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Methodology to Develop a Home Energy Management System Architecture

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Abstract. This paper is concerned in to propose a complete methodological architecture that is used to develop a complete demand system. The general methodology could be subdivided into three modules. The first module is focused on data consumption emulation, in it is implemented Monte Carlo method to generate data behavior of household appliances set over time getting a user profile. The second module is about developing a user interface that lets the user interact with the system, through the interface is possible that the user feeds the system with the features that describe the context. The interface gives feedback to the user with graphical information about consumption and a possible household appliances behavior which decrease the consumption, with that the user could get more conscious about his consumption behavior. In the third module is implemented a metaheuristic that analyzes the data consumption and searches the optimum using an objective function which is obtained from a mathematical model. The mathematical model contemplates how household appliances consume.

Keywords. Demand system, data simulator, methodology architecture.

1 Introduction

Accordingly, with the International Energy Agency (IEA), the global energy demand is 2% to 2.3% higher than in the year 2000. The global electricity demand is going to grow at 2.1% per year till 2040.

One-fifth part of the global demand is destined to satisfy heating and cooling needs. 30% of the total global energy produced is destined for domestic use.

House consumption depends on six factors: climate, infrastructure, service system and use of electricity, the inner design, house´s maintenance and uses, and occupant behavior [1].

Every each of the first five factors has been significant progress using different strategies like using renewable energies, house designing, implementing home energy management systems, and others, the last factor is an open research area.

Home energy management systems have been developed from different approaches focusing on an interface, the implementation and development of search techniques for optimal use and consumption, the detection of patterns behavior device use, obtaining user needs, usage rules, and sensor architecture design with the main goal of reducing domestic consumption.

To the knowledge of the author, there is not a development methodology that involves all of them. Following the data flow in this kind of project makes sense to propose a methodology focusing on it.

Dataflow by itself defines the modules that conform to the methodology that we are developing: Home Energy Management System Architecture (HEMSA).

1.1 Home Energy Management System

A methodological HEMSA proposition was obtained from reviewing papers about what is a demand system [2], which are its components, and what are the variables that are necessary to consider in the development. In the review, there are two main topics: demand system architecture (components, data kind, and characteristics) and conscious systems (it is about data flow in projects) [3].

From an architectural perspective, a demand system consists of five parts: sensors array, three modules (programming, monitor, and prediction), and one logical control unit [4]. In conscious system dataflows passes through five layers: sensor, physic, conscious of behavior, digital, and meta; between physics and conscious of behavior layers there is a fusion of information module. So, the data flow itself determines how the data is acquired, its processing, and how the results are displayed.

From architectural demand system and the conscious system has conceptualized a methodology that embeds three main parts: sensor layer (SL), intelligent ambient (IA), and prediction module (PM).

To design SL which considers the occupant behavior (action when the occupant turns on/off household appliances and time-consumption of household appliances). How the devices are used affects the consumption that is being generated and allows us to predict how this consumption is carried out. SL is made by implementing a simulator that generates consumption and uses profiles of household appliances. These profiles allow emulating household appliances (room air conditioner, heater, washing clothes and furnace fan) On/Off behavior.

IA is the user interface through which the user feeds the system with de context features and gets feedback with graphical information about data consumption.

PM is the part where data consumption is analyzed and is obtained an optimal consumption, in this module is implemented a bioinspired metaheuristic (Particle Swarm Optimization (*PSO*)).

This paper is organized as follows. Section 2 presents the related work. Section 3 the topics that conform to the parts of the home energy system architecture methodology. In section 4 is presented the case study. The experimental results and validations are presented in section 5. Finally, conclusions and further work are presented in section 6.

2 Related Work

From the literature review, the general objectives for the implementation of an electricity consumption analysis system are identified, these can be focused to maintain a comfortable environment for the user, reduce the consumption that is made in the implementation environment, helping to reduce consumption costs, and voltage peaks [5], the most referenced is the one that focuses on meeting the needs of the user, followed by the reduction of cost and consumption (which are directly related to each other) and finally reduce voltage peaks when turning on a device.

For a demand system, it is necessary to have a consumption database, and for the construction of this, the characteristics of the devices must be identified, these are average consumption, frequent use time, and type of device to which it belongs (interruptible, uninterruptible, flexible and not flexible) [6].

Consumption data is obtained from a sensor architecture; but, when one does not have one, then a simulator is used to generate usage and consumption profiles. Vectors are used in the simulator to store consumption data for each of the devices being simulated. Each of the vectors that are constructed corresponds to a specific time in the range from 0 to 23 (the hours that make up a day) [7].

An important part of the design of a demand system is the mathematical modeling of the consumption is carried out by the devices that characterize the context to obtain the objective function [8].

The implementation of an interactive system [9] as part of an energy management system for the home, encourages the user to make changes in consumption behavior, as this makes them act efficiently and conscious, thus generating a transparent, dynamic, controllable, and intelligent

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environment, it provides comfort by simplifying the control and management of electrical devices [10]. The interactive system is a means that serves to make a virtual representation [11] creating objects [12] of the identified context [10], the interactive system groups the data concerning the implementation objective [13]. The system interface must have the characteristic of being flexible, accessible, and intuitive[14] as a SCADA system [15] by allowing the inclusion of more virtual objects to the system. Presenting consumption data through the interface [16] reduces consumption by between 3% and 13% [13].

In the system, there is a module in which the procedure uses the implementation objective to propose an optimized consumption [17]. In the literature, four types of linear programming procedure, genetic algorithms, metaheuristics, and game theory are identified [6]. Being one of the most implemented metaheuristics [17].

In the reviewed works, it is observed how the development approach focuses only on one of the parts that make up a demand system, that is, only some of the parts are improved and the others are only approached in a shallow way or are not developed.

3 System Architecture Topics

3.1 Energy Consumption Model

A mathematical representation of electric consumption in a house is made by a mathematical model. The sort of devices and their characterization are used to model them. The device's description is done by every kind of household appliance, the minimum, and maximum consumption, and they frequently use time. The on/off household appliances´ states are represented by 1 and 0 respectively.

3.2 Household Appliances

According to the way which the household appliances work, they can be sorted into flexible (F), not flexible (NF), interruptible (I), and uninterruptible (NI) devices. The flexible devices are the devices of electric consumption whose function can be interrupted and continue at another moment [18]. Flexible devices can be put on standby. The not-flexible appliances are devices of electric consumption that cannot be turned off, this type of appliance has a constant operation [17]. Interruptible appliances are electrical consumption devices that can be used at any time, the time of use varies according to the user´s needs [17]. Uninterruptible appliances are electrical devices that stop to function has finished; the electric consumption can be constant or variable [18].

3.3 Household Appliances Consumption

The set of devices in a context is represented by A, and i −device is represented by a_i. Set A have four subsets AI, $ANI,\ AF$, and ANF. Set $A = AI \cup ANI \cup AF \cup ANF$, every subset represents a kind of device, $a_I \in AI, a_{NI} \in ANI, a_F \in AF, a_{NF} \in ANF$.

The on/off devices state in the ꓕ moment is represented by $\tau(t) \in \{0,1\}$, 1 represents ON and 0 represents OFF. There are considered 24 moments in the modeling, $\tau \in T$, $T = \{\tau_1, \tau_2, \dots, \tau_{24}\}$.

The cardinality of set A and its subsets are represented as $|A| = m$, $|AI| = n$, $|AN| = p$, $|AF| = q$, $|ANF| = r$. So, $n + p + q + r = m$, and $A = \{a_1, a_2, \dots, a_m\}$.

Set A can have devices belonging to the same type of device with different identifiers. The household appliances consumption function takes the elements of the set A in every moment in set T and generates the consumption measured in watts. The kind of values is $\varepsilon\colon \mathrm{A} \times \mathrm{T} \rightarrow \mathrm{R}^{+}$, the hourly consumption of a device at a specific time is:

$$\varepsilon(a_i, \tau_i) = \Upsilon_{a_i}^{\tau}. \tag{1}$$

The total consumption of the set is represented as the sum of daily devices consumption (where ε_I represents the daily total consumption of interruptible devices group and is the same for the others ε_i), it is represented as:

$$\varepsilon = \varepsilon_I + \varepsilon_{NI} + \varepsilon_F + \varepsilon_{NF}. \tag{2}$$

The hourly consumption is the sum of the consumption that is carried out at a specific moment by every device group (here Υ_I^{τ}

represents the total hour-consumption interruptible group in τ moment, it is the same for the other groups), it is:

$$\Upsilon^{\tau} = \Upsilon_I^{\tau} + \Upsilon_{NI}^{\tau} + \Upsilon_F^{\tau} + \Upsilon_{NF}^{\tau}. \quad (3)$$

The minimum consumptions per day is:

$$\varepsilon_{min} = \varepsilon_{NF} = \sum_{a_{NF} \in A_{NF}} \sum_{\tau=1}^{T} \Upsilon_{a_{NF}}^{\tau}. \quad (4)$$

And per hour consumption is:

$$\Upsilon_{min}^{\tau} = \sum_{a_{NF} \in A_{NF}} \Upsilon_{NF}^{\tau} \quad \forall \tau, \tau \in T. \quad (5)$$

The maximum consumptions per day is:

$$\begin{aligned} \varepsilon_{max} &= \varepsilon_I + \varepsilon_{NI} + \varepsilon_F + \varepsilon_{NF} \\ &= \sum_{a_i \in A} \sum_{\tau=1}^{T} \Upsilon_{a_i}^{\tau} \ , \ \alpha_{a_i}(\tau) = 1. \end{aligned} \quad (6)$$

And per hour, are represented as:

$$\begin{aligned} \Upsilon_{max}^{\tau} &= \Upsilon_I^{\tau} + \Upsilon_{NI}^{\tau} + \Upsilon_F^{\tau} + \Upsilon_{NF}^{\tau} \\ &= \sum_{a_i \in A} \Upsilon_{a_i}^{\tau} \quad \forall \tau, \tau \in T. \end{aligned} \quad (7)$$

For the model, it is identified that $\varepsilon_{mín} < \varepsilon_{opt} < \varepsilon_{max}$, where ε_{opt}t it meets the needs of the user minimizes consumption and reduces the peak average ratio.

$AI = \{a_{I1}, a_{I2}, \dots, a_{In}\}$, $|AI| = n < m$, and $\exists\, a_{Ii}, a_{Ij} \in A_I,\ i \neq j \ \rightarrow \ a_{Ii} = a_{Ij}$.

The total consumption of the subset AI is obtained from (8) and represents the sum of the total consumption of every device belonging to this subset and whose consideration depends on the state of the device (on / off) for each moment. The partial consumption is obtained in (9) (consumption per hour), which is the sum of the consumption made by all the devices that are on in the moment T.

$$\varepsilon_I = \sum_{a_{Ii} \in A_{Ii}} \left[\sum_{\tau=1}^{T} \left(\Upsilon_{a_{Ii}}^{\tau}\ x\ \alpha_{a_{Ii}}(\tau) \right) \right], \quad (8)$$

$$\Upsilon_I^{\tau} = \sum_{a_{Ii} \in A_I} \left(\Upsilon_{a_{Ii}}^{\tau}\ x\ \alpha_{a_{Ii}}(\tau) \right) \quad \forall \tau, \tau \in T\,. \quad (9)$$

To define the subsets ANI, AF, and ANF are used similar expressions to those exposed for the subset AI. For ANF, $\alpha(\tau)$ =1, because they are turned on all time.

A window represents the range of hours between which a device can operate, $[\sigma_{a_I}, \psi_{a_I}]$, To define the window device, are identified four parameters: the device on time $\sigma_{a_{Ii}}$, the time for which the device will no longer turn on $\psi_{a_{Ii}}$, the frequent operating time $\xi_{a_{Ii}}$, and the time $\varsigma_{a_{Ii}}$ at which the device a_{Ii} has been turned on.

These four parameters fulfill the following constraints: $\sigma_{a_{Ii}} \leq \psi_{a_{Ii}}, \varsigma_{a_I} \geq \sigma_{a_I}$ y $\varsigma_{a_I} \leq \psi_{a_I} - \xi_{a_I}, \varsigma_{a_I} \geq \sigma_{a_I}$ y $\varsigma_{a_I} \leq \psi_{a_I} - \xi_{a_I}, \varsigma_{a_I} \in [\sigma_{a_I}, \psi_{a_I} - \xi_{a_I}]$.

The objective function is defined to minimize the daily consumption, it is:

$$mín \sum_{\tau=1}^{T} \left(\sum_{a_i \epsilon A} \Upsilon_{a_i}^{\tau} \right). \quad (10)$$

3.4 Monte Carlo Method

A strategy to approximate an unknown quantity μ is using random sampling, referred to as Monte Carlo Methods. This method is based on finding a sequence $X_1, X_2, \dots, X_n$ of mutually independent, identically distributed random variables, such that the expectation $\mathrm{E}X_i = \mu$ exits for $\mathrm{i} = 1,2, \dots, \mathrm{n}$. Let be $S_n = X_1 + X_2 + \cdots + X_n$, the Weak Law of Large Numbers states that, for every $\varepsilon > 0, \lim_{n \to \infty} pr\left(\left| \frac{S_n}{n} - \mu \right| > \varepsilon \right) = 0$.

Besides, when the expectation $\sigma^2 = E(X_i - \mu)^2$ exits the Central Limit theorem asserts that $pr\left(\left| \frac{S_n}{n} - \mu \right| < \frac{3\sigma}{\sqrt{n}} \right) \approx 0.997$.

Then the mean of S_n/n will be approximately equal to μ.

3.5 Methodology to Implement a Simulator

The simulator was programmed in MATLAB R2018a following the Monte Carlo method with the Acceptance-Rejection technique to generate the fins. This technique supposes that there is a method for simulating a random variable from the probability mass function. First is simulated a random variable "Y" from the mass function "q_j" and then accepting this simulated value with a probability of p_j/q_j. The constant c is defined as getting the maximum of p_j/q_j, where $p_j > 0$. So, the simulated value Y with the probability mass function q_j generates a random number U, if $U >$

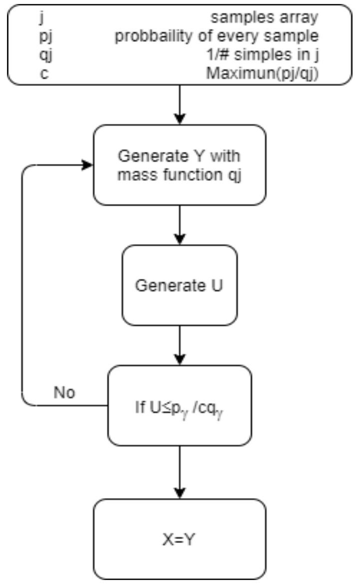


Fig. 1. Acceptance-Rejection technique diagram

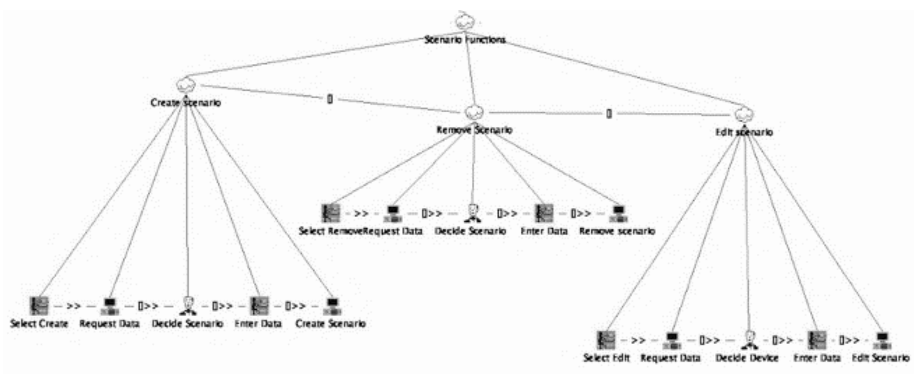


Fig. 2. Task Model of the definition of demanding Home Energy Management System

p_j/cq_j set $X = Y$ and stop, otherwise generating a new Y.

The diagram of the Acceptance-Rejection technique is shown in Figure 1.

3.6 Model-Driven

The benefit of developing software with a rational ser of principles includes reproducibility. The task model describes each task in a system workflow like enable access, user functions, device functions, scenario functions, report functions. Enable access refers to validation when a user is in the system. The user´s needs include CRUDs for the user, devices, scenarios, reports, and special comments on data visualization. Scenario specification refers to creating scenarios tasks (see Figure 2) and adding devices to them. Report functions convey data to the user.

To get a class model, first, the scenarios to be characterized are identified. Second, the frequent devices. Third, the list of devices and devices' characteristics. Fourth, for every device the most common data of minimum, maximum and standby power, and the frequently daily time use. Fifth, the

Table 1. Velocity and position equations components

Variable	Description
i	1…, s
j	1…, n
w	Inertia factor
$\varphi_{1j}(t)$	$c_1 r_{1j}(t)$
$\varphi_{2j}(t)$	$c_2 r_{2j}(t)$
s	Number of swarm particles
n	Number of parameters
c_1, c_2	Acceleration coefficient 0<c1, c2<1, c1 cognitive weight and c2 social weight
$r_{1j}(t), r_{2j}(t)$	U (0,1), uniform distribution in (0,1)
$x_i(t)$	Particle i-position in t-moment
$v_i(t)$	Particle i-velocity in t-moment
$y_i(t)$	The best particular solution found by particle I in t-moment
$\hat{y}_i(t)$	Best global position found I in t-moment

Table 2. Particle velocity components

Components	Description
$v_i(t)$	To prevent oscillation in the direction research
$\varphi_1(t)(y_i(t) - x_i(t))$	Cognitive component
$\varphi_2(t)(y_i(t) - x_i(t))$	Social component
$y_i(t)$	Best global solution found by i-particle

devices are categorized into the group to which they belong.

The user interface design was introducing sources of data and introducing an aspect of social computing to reinforce the current perspective of the framework and gamification strategies. Finally, the prototyping is created by considering User Interface (UI) design patterns. To exemplify the challenges that the potential users may face is using storytelling with which is possible to see different situations from a general point of view as designers of the project.

3.7 Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a social behavior metaphor of birds and fishes. PSO is a stochastic search that uses swarm particles, everyone particle moves through the cluster adjusting its trajectories to find the best solution using the objective function. The position of every particle, x_i, is determined by the velocity v_i, the acceleration coefficient, inertia, and the size of the cluster of particles. The velocity and position equations [19] are:

$$v_{ij}(t+1) = wv_{ij}(t) + \varphi_{1j}(t)\left(y_{ij}(t) - x_{ij}(t)\right) + \varphi_{2j}(t)\left(\hat{y}_{ij}(t) - x_{ij}(t)\right), \quad (11)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{1j}(t+1). \quad (12)$$

Table 1 describes the components of (11) and (12).

To warranty the PSO algorithm convergence is needed to satisfy that $0 < c_1, c_2 < 1$, and aleatory r_1, r_2 evenly distributed in $(0,1)$ [20]. The particle velocity is defined by the components which are described in Table 2.

4 Case Study

4.1 Simulation phases

Problem definition: the implementation objective of a demand system is defined accordingly with the context, geographical area, and variables that define the electricity consumption. The devices, the moments in which each of the devices is on, and their consumptions features are identified in Table 3, the features were obtained from their datasheet's device.

System´s conceptualization: identify devices that characterize the context of use, and then classify them according to the type of device to which they belong see Table 3. Once the devices are identified, the associations and correlations that exist between the devices concern the moments of use.

Model representation: the relationships between devices are formalized by equations that identify the states of devices at specific and daily moments and consumption.

Behavior model: behavior representation and devices consumption over time are represented in the behavior matrix and consumption matrix.

Model´s evaluation: it is observed the behavior of devices' probability distribution function (PDF) [21], the devices are furnace fan, space heater, room air conditioner, and clothes washer. For every device PDF, the (x, y) coordinates obtained from their graphs [21] are shown in Table 4, the coordinates were obtained by manual and visual graph analysis.

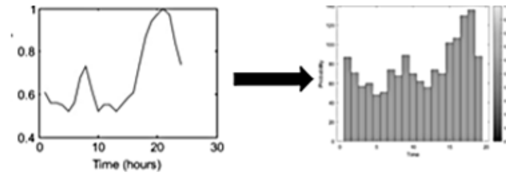


Fig. 3. Furnace fan histogram

Table 3. Household appliances features

Device	Power (kW)	Daily Freq. use time	Kind of Device
Furnace fan	1000- 2000	3	I
Space heater	763-1500	4	I
Room air conditioner	1000-2950	4	I
Clothes washer	550- 2850	0.57	F

4.2 Validating Simulator

The simulator is validated generating almost 1000 data. The data were graphed in a histogram, the waves between the histogram and Probability Distribution Function's (PDF) furnace fan histogram [21] are similar (Figure 3). The same procedure is followed with room air conditioner, heater, and washing clothes in [21].

The simulation of the trial was carried out for furnace fan, space heater, air conditions, and clothes washer. Four arrays were made per device, every array has #number_of_experiments rows by 24 columns, each array corresponds to schedules, turn on device, usage profile, and consumption profile. From the arrays were generated two more, in the first one is storage the total consumption and in the second one the total use time per experiment per device.

The number of experiments by each simulation is defined:

- Choose an acceptable value for $d = 10^{-3}$ to estimate the standard estimation.
- Generate 100 experiments.

Table 4. Table Fan coordinates

	Furnace Fan	
Coord	**x**	**y**
1	0	0.7879
2	1	0.6069
3	2.0482	0.5620
4	3.0120	0.5620
5	3.9759	0.5517
6	5.0602	0.5207
7	6.1446	0.5620
8	6.9879	0.6828
9	7.8313	0.7569
10	10	0.5207
11	10.8434	0.5517
12	11.9277	0.5517
13	13.0120	0.5207
14	15.7831	0.6069
15	18.1928	0.8689
16	19.1566	0.9379
17	20.9639	1
18	22.1687	0.9724
19	24	0.7879
20	-	-

- Generate more experiments, when has been generated k values and $\frac{s}{\sqrt{k}} < d$, where S is the standard deviation of k test sampling.
- To estimate θ is from $\bar{X} = \sum_{i=1}^{k} {X_i}/{k}$.

The margin of error of the system is calculated using the standard deviation, and considering that the experiment is non-sensitive, it was established at 5%. When the standard deviation is no longer significant then the simulation is stopped, the number of experiments necessary per device is almost 189 for a furnace fan, 388 for a space heater, 419 for a room air conditioner, and 100 for a clothes washer.

4.3 Model-Driven Map

To build and share customer knowledge across the organization about what they need at each point in their day and how these requirements are being met and provide insight into customer paint points were used Card Sorting technique and Journey Map. An empathy map (see Figure 7) is used too to model the user´s care about his electricity consumption and environment.

Finally, the codesign Framework focuses on Social Computing to achieve a perfect balance between social behavior and computational systems. it seeks to create new practices that allow socialization through technology. The demand home management system includes certain actions that family members or acquaintances, in the case of shared floors, can perform, since the application will be used by any member of a community using the same devices. For instance, share a limit of energy expenditure, an alert will be sent to each of the participants warning the current consumption and to know a little more in-depth the electrical activity, can be complemented with smart connected devices to the current in which through Siri or Alexa, you can identify the devices that consume more energy, and in this way the different members can see the consumption of other participants and send messages warning of excessive consumption in some area of the house or even emojis, allowing interaction between participants of the same family, plus if the monthly goal of maximum energy consumption is achieved, it can be shared on social networks like Facebook. User stories are written once the co-design is finished.

4.4 PSO Constraints

The space research is formed by consumption arrays of ten devices and swarm with 1000 particles. For the experiments, the inertia is 0.8, cognitive weight is 1, social weight is 1.

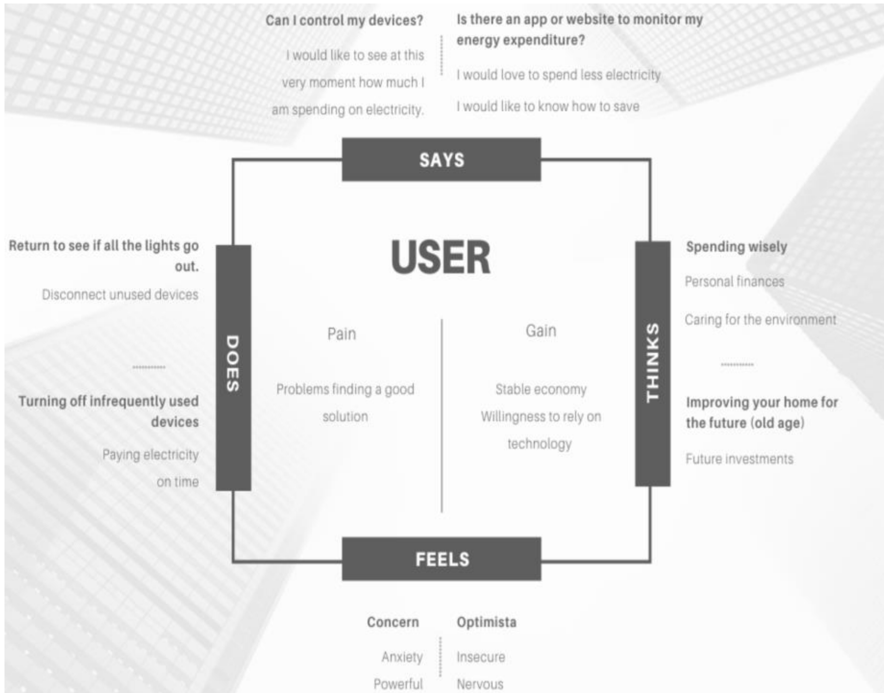


Fig. 7. Empathy maps of the user of a demanding HEMS

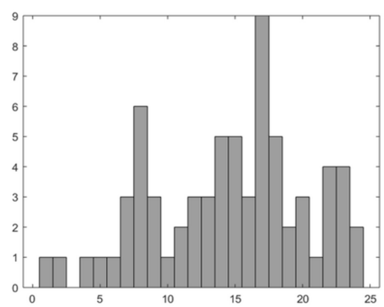
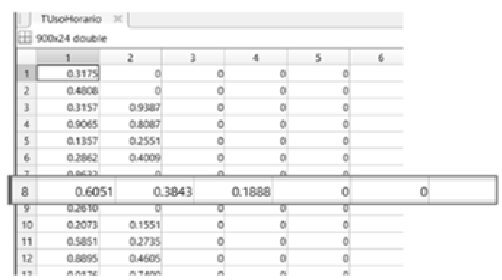


Fig. 8. Furnace fan simulated behavior



	1	2	3	4	5	6
1	0.3175	0	0	0	0	
2	0.4808	0	0	0	0	
3	0.3157	0.9387	0	0	0	
4	0.9065	0.8087	0	0	0	
5	0.1357	0.2551	0	0	0	
6	0.2862	0.4009	0	0	0	
8	0.6051	0.3843	0.1888	0	0	
9	0.2610	0	0	0	0	
10	0.2073	0.1551	0	0	0	
11	0.5851	0.2735	0	0	0	
12	0.8895	0.4605	0	0	0	

Fig. 10. Consumption per on time – schedule 8

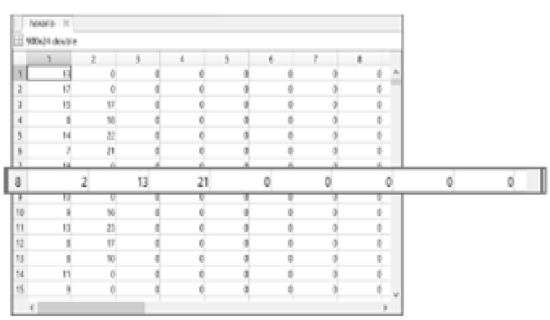
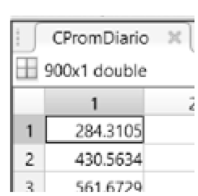


Fig. 9. Time the device is turned on per trial



	1
1	284.3105
2	430.5634
3	561.6729

Fig. 11. Average consumption per trial

To stop criteria is 50 cycles or when the minimum value is repeated five times. The code was written in Python using Jupyter in a Dell laptop with an Intel Core i7 processor, 8.0 Gb ram, Windows 10, the PSO program uses the objective function (11).

5 Results

As an example of simulated behavior, Figure 8 shows the simulated behavior of the furnace fan. Extracts of the time of use and consumption profiles are shown in Figure 9 and Figure 10, respectively.

Parts of the results of time and average consumption are also shown in Figure 11 and Figure 12, respectively. The percentage of On/Off time household appliances (furnace fan space heater room air conditioner, and washing clothes) are reported in Table 5.

5.1 Intelligent Ambient Evaluation

At the beginning design of the interface, the participants were required to design a user interface in which they could define the electrical devices they have at home. The interface used architectural plans of their houses to represent the physical spaces. In this work, we compared preferences vs performance during the experiment. To this work were compared preferences vs performance during the experiment, a vignette study was conducted. Collecting prospective users was a problem due to the pandemic, so a sample for convenience around the family and acquaintances is used. Ten Participants were presented our graphical mock-ups for the scenario specification, In Figure 13, the two alternatives are shown, the rationale behind each option is described as follows:

- The solution is alike to commercial tools, a look and feel like the Apple Home app was designed, depicted in Figure 13-A.

- A blueprint solution. Trying to deal with the workload problem of commercial solutions to handle multiple rooms and devices, selecting proper devices and their locations is time-consuming as you base everything just on icons. The blueprint-like selector to design scenarios was the first approach to do something different from existing solutions, this option is shown in Figure 13-B.

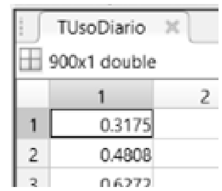


Fig. 12. Average time-use in each trial

Fig. 13. User interface alternatives to create scenarios

Table 5. Household appliances percentage status time

Device	% time is turn On	% time is Turn Off
Furnace fan	6-7	94-93
Space heater	15-14	85-86
Room air conditioner	13-14	87-86
Clothes washer	6-7	94-93

To control the presentation of multiple pairs, we employed the A/B testing method, apart from being popular it is well accepted in research to elicit preferences. Although preference and performance are sometimes indirectly related, not as expected, it frequently happens that you might prefer the tool that is not necessarily the one in which you are performant. On the contrary, it could happen exactly the opposite. In the end, you learn to use the tool even if you have poor performance. In our case, we can confirm this scenario. Our user performs better in the blueprint scenario but prefers the solution that is similar to existing solutions in the A/B testing and IBM CSUQ as usability measurements. A web page was used for collecting preferences of A/B testing. Figure 13 shows two alternatives to create scenarios, in A) the preferred solution, a list of scenarios is listed to the right and the object in each scenario are listed in the middle with representative icons. In B) a blueprint of a house.

The application design and its process are carried out with the co-design technique, supported by known techniques of analysis and user experience design. The prototype proposal was evaluated with a convenience sample and the final decision gives us a clue of what the interactive system should look like that helps people make decisions regarding their electricity consumption, how they can design spaces or scenarios of houses room. The application design uses icons that allow the user to interact intuitively, the characterization of the rooms (Figure 14) choosing the device

The consumption of all devices is plotted and showed it through application to the user (Figure 15).

Fig. 14. Selection and identify the type of room

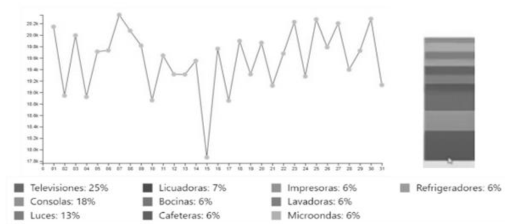


Fig. 15. Graph of the month- consumption

Fig. 16. Real consumption – proposed PSO consumption

5.2 PSO Implemented

PSO was implemented in a database with 24 by 365 records. Each record is used to make a comparison with the vector found by PSO. 100 repetitions for the experiment were made for each record. The Analysis was made with the data obtaining the average for the 100 experiments for every device. The device-experiment average and standard deviation are calculated. The results are shown in Table 6.

The PSO implementation lets to propose consumption that each device should have to lower the total consumption without having to turn

Table 6. Household appliance average and standard deviation

Household appliance	Average(kW/h)	Standard Deviation
Room Air conditioner	1496.341	9.0e-05
Space Heater	808.00005	5.760072e-02
Furnace fan	1425.0	0
Clothes washer	895.5	0

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off any device that is in an inactive state. The proposal generated is displayed in the application transposing the real consumption graph (graph above) with the proposed by PSO (graph below) (Figure 16).

6 Conclusions and Further Work

Current solutions around the development of software for an electrical demand system are focused on data processing, but little on the interactive application that, regardless of the user, can use it. The design of the application and its process is carried out with the co-design technique, supported by analysis techniques and user experience design. The prototype proposal was evaluated with a convenience sample and the final decision indicates how the interactive system should be that helps people make decisions about their electricity consumption, how they can design spaces or room scenarios of the houses. Much has been discussed on how to communicate this information and, in the end, we found that the solution must go beyond the sketches; But without a doubt, a device list, a common solution in most device applications, is far from an adequate solution. The implementation of this prototype has many technological challenges that undoubtedly leave open the debate on the interoperability of the devices currently available in the technological context.

An architecture for data analysis in a home energy management system is presented. The concept takes into account the characteristics of the data, considers how consumption data flows from its origin, processing, and use for the proposal of the regulation of consumption. The factors that involve the development of an architecture for the design of a demand system require an analysis of the data flow.

The electricity consumption analysis methodology serves to define a strategy for solving problems and can be replicated in other contexts.

Further work, to develop a flexible and scalable sensor architecture that allows generating consumption data in real-time. Develop an interface that detects the devices that make up the context, and that the interface can be installed on a server so that it can be used remotely.

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