, "Residential Energy Consumption Controlling Techniques to Enable Autonomous Demand Side Management in Future Smart Grid Communications," 2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications, Compiegne, France, 2013, pp. 545-550, doi: 10.1109/BWCCA.2013.94.
17. M. U. Saleem, M. R. Usman, M. A. Usman and C. Politis, "Design, Deployment and Performance Evaluation of an IoT Based Smart Energy Management System for Demand Side Management in Smart Grid," in IEEE Access, vol. 10, pp. 15261-15278, 2022, doi: 10.1109/ACCESS.2022.3147484.
18. Y. -C. Chen, Y. -L. Ko and W. -C. Peng, "An Intelligent System for Mining Usage Patterns from Appliance Data in Smart Home Environment," 2012 Conference on Technologies and Applications of Artificial Intelligence, Tainan, Taiwan, 2012, pp. 319-322, doi: 10.1109/TAAI.2012.54.
19. S. Guillemin and D. L. Ha, "Fuzzy and parametric method for self-configuration of home energy manager system," 2013 IEEE Grenoble Conference, Grenoble, France, 2013, pp. 1-6, doi: 10.1109/PTC.2013.6652241.
20. M. A. Devlin and B. P. Hayes, "Non-Intrusive Load Monitoring and Classification of Activities of Daily Living Using Residential Smart Meter Data," in IEEE Transactions on Consumer Electronics, vol. 65, no. 3, pp. 339-348, Aug. 2019, doi: 10.1109/TCE.2019.2918922.
21. Fahim, M., Kazmi, S.M.A. & Khattak, A.M. ApplianceNet: a neural network based framework to recognize daily life activities and behavior in smart home using smart plugs. Neural Comput & Applic 34, 12749–12763 (2022). https://doi.org/10.1007/s00521-022-07144-1.
22. Jackson Codispoti, Atieh R. Khamesi, Nelson Penn, Simone Silvestri, and Eura Shin. 2022. Learning from Non-experts: An Interactive and Adaptive Learning Approach for Appliance Recognition in Smart Homes. ACM Trans. Cyber-Phys. Syst. 6, 2, Article 16 (April 2022), 22 pages. https://doi.org/10.1145/3491241.
23. Du, S.; Li, M.; Han, S.; Shi, J.; Li, H. Multi-Pattern Data Mining and Recognition of Primary Electric Appliances from Single Non-Intrusive Load Monitoring Data. Energies 2019, 12, 992. https://doi.org/10.3390/en12060992.
24. Gajowniczek, K.; Ząbkowski, T. Data Mining Techniques for Detecting Household Characteristics Based on Smart Meter Data. Energies 2015, 8, 7407-7427. https://doi.org/10.3390/en8077407.
25. Yu, Z., Fung, B.C.M. & Haghighat, F. Extracting knowledge from building-related data — A data mining framework. Build. Simul. 6, 207–222 (2013). https://doi.org/10.1007/s12273-013-0117-8.
26. Y. Gao and H. Yang, "Non-Intrusive Load Identification by Fuzzy Cluster Analysis Based on Active Power," 2012 Asia-Pacific Power and Energy Engineering Conference, Shanghai, China, 2012, pp. 1-4, doi: 10.1109/APPEEC.2012.6307566.
27. A. Ridi, C. Gisler and J. Hennebert, "ACS-F2 — A new database of appliance consumption signatures," 2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR), Tunis, Tunisia, 2014, pp. 145-150, doi: 10.1109/SOCPAR.2014.7007996.
28. L. Jiang, S. Luo and J. Li, "Intelligent electrical event recognition on general household power appliances," 2014 IEEE 15th Workshop on Control and Modeling for Power Electronics (COMPEL), Santander, Spain, 2014, pp. 1-3, doi: 10.1109/COMPEL.2014.6877183.
29. W. S. Lima, E. Souto, T. Rocha, R. W. Pazzi and F. Pramudianto, "User activity recognition for energy saving in smart home environment," 2015 IEEE Symposium on Computers and Communication (ISCC), Larnaca, Cyprus, 2015, pp. 751-757, doi: 10.1109/ISCC.2015.7405604.
30. Q. Sun et al., "A Comprehensive Review of Smart Energy Meters in Intelligent Energy Networks," in IEEE Internet of Things Journal, vol. 3, no. 4, pp. 464-479, Aug. 2016, doi: 10.1109/JIOT.2015.2512325.
31. E. Salihagić, J. Kevric and N. Doğru, "Classification of ON-OFF states of appliance consumption signatures," 2016 XI International Symposium on Telecommunications (BIHTEL), Sarajevo, Bosnia and Herzegovina, 2016, pp. 1-6, doi: 10.1109/BIHTEL.2016.7775722.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 19 December 2023
doi:10.20944/preprints202312.1456.v1

32. C. Klemenjak and W. Elmenreich, "On the applicability of correlation filters for appliance detection in smart meter readings," 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm), Dresden, Germany, 2017, pp. 171-176, doi: 10.1109/SmartGridComm.2017.8340730.
33. A. Gupta and P. Murarka, "A Ubiquitous Sensor Network for Domestic Energy Monitoring and Energy Consumption Optimization," 2012 IEEE International Conference on Green Computing and Communications, Besancon, France, 2012, pp. 58-65, doi: 10.1109/GreenCom.2012.19.
34. Baier, C.R.; Hernández, J.C.; Wheeler, P. Measurements, Predictions, and Control in Microgrids and Power Electronic Systems. Sensors 2023, 23, 4038. https://doi.org/10.3390/s23084038.
35. Sami Ben Slama, Marwan Mahmoud, A deep learning model for intelligent home energy management system using renewable energy, Engineering Applications of Artificial Intelligence, Volume 123, Part B, 2023, 106388, ISSN 0952-1976, https://doi.org/10.1016/j.engappai.2023.106388.

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