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An Efficient Demand-Side Management Mechanisms in Residential Energy Consumption Automation

Tiago Bornia Castro, Marcio Zamboti Fortes*, Fernanda Passos and Natalia C. Fernandes

Engineering School, Universidade Federal Fluminense (UFF),156 Passo da Pátria, Niteroi, 24210-240, Rio de Janeiro, Brazil

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Abstract

Maintaining a balance between energy production and consumption is essential for power grid stability. This article proposes two demand-side management mechanisms for residential users, called SREM-BS (Smart Residential Energy Management for Billing Savings) and SREM-EE (Smart Residential Energy Management for Emergency Events). SREM-BS is an energy-saving mechanism using variable tariffs, and SREM-EE is a mechanism designed to reduce demand during emergency events. The proposed mechanisms are based on heuristics, where the devices in the house are classified and adjusted progressively until reaching the percentage of savings established by the user or by the emergency event. The aim is to achieve high performance using low CPU power and a small set of input variables that are naturally available in power systems. We compared the proposals to others of the literature using simulation. For that purpose, a simulator was developed by integrating EnergyPlus (E+), used to calculate the consumption of the electric grid, and NS-3, to simulate the telecommunication network. The test results showed that the mechanisms can adjust demand to the user's consumption targets or in the face of emergency events and are more efficient than other literature proposals.

Keywords: Smart Grids; Smart Homes; Demand-Side Management; Demand Response.

1. Introduction

Smart grids appear as an evolution of the power grid. The key idea is to incorporate telecommunications networks into the electric grid, allowing real-time monitoring, fast detection/treatment of failures, more natural integration of renewable sources, and other new services [1]. With the Advanced Metering Infrastructure (AMI), the utility has real-time information about users' power demand and users have detailed information about their consumption.

In this scenario, the increasing number of renewable sources turns the energy-producing plans more difficult. The generation prediction becomes more complex due to the intermittent nature of these sources [2]. As a consequence, the maintenance of the balance between energy production and consumption, which is essential for energy grid stability, gets affected. Therefore, a paradigm-changing is required due to grid modernization: in the traditional energy grid, production adapts to demand, but in smart grids, demand should adapt to production to make the grid more efficient [3].

Demand Side Management (DSM) programs arise as one of the solutions to adjust user consumption to generation through actions or decisions taken by the energy company to change or model the user's consumption pattern. It is essential noticing that each residential consumer unit represents a minimal impact on the total energy demand of the grid. However, the set of residential users corresponds to about 26% of the electricity consumption in developing countries, such as Brazil [4]. So, when DSM programs reach a large number of customers, they become relevant solutions to support the balance between production and consumption.

The distribution grid, designed to attend peak hours demand, is underutilized in other hours of the day, which increases both the capital used to expand the grid (CAPEX) and the operating cost to maintain the grid (OPEX). Again, DSM programs can remodel power demand, reducing peak requirements and, consequently, reducing utility costs.

When considering both the impact of renewable sources and the marginal costs of the distribution grid, the need for flexible DSM models that meet different profiles of electricity customers arises. The DSM program must also be appealing to achieve a significant number of adept residential users. As an opt-in program, it usually depends on the cooperation of the consumer.

In this paper, we propose two DSM mechanisms called SREM-BS and SREM-EE to reduce the distribution grid planning and maintenance costs and simplify fast and small adjustments to residential user demands. The user will be able to opt into one of the programs or even both simultaneously. SREM-BS is an energy-saving mechanism based on a dynamic tariff model. It creates autonomic management of residential energy consumption to save energy during peak hours while respecting the thresholds of comfort set by the user. Using SREM-BS, the user can reduce energy bills without severe routine modifications, which brings advantages for both the user and the utility. SREM-EE is an emergency mechanism aimed at reducing demand during events in which keeping system stability depends on a fast reduction of consumption in large areas. Instead of shutting off an area due to problems in energy production or transmission, the utility can start SREM-EE to reduce energy consumption in a larger area up to some threshold. In this case, users are encouraged to join SREM-EE through economic incentives, which are paid off to the utility by avoiding fines for power interruption.

*E-mail address: mzamboti@id.uff.br

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The main DSM-related works propose strategies based only on shifting loads during peak hours, that is, rescheduling the operation of some devices from peak hours to off-peak hours [5, 6]. Other proposals use only the adjustment of Heating, Venting, and Cooling (HVAC) system to save energy [7, 8]. Our models propose efficient heuristics that implement both strategies, as well as the power regulation of the adjustable devices. These adjustable devices are devices that can operate at different powers, for example, the fan (when operating at different speeds), smart showers, or even smart lamps. Thus, with the proposed mechanisms, it is possible to create a residential DSM program with a greater possibility of large-scale deployment, without being restricted to users with air conditioning. Moreover, our mechanisms base the power consumption reduction actions on user preferences, adapting the impact to each profile in a simple way and without requiring high computational power. These characteristics make SREM-BS and SREM-EE more appealing, improving the chances of the DSM program application.

We validated the mechanisms through simulation. For this validation, it is important to have software that not only simulates the electrical system, but also the communication network. However, the authors did not find any simulator with these characteristics in the literature. Li and Zhang use eQuest to simulate the electrical system, and MatLab to perform the response actions to the demand [7]. Inspired by them, we developed a simulator that integrates EnergyPlus [9] to simulate energy consumption, with NS-3 simulator, to simulate communication between smart devices. Our simulator, which we call Energy and Communication Network Simulator (ECNS), analyzes different DSM programs, considering different consumption patterns. Through ECNS modular design, it is possible to add different DSM programs and evaluate their impacts on the power system. SREM-BS and SREM-EE were tested and showed the ability to achieve the consumption objectives in more efficient ways than other proposals from the literature.
Therefore, this paper brings three main contributions:

- The design of a mechanism called SREM-BS to perform load adjustment according to user preferences, causing the least impact on the user experience quality; This mechanism uses fewer inputs than other proposals as well as it presents more efficient results, which make it simple to implement and be accepted by the general public;
- The design of a mechanism called SREM-EE to perform load adjustment in a fast and efficient way during emergency events, providing a pragmatic response and reducing the probability of power service interruption in the area; and
- The development of a modular stochastic event-driven simulator called ECNS that effectively integrates power and telecommunication systems, allowing the evaluation of different DSM models and smart grid applications in a simple way.
- The remaining of this article is organized as follows. Section 2 introduces the concepts related to the smart homes and DSM and Section 3 presents related works. Section 4 shows the design of SREM-BS and SREM-EE, while Section 5 covers the development and operation of our simulation tool. In the sequence, in Section 6, presents the simulation environment, results and discussion.

2. Smart Homes and DSM

Automatic DSM mechanisms usually depend on the concept of smart homes. The devices considered in this work are smart appliances, which have a communication interface allowing remote monitoring and control of the equipment. Different smart appliances are already available in the market, while other proposals are under development or are expected to be developed shortly. We also consider the use of a smart meter, which periodically reports the user's energy consumption. This type of infrastructure allows, among other features, the smart grid to send information such as dynamic prices of the energy tariff conditioned to the time of use [10].

Fig. 1 shows the network architecture of a smart home, which presents internal and external areas, defined considering the control of the power system. The limit of the internal area is the Energy Management System (EMS), which communicates with the internal loads and manages them. The devices periodically send consumption information to the EMS, which uses that information to feed the operating algorithms that are the core of the DSM program implementation. The smart meter and the Energy Service Interface (ESI) define the limits of the outside area. They work like gateways and exchange data, such as energy price or consumption measurement data, between the consumer and external domains.

Smart meters usually handle only the aggregated measurement data [11]. On the other hand, ESI supports remote service control, demand response programs, monitoring of renewable energy sources, and monitoring of electric vehicles. Despite performing different functions, ESI and smart meters can be physically integrated into the same device [10].

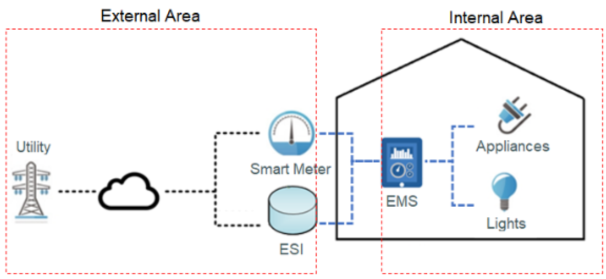

Fig. 1. Smart home architecture adapted from [10].

The DSM programs are defined as the planning, implementation, and monitoring of utility activities that influence customer usage of electricity [12]. These influences aim mainly to change the consumption pattern by flattening the peak hour curve or even to model the consumption curve according to energy production. We use two load modeling techniques: load shifting and flexible load shaping [13]. When a device is rescheduled, the technique used is load shifting. In other words, the operating time of the device is shifted from peak to next off-peak time. However, when the power of a device is adjusted, the technique used is flexible load modeling.

One way to implement DSM is through variable price rates. In a fully connected system, it is possible to vary the price during the day according to the consumer demand and distributed energy generation. This tariff model is called Real-Time Pricing (RTP) [14-16]. More usual tariff models increase the energy price during peak hours, which is called Time-Of-Use (TOU) model [17-19]. For instance, Brazil uses a variable tariff called white tariff, which is a TOU model of pricing [20]. In this tariff, there are three different prices for kWh throughout the day. In the off-peak period, the energy price is lower than the traditional tariff, which has a fixed price throughout the day [20]. In the intermediate period, the price is slightly higher than the traditional tariff. However, in the peak period, the energy price is much higher than in the traditional tariff.

3. Related work

Several initiatives have been proposed to enable the application of DSM, reducing costs for distribution companies and customers of the power system. Kinhekar et. al. encourage the use of variable price tariffs in India as an alternative to reduce operational costs. They propose a DSM mechanism based on the load shift from peak hours to lower demand hours [5]. Prices are established throughout the day and a desirable consumption curve is calculated, which is inversely proportional to the price curve. Load shifting is used to reschedule the operation of some equipment, adjusting the final consumption curve to the desired curve.

Conejo et. al. describe an optimization model to adjust the load level of a given consumer in response to hourly electricity prices [21]. The system uses a price variation forecast to draw a consumption plan using a linear programming algorithm. Every hour, the utility sends the real price, and the algorithm is fed back, thus drawing up a new consumption plan for the rest of the day and updating the forecasting algorithm.

Tham and Zhou propose a program based on points collecting and environmental sensing, where the idea is to penalize the misuse of energy and the reward for the correct use [22]. The temperature and relative humidity of the air are collected and used in a calculation to establish if it is a hot day or a cold day. If on a hot day the user takes a hot shower, he will lose points, but if on a cold day the user takes a cold shower, he will earn points. At the end of the month, points are converted into discounts or fines on the consumer's energy bill. This kind of approach depends on different input variables that are not available on the user’s residence or energy distribution company domains. Temperature and humidity vary a lot in large area cities and may not be available in real-time for smaller cities.

Jindal et. al. propose a system that is based on a heuristic technique [6]. The idea is to schedule residential loads considering not only the power available from the grid but also the distributed energy resources. Every smart home has a battery energy storage system, a solar photovoltaic panel, and is connected to an aggregator. An aggregator gathers a day-ahead load demand from smart homes in a region and sends it to the electric utility. The utility then checks the availability of power and provides the day-ahead power for 24 h duration to the aggregator. So, the system schedule residential loads considering the power supply from the utility, power from the solar photovoltaic panel, battery energy storage system, and the user’s priority. This approach, however, depends on the distributed power generation, which is not available for most residential clients.

Remani et. al. introduce a load scheduling model considering consumer comfort, renewable sources, and any type of tariff [3]. Loads of smart homes are divided into schedulable and non-schedulable. The schedulable loads have a parameter that captures the degree of discomfort due to the delay in switching. The smart home here also has a photovoltaic solar panel and to solve the problem of load scheduling, a reinforcement learning approach is used. It is important noticing that machine learning efficiency depends on proper training of the algorithm. As a consequence, the efficiency of the algorithm will vary with time, as users may acquire or discard devices as well as change usage patterns, causing concept deviation.

Li and Zhang present and compare some models that work with ambient air conditioning systems, which can be classified as Heating, Venting, and Cooling (HVAC) [7]. The idea of these mechanisms is to change the thermostat of the devices according to the variation in the energy price. Generally, these models are very effective and great savings are achieved by varying a few degrees of the ambient temperature.

Rezaei and Dagdougui present a building energy management system that integrates a local shared renewable power generation, energy storage system, and electric vehicles [23]. It also controls the HVAC system in each apartment of the building to reduce the electric bill of the building and improve the matching performance between the local generation and consumption. The proposed algorithm aims to maintain the temperature in a pre-defined comfort range, which means that each apartment requires a specific comfort range.

Tavakkoli et. al. propose a demand response scheme for a small residential area including several houses using an HVAC system to reduce the demand [8]. It is supposed that residential consumers are connected to an aggregator, and the Stackelberg game is adopted to consider the interaction between the aggregator (leader) and consumers (followers). The leader sends a series of bonuses to consumers to encourage them to participate in the DR. The followers define the demand reduction strategy to maximize the bonus and send it to the leader. The leader at this stage can update his strategy and send it back to followers. This process is repeated until the necessary demand reduction is obtained.

Arun and Selvan introduce an intelligent residential energy management system for prosumers of smart residential buildings [24]. The system manages the battery energy storage, renewable energy resources, and residential loads. Residential loads are divided into non-interruptible and non-schedulable loads (NINSLs), interruptible and non-schedulable loads (INSLs), and schedulable loads (SLs). NINSLs are loads controlled only by the consumer. INSLs are temperature-controlled loads. SLs are loads that can be scheduled.

Zhang et. al. present a mechanism that combines machine learning, optimization, and data structure design to build a demand response and home energy management system [25]. The loads are divided into three categories: fixed loads, adjustable loads, and deferrable loads. Fixed loads include stoves, lights, and home computers, which must be used when needed. The second may include an HVAC system, which can be regulated but cannot be delayed. The third may contain dishwashers and dryers which can be delayed but cannot be regulated.

No solution on the demand-side management is excellent for all scenarios. Each region or country must take into account its scenario to propose a better solution. However, it must not be forgotten that a single residence causes a very small impact on the grid. In other words, the feasibility of large-scale deployment is critical to a residential solution. In some countries, only the temperature adjustment of HVAC systems is sufficient for large-scale deployment. But there are other countries where HVAC systems are not common to a large part of the population.

Most residential solutions work only with load scheduling and residential renewable energy resources or only with temperature adjustment of the HVAC systems, conditioned to the price variation. Our work proposes residential mechanisms that combine load scheduling, temperature adjustment of HVAC system, and power adjustment of some devices (for example, lighting and shower), also considering a variable tariff. The idea is to attract as many consumers' profiles as possible in countries where HVAC systems and residential distributed generation sources are not common to a large part of the population. Hence, our proposal focuses on developing countries, where smart appliances and smart meters are already a reality, but distributed generation, electrical vehicles, and residential battery banks are not usual. Also, our proposal uses information available on the power system and residential domains only, depends on low computation power, and does not suffer from concept deviation, as the heuristics adjust to user preferences and different usage profiles.

4. Proposed Residential Demand-Side Management Mechanisms

The proposed mechanisms aim to create a flexible program for developing countries that adapts to different customer profiles, helping to save energy during peak hours or in emergency events.

The mechanisms consider some requirements and restrictions. First, the system must be economically viable. In developing countries, most of the population does not have access to electric vehicles, solar photovoltaic panels, and energy storage batteries. Although HVAC systems present an excellent opportunity to save energy, the mechanisms cannot be based only on them, as they are also not widespread in these countries. The system must also require little computational power and consider user comfort thresholds to define in which load to act.

Considering these requirements, we developed two models: SREM-BS and SREM-EE. SREM-BS is a mechanism to save energy during peak hours of TOU tariffs. The user sets the percentage of savings, so the system automatically implements actions on the house devices, seeking to achieve the desired savings. SREM-EE is a mechanism to reduce energy demand during emergency grid events. The utility sends a demand reduction message to users' systems who participate in this program. In this case, the home system is obliged to reduce demand.

SREM-BS and SREM-EE are different solutions, with different purposes. However, nothing prevents the user from using both at the same time. Both use two load modeling techniques: flexible load shaping and load shifting. The flexible load will be used with the variation of the HVAC system thermostat or power variation of devices that can be adjusted. The load shifting will be done with load scheduling, such as the washing machine, shifting its operation to off peak-hours.

SREM-BS and EE modules are shown in Fig. 2. Most modules are common to each other and the difference lies in the Control Logic module, described in Subsections 4.2.1 and 4.3.1 respectively.

The first module, Authentication, relates to the association and authentication of the devices in the house with the energy manager. This is important to ensure privacy and avoid attacks against house infrastructure. This module depends on and must support the security and privacy standards implemented in each smart device of the residence.

The Load Monitoring module tracks the energy consumption of each smart device connected to the system. First, it recognizes all available smart devices that have been able to authenticate themselves to the system. After this bootstrap phase, the module gathers and stores energy usage data per smart device, providing rich information for clients, through a graphic user interface, and for the Control Logic module.

The Settings module allows the user to check and modify the system parameters, such as their comfort level and the percentage of savings on SREM-BS. It depends on the bootstrap phase of the Monitoring module, as the list of authenticated devices must be available to set default parameter values and to allow users to personalize the parameter set.

Following, there are three modules related to the Control System, which are:

- Control Logic - presents the control algorithm. It interacts with the Target Calculation and History Update modules to define which devices must be rescheduled or have their power adjusted.
- Target Calculation - defines what the consumption target should be at each moment to achieve the savings percentage configured by the user or defined by the emergency event. This target is used by the Control Logic module.
- History Update - This module stores information about the household's consumption history throughout the day per smart device and also by the set of conventional devices. These historical data assist in the calculation of the target, performed by the Target Calculation module. The consumption history at each time of the day is calculated using a weighted moving average. This calculation depends on the weight (α), which varies in the range between 0 and 1. The weight determines the impact of that the last measurement over the consumption history update for that period of the day. The weighted moving average was chosen to avoid storing a large number of measurements to define the usage pattern.

The last four modules, called Meter Communication, Turn off Loads, Turn on Loads, and Load Regulation, execute commands sent by the Control Logic module on the equipment of the system. The Meter Communication module is responsible for feeding the Control Logic with the energy measurements of the house in real-time. Whenever necessary, the Control Logic module uses this module to send messages to the smart meter, requesting instantaneous energy demand. Besides, during an emergency event, the utility sends a message to the smart meter, which in turn forwards the message to the SREM through the Meter Communication module.

Turn off Loads module is in charge of disconnecting devices. When the Control Logic decides to shut down or reschedule a device, this module is responsible for sending a command message to this device.

Turn on Loads module is responsible for rewiring a device. When the Control Logic decides to rewire a device, it sends a message through this module.

Load Regulation is a module that acts in the power regulation of the devices. As we will see in Subsection 4.1 some devices have adjustable power, and this can be used to save energy. If the Control Logic wants to use this power setting, this module will send a message to the devices.

4.1. Classification of home appliances

The household electrical devices are divided into four groups: Adjustable, Flexible, Dispensable, and Indispensable. Devices that have the power regulation ability are classified as Adjustable. For example, HVAC systems, smart lamps, and smart showers. Devices that the user allows to be rescheduled are classified as Flexible. For example, washing machines, clothes dryers, and cleaning robots recharge. Dispensable are devices that are neither Flexible nor Adjustable, but their interruption has little impact on customer comfort. For example, water filters or decorative ambient lights. Indispensable is equipment that the interruption would cause great discomfort to the customer. For example, television and computer.

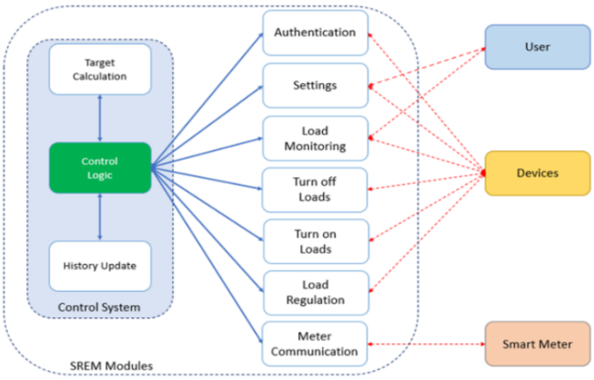

Fig. 2. SREM-BS and SREM-EE modules.

The system, in the bootstrap phase, defines a standard classification of devices in each of these classes. The user can change the classification among Dispensable and Indispensable, as well as to define comfort thresholds for Adjustable devices.

SREM-BS operates in the first two groups, Adjustable and Flexible. It regulates the power of the Adjustable devices, changes HVAC system temperature, or reschedules Flexible devices. SREM-EE operates in four groups. It prioritizes the operation in the first two groups, but, whenever necessary, it turns off the Dispensable and Indispensable Devices.

4.2. SREM-BS

SREM-BS (Smart Residential Energy Management for Billing Savings) aims to save energy during peak hours of TOU tariffs. After a few user inputs, SREM-BS implements automatic management of smart appliances seeking to save energy during peak and intermediate hours. The mechanism performs energy economy by load shifting and power consumption reduction of some devices, however always respecting the user's comfort parameters. The user configures three parameters in the system: classification of devices, comfort parameters, and percentage of savings.

The system implements user comfort through a parameter called Intensity. The Intensity is an integer variable that ranges from 1 to 5. Intensity 1 represents the lowest operating power value of the device. Intensity 5 represents the highest operating power of the device. Device operating power is directly proportional to the Intensity. This parameter represents the lowest operating power allowed by the user. For instance, if a device is configured with Intensity 3, the system will regulate the power of this equipment between Intensity 3 and Intensity 5. For HVAC systems, each Intensity value corresponds to a temperature value. The user then sets the minimum and maximum operating Intensity.

The savings percentage represents the amount of energy that the customer wants to save during peak and intermediate times. The system calculates a demand target to be reached using this parameter. The savings target, $Trg(t)$, varying in the time t, is calculated using Eq. 1 and 2. On the first day, at the beginning of an intermediate or peak tariff period, the initial saving target, $Trg(t)$ is calculated based on the current demand, $D(t)$, and the percentage of savings defined by the user, P_{eco}. Then, for the others days, $Trg(t)$ is updated in a time window of size W. For each t-th time interval, $Trg(t)$ is recalculated based on the historical average of demands for this time interval ($Avg_{hist}(t)$) and the percentage of savings defined by the user (P_{eco}). So, the target is dynamic, changing according to the period of the historical average. The historical average update period (T_s) must not be too short, which would make the target highly dynamic. However, in large periods, such as an hour or half an hour, the average demand does not reflect the real demand of the user, as this masks the functioning of devices such as microwaves, which have great power but are used for short periods.

$$Trg(t) = D(t) \times P_{eco} \quad (1)$$

$$Trg(t) = Avg_{hist}(t) \times P_{eco} \quad (2)$$

The historical average is updated using the Eq. 3 where $Avg_{hist}(t)$ is the new expected demand average, $D(t-1)$ is the actual demand of the last period t-1 and α is the weight, chosen between 0 and 1.

$$Avg_{hist}(t) = \alpha \times \frac{D(t-1)}{P_{eco}} + (1-\alpha) \times Avg_{hist}(t-1) \quad (3)$$

The steps of SREM-BS are illustrated in Fig. 3 and described as follows:

- Configuration - the user sets the percentage of savings, classification of devices, and comfort parameters in the energy management system. The user needs to perform this step only once, then the mechanism automatically implements the remaining steps each day.
- Connection and authentication - establishment of connection and authentication between manager and smart meter, and between devices and manager.
- Status update - at the end of each time window t, with duration T_s, the manager sends messages requesting the demand for each device and the current demand registered on the smart meter. In the meantime, the manager checks whether the current period corresponds to off-peak, peak, or intermediate. In these messages, the devices send the demand, status (on or off), and power status (minimum, maximum, or intermediate).
- SREM-BS Module - during the intermediate or peak period, the manager calculates how to achieve the target $Trg(t)$ using the Algorithm 1 and applies the changes to the devices.
- Normalization - at the end of a peak/intermediate period, the manager normalizes the operation of the devices, by sending a normalization message. It resets devices that have had Intensity adjustment and reconnects those that have been turned off.

4.2.1. SREM-BS Module

The logic of the SREM-BS Module is shown in the heuristic Algorithm 1. It receives the following input: Trg(t) (Eq. 1 or 2), T_A and T_S. T_A is the minimum period of time to readjust an adjustable device, regulating power consumption. This period is important because some Intensity adjustments take some time to stabilize, such as the consumption of HVAC systems. T_S is the period between each round of the algorithm after the target has been reached.

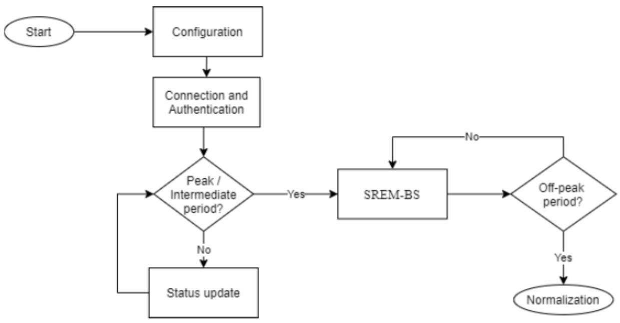

Fig. 3. Flowchart of the steps of SREM-BS.

Algorithm 1: SREM-BS Saving Mechanism.

```
input : Trg(t), T_A, T_S
1  Counter_Adjustable = 0 ;
2  while period ∈ {peak_periods} U {intermediate_periods} do
3      Demand_total, Demand_flexible = Read_monitored_data() ;
4      Counter_reduced = 0 ;
5      if Demand_total > Trg(t) then
6          if Counter_Adjustable = 0 then
7              for Device ∈ Adjustable do
8                  if Device.status ≠ minimum then
9                      Reduce_Intensity(Device) ;
10                     Insert(List_reduced, Device) ;
11                     Counter_reduced + + ;
12                 end
13             end
14             if Counter_reduced = 0 then
15                 Counter_Adjustable = minimum ;
16             else
17                 Wait(T_A) ;
18             end
19         else if Demand_Flexible > 0 then
20             device = Select_Flexible_On() ;
21             Turn_off(device) ;
22             Insert(List_Turned-off, device) ;
23         else
24             Notify_user() #Target cannot be reached ;
25         end
26         Wait(T_S) ;
27     else
28         if List_reduced ≠ empty then
29             Rewire() ;
30         else
31             Increase() ;
32         end
33         Wait(T_S) ;
34     end
35 end
```

The savings algorithm works in phases. In the first phase, 〖Demand〗 _total and 〖Demand〗 _Flexible are updated (line 3). 〖Demand〗 _total is the total demand of the house devices and 〖Demand〗 _Flexible is the total demand of the Flexible devices. Then, it checks if consumption is below or above the target Trg(t) (line 5).

If the total demand is above the target, the algorithm starts a slight power reduction of the Adjustable equipment (lines 7-13). Each round the mechanism reduces the Adjustable Intensity by one level, unless the device Status is at the minimum. The function 〖Reduce〗 _(Intensity) () performs the Intensity reduction and updates the Device Status (line 9). The reduced devices are inserted in the 〖List〗 _Reduced (line 10), and the time T_A is waited (line 17).

This reduction continues until the target is reached or until all adjustable equipment has reached the tolerable adjustment limit. The internal variables 〖Counter〗 _reduced and 〖Counter〗 _Adjustable assist in this step (lines 15-16). The variable 〖Counter〗 _reduced stores the number of Intensity reductions made in the Adjustable devices and it is reset at the beginning of each round (line 4). If during the round no device is reduced, then Status_Adjustable is set as a minimum. The variable 〖Counter〗 _Adjustable represents the status of the Intensity parameter for all Adjustable devices. If 〖Counter〗 _Adjustable is set as a minimum, it means that all the Adjustable are operating at the minimum power allowed by the user.

If the target is not reached after all Adjustable devices are set to a minimum, the load shifting phase begins (lines 19-22). Each round, if the demand is greater than the target, a Flexible device is selected (line 20) and turned off (line 21). When it is turned off, it is inserted in the 〖List〗 _(Turned-off) (line 22). So, Flexible devices are rescheduled until reaching the target.

If the total demand remains above the target, the user is notified (line 24), because the system performed all possible actions to save energy, respecting the user's comfort. In this case, the customer must take some action on his own to reach the target.

In the case where the target is reached (line 27), an adjustment phase is initiated. The mechanism analyzes if it is possible to rewire any Flexible device or to increase the power of any Adjustable device. This is performed by the functions Rewire() and Increase() (line 28-32), described in the Algorithm 2 and Algorithm 3, respectively. After reaching the target, the interval between rounds is T_S (line 33).

The function Rewire() acts by turning on Flexible devices. It receives the following input: Trg(t), 〖Demand〗 _total, and 〖List〗 _(turned-off). 〖List〗 _(turned-off) is the list of rescheduled devices. The list is used to store the device states during the execution of Algorithm 1. At the beginning of Algorithm 2, 〖List〗 _(turned-off) is sorted in increasing order of power (line 1). So, the lower power devices will be turned on first and, consequently, a greater number of devices will be rewired. When a device is rewired (line 6), it is moved from 〖List〗 _(turned-off) to 〖List〗 _rewired (lines 7-8). In the rewiring step, an appliance could be on the edge between reaching and not reaching the target. The system would then turn this appliance on and off, generating instability. So, if a device has been reconnected before, it will not be reconnected a second time (line 3). It will only be activated after a normalization message (normalization step of Fig. 3). So, all devices turned off by the control logic will be rewired and the 〖List〗 _rewired will be reset.

Algorithm 2: Function Rewire().

```
input : Trg(t), Demand_total, List_turned-off
1  Sort_ascending(List_turned-off) ;
2  for Device ∈ List_turned-off do
3      if Device ∉ List_rewired then
4          Demand_total = Read_monitored_data() ;
5          if Trg(t) > Demand_total + Device.demand then
6              Turn_on(Device) ;
7              Remove(List_turned-off, Device);
8              Insert(List_rewired, Device) ;
9          end
10     end
11 end
```

The function Increase() acts by increasing power of Adjustable devices. It receives a single input, 〖List〗

_reduced, as shown in Algorithm 3. 〖List〗 _reduced is the list of devices whose Intensity has been reduced. 〖Size〗 _reduced is a global variable that stores the size of the reduced list.

The main logic of the increase function occurs on lines 4-6. The device is removed from the 〖List〗 _reduced (line 4), then the function increases the power of it (line 5), and the variable 〖Size〗 _reduced is decremented (line 6). Similar to the previous function, a power adjustment could be at the limit between reaching or not reaching the target. In this scenario, the system could cause instability in this device, increasing and reducing its Intensity. So, at the first time that the Increase function is activated, the variable 〖Size〗 _reduced stores the size of the 〖List〗 _reduced (line 2). Every time the function is called, it checks if 〖Size〗 _reduced is equal to Size(〖List〗 _reduced) (line 4). If 〖Size〗 _reduced is different from Size(〖List〗 _reduced), this means that there was a reduction in the power of some device in the meantime, and the mechanism no longer increases the power of any device.

Algorithm 3: Function Increase().

input : $List_{reduced}$

```
1 if First time the function is called then
2 |   Size_reduced = Size(List_reduced);
3 else if Size_reduced = Size(List_reduced) then
4 |   Remove(List_reduced, Device);
5 |   Reduce_Intensity(Device) ;
6 |   Size_reduced − − ;
7 end
```

4.3. SREM-EE

SREM-EE (Smart Residential Energy Management for Emergency Events) is the second proposed mechanism. It aims to reduce user demand during emergency grid events. Emergency events can occur to avoid overload or for any other reason that the reduction of power consumption in a large area is required.

SREM-EE is an alternative to the Direct Load Control (DLC) program [26,27]. In the DLC, the utility has control over a user's device and can turn off this device if necessary [28]. In this type of program, a contract should be established between the consumer and the utility to regulate the maximum number of interventions and the maximum period for these interventions. The customer is rewarded with discounts on the energy bill when participating in the program. In American models [29], the discount is proportional to the power of the equipment under the control of the utility.

In SREM-EE, instead of the utility controlling the user's electrical loads, it sends demand reduction messages to these customers. Hence, in emergency events on the grid, the energy company sends a message with a percentage of load reduction to the customer, who is obliged to answer the request. The way the user will fulfill the order is transparent to the energy company. Unlike the SREM-BS, the SREM-EE program allows the energy company to have a more direct influence on the user's consumption pattern.

In the emergency mechanism, the user performs two configurations in the system: classification of devices and comfort parameters. In the first configuration, the user classifies the house devices according to the categories described in Subsection 4.1. This configuration is slightly different from SREM-BS since SREM-EE works in the four device groups. The comfort parameter configuration is identical to SREM-BS, described in Subsection 4.2.

The emergency period begins when the user receives a message from the utility device. This message is called emergency message and contains a percentage value, called reduction percentage. The calculation of the emergency target uses this percentage value as shown in the Eq. 4.

$$Trg\_emer = D\_current \times P\_emergency \quad (4)$$

Target Trg_emer is the demand goal during the emergency period, D_current is the demand at the beginning of the emergency event, and P_emergency corresponds to the reduction percentage received in the emergency message.

Upon receiving the reduction percentage, the SREM-EE algorithm seeks to respect the comfort conditions established by the user, but they are not a limiting factor in reaching the target. The main idea is to deal with critical situations in which the user would remain without the service if no demand control is performed. So, the power demand must be reduced, and the user will receive discounts on the energy bill for joining the program.

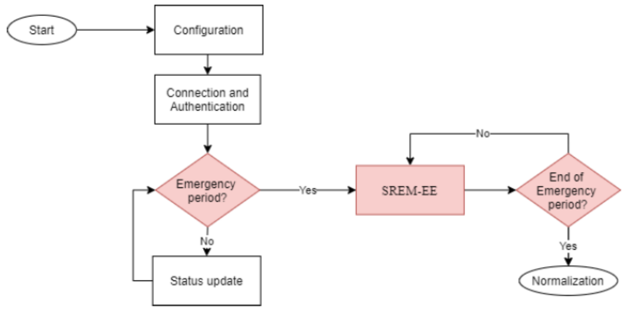

Fig. 4. Flowchart of the steps of SREM-EE.

4.3.1. SREM-EE Module

The flowchart of the SREM-EE, illustrated in Fig. 4, is similar to that of SREM-BS, described in Subsection 4.2. The contrast between both is being highlighted in Fig. 4 The first difference between the mechanisms is the period of operation, which is now emergency. The other difference is about the new logic of SREM-EE that must be more aggressive and assertive. Upon receiving a message from the concessionaire indicating an emergency event, the proposed manager guarantees demand below a certain target, according to the Algorithm 4. At the end of the emergency event, the normalization stage begins, which is initiated by a normalization message from the utility.

As shown in Algorithm 4, the SREM-EE mechanism receives the following inputs: the target Trg_ emer (Eq. 4) and the period waited after regulating the adjustable devices, T_A.

The heuristic emergency algorithm acts on the four load groups (adjustable, flexible, dispensable, and indispensable). Hence, in line 3, the energy demands of each group are updated. 〖Demand〗 _Flexible is the total demand of the flexible devices. 〖Demand〗 _Dispensable is the total demand of the dispensable devices. 〖Demand〗 _Indispensable is the total demand of the indispensable devices.

As it is an emergency event on the power grid, it is important to reach the target in a short time. Hence, the next step is to reduce the power of the devices classified as adjustable to the minimum (line 6). The variable 〖Counter〗 _Adjustable makes sure that this step is performed only once (lines 5-7). The HVAC system belongs to the adjustable group, so the mechanism waits the period T_A to stabilize the demand of the HVAC system. If demand remains above target, it goes to the second step. The algorithm verifies if it is possible to reach the target by rescheduling the flexible devices (lines 9-15).

Up to now, the emergency model is operating similarly to the economic model. Acting in the first two groups and respecting the user's comfort. However, if the demand remains above the target, the mechanism becomes more severe. On the third step, it analyzes the possibility of reaching the target by turning off the dispensable devices (lines 16-23).

Algorithm 4: SREM-EE mechanism.

```
input  : Trg_emer, T_A
1  Counter_Adjustable = 0 ;
2  while Period = emergency do
3      Demand_total, Demand_Flexible, Demand_Dispensable,
       Demand_Indispensable = Read_monitored_data() ;
4      if Demand_total > Trg_emer then
5          if Counter_Adjustable = 0 then
6              Reduce_min(Adjustable) ;
7              Counter_Adjustable + + ;
8              Wait(T_A) ;
9          else if Demand_Flexible > Demand_total − Trg_emer then
10             for Dev ∈ {Flexible} do
11                 Demand_total = Read_monitored_data() ;
12                 if Demand_total − Trg_emer > 0 then
13                     Turn_off(Dev) ;
14                 end
15             end
16         else if Demand_Dispensable + Demand_Flexible >
           Demand_total − Trg_emer then
17             Turn_off(Flexible) ;
18             for Dev ∈ {Dispensable} do
19                 Demand_total = Read_monitored_data() ;
20                 if Demand_total − Trg_emer > 0 then
21                     Turn_off(Dev) ;
22                 end
23             end
24         else if HVAC.status ≠ turn − off then
25             Turn_off(HVAC) ;
26         else if Demand_Dispensable + Demand_Flexible +
           Demand_Indispensable > Demand_total − Trg_emer then
27             Turn_off(Flexible, Dispensable) ;
28             for Dev ∈ {Indispensable} do
29                 Demand_total = Read_monitored_data() ;
30                 if Demand_total − Trg_emer > 0 then
31                     Turn_off(Dev) ;
32                 end
33             end
34         else
35             Turn_off(All) ;
36         end
37     end
38     if Demand_total < Trg_emer then
39         Rewire() ;
40     end
41 end
```

In the fourth step to reach the target, the HVAC system is turned off (lines 24-25). The HVAC system is the most powerful equipment in the house and its temperature adjustments take time to stabilize. In the fifth step, the system seeks to reach the target by turning off Indispensable (lines 26-33). If the target is not reached, the algorithm evolves and increases the number of action groups. If necessary, all manageable equipment in the house can be turned off (line 35). However, the idea is to avoid turning off indispensable devices as much as possible.

Upon reaching the target, the rewire function is checked to verify if it is possible to turn on some devices (line 39). Hence, the function Rewire orders the devices by the energy power attribute, prioritizing the Indispensable.

5. Energy and Communication Network Simulator (ECNS)

The proposed mechanism was validated through simulation. The use of simulators in the study of smart grids is necessary for several aspects. An environment created with real equipment for testing and research is limited, compared to the flexibility of a simulator, and requires a high financial investment. Also, the simulation tools facilitate the research, the evolution of the system, and allow a faster analysis of the network.

The proposed mechanism is a control system for household electrical devices, so it is necessary to implement the control logic, the response in the electrical network, and the exchange of messages between network elements. In other words, the simulation program must simulate both the electrical grid and the telecommunications network. However, no widely used software simulates both networks and provides flexibility for the necessary modeling of these algorithms.

Li and Zhang validated his proposal by developing the integration of the eQuest tool, to simulate the electrical part, and MatLab, to implement the demand response logic [7]. Inspired by this integration, we propose and develop the Energy and Communication Network Simulator (ECNS). ECNS is a simulation tool that uses Network Simulator 3 (NS-3) [30] to evaluate the telecommunication network and EnergyPlus (E+) [9] for the electrical system.

NS-3 is a discrete event simulator for communications networks. It is well-known software widely used for simulating telecommunications networks [31-33]. All DSM control logic of ECNS is implemented on NS-3, which allows a modular development of new mechanisms.

E+ is a computer program distributed by the United States Department of Energy, developed for thermal load simulation and energy analysis of buildings. Its application in research and evaluation of real cases is widespread in the academic literature, as in [34-36]. During the selection of the simulator for the electrical system, the use of eQuest [37] was considered, but E+ demonstrated much superior performance and had more adequate parameters for validating these mechanisms. The E+ receives a text file as input with the description of the building, type of material, internal loads, systems to be calculated, and returns a series of files as output, including a report with the variables requested by the input file. It also receives a file with regional climate history to be simulated as input.

5.1. Integration between NS-3 and EnergyPlus

E+ is a simulator that receives as input an Input Data File (IDF) and returns as output a CSV file. Periodically, the functions of the NS-3 application modules trigger the operation in E+ through Python scripts and receive the output, which is treated also in Python providing useful information for NS-3.

Fig. 5 presents the architecture of the integration scheme between NS-3 and E+, whose components are:

- NS-3 Initialization: This component has a script developed to initialize NS-3. The simulation input parameters are defined, as well as the house devices and their usage pattern;
- NS-3 Core: This component represents the NS-3 simulator. After being triggered by the NS-3 Initialization Component, the simulator core begins to run (arrow 1), simulating the programmed events. When the control algorithm changes the behavior of some equipment or requires some monitoring data, an updated IDF file is created for E+ simulation (arrow 2);
- Generation of IDF files: Component written in Python, which handles the data received from NS-3, generates the IDF file (which describes the simulation scenario), and triggers the execution of E+ (arrow 3);
- Execution of E+: This component represents the E+ Simulator. The component is executed, receiving the IDF

file and EPW (Climate file) as input, and returns a CSV file as output (arrows 4);

- CSV File Parser: NS-3 triggers the CSV File Parser component (arrow 5), which extracts energy demand information from the CSV file and returns it to NS-3 (arrow 6).

The E+ program is used to run simulations for long periods since its main purpose is the dimensioning of building systems. It is used for planning energy efficiency projects, for dimensioning ventilation systems, air conditioning systems, among others. The program has a minimum execution time limitation. It is possible to simulate 1 day, with 60 time-steps per hour, that is, a day with minute-by-minute measurement details. Scheduling loads for the whole day is already established in the IDF file. When there is a demand response event that changes the scheduling of loads, a new IDF is generated and executed, generating a new CSV with demand information per minute.

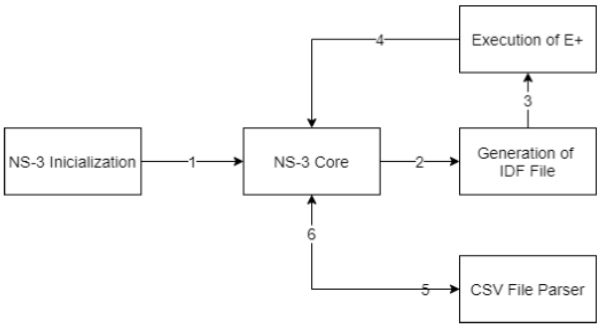

Fig. 5. Integration of NS-3 with E+.

5.2 Simulating the control logic in NS-3

We developed three modules in NS-3 to model the control logic of a DSM mechanism, namely Device, Smart meter, and Manager. As a modular simulator, the modules can be modified at any time, allowing, for instance, the implementation of different DSM control logics.

5.2.1 Device Module

The Device module represents the household appliances. Tab. 1 shows its configuration attributes, and Fig. 6 illustrates its operation sequence.

Table 1. Description of Device module attributes.

Attribute	Description
Name	Device name
Wattage	Average device power (W)
Type	Adjustable, Flexible, Dispensable, Indispensable
Call time	Time the device will be turned on
Operating Time	Device operating time
Intensity	Attribute intended for adjustable devices
Seed	Call time schedule randomness

Appliances can be switched on at exactly the specified time or randomly within 15 minutes of the specified time. For this last purpose, an attribute called Seed was created, which stores the seed of the random function. If the seed is zero, the simulator will respect the configured time. If the seed is an integer greater than zero, it will draw a time to start. The use of the same seed in more than one simulation round guarantees the use of the same hour of operation.

According to the flowchart in Fig. 6, the operation steps of the Device module work as follows:

- First, the module schedules the appliance's operating hours;
- The device then establishes the connection to the Manager module. It sends this information to the manager: Name, Type, Energy, Time to turn on, Time to turn off, Status Intensity and Intensity;
- The device waits for the Manager module to send a message. The messages can be one of the following types:
    - Status - Manager module requests status. In this case, the device responds with its Status (on or off), current power, the value of the variable Intensity, and Intensity status (minimum, maximum, or intermediate). Intensity fields are only for devices in the adjustable group;
    - Turn off - Message for requesting shutdown. The Device module responds to the turn off message stating the shutdown time to be changed in the E+ file;
    - Turn on - Message for rewiring a specific device. The Device module responds by informing the rewire time. This time is used to change the E+ file;
    - Intensity - Message sent by the manager to change the adjustable device's Intensity, which in turn responds confirming the change. The change is then recorded in the E+ file;
    - Normalize - Message received after the end of emergency or peak period. The device confirms the status after the normalization of the operation. This response is obtained in the E+ IDF file.

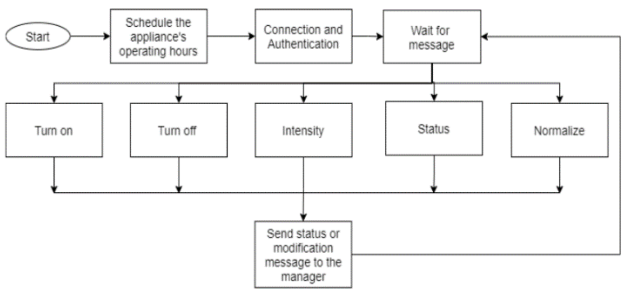

Fig. 6. Flowchart of operation of the Device module.

5.2.2. Smart Meter Module

The second module developed on the NS-3 is the Smart Meter. Tab. 2 shows its configuration attributes, and Fig. 7 illustrates its sequence of operation.

Table 2. Description of Smart Meter module attributes.

Attribute	Description
Day	Simulation Day. Used in the treatment of E+ CSV
Month	Simulation Day. Used for E + CSV treatment
Operation mode	With or without emergency event during the day
Reduction percentage	Reduction percentage of the emergency signal
Emergency event time	Time when the emergency signal will be sent
Seed	Emergency event time schedule randomness

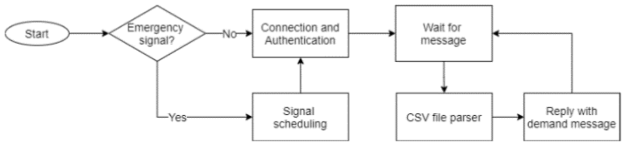

Fig. 7. Flowchart of the Smart Meter module.

Based on Fig. 7, the Smart Meter module works as follows:

- In the case of an emergency signal (for the SREM-E simulation), the Smart Meter starts scheduling the emergency signal by the Signal Schedule component, simulating an emergency message received from the utility;
- Then it establishes a connection with the Manager module;
- Smart Meter waits for a message from the Manager requesting the Demand;
- Upon receiving a message from the Manager, it triggers the Python script to handle the CSV file (generated previously by the Manager module) and send an energy demand message for that moment.

5.2.3. Manager module

The third module is the Manager, which is the most complex module because it implements the DSM control logic and performs the integration between NS-3 and E+. Tab. 3 shows its configuration attributes and Fig. 8 illustrates its operation steps.

First, the Manager connects with all the devices and the smart meter. Then, the Manager triggers a Python script inputting a list of devices, powers, and operating status. This script creates and runs an input file for E+, thus generating the output CSV file. After these steps, it sends a message requesting status to devices and demand to the Smart Meter.

The next steps depend on the operating mode. If it is normal, which means the non-peak and non-emergency period, the module sends messages requesting status for each device every 10 minutes. This is represented in the flowchart as Operation Mode Case 1. Operation Mode Case 2 refers to emergency events. In the SREM-EE operation mode, the emergency period starts when the Manager receives an emergency message with a reduction percentage. If it is not Operation Mode Case 1 or 2, then the simulator understands the beginning of the Billing Saving mode. As a consequence, Operation Case 2 triggers SREM-EE and Case 3 triggers SREM-BS. Other DSM algorithms can be implemented replacing SREM-BS.

During the SREM-BS or SREM-EE operation, if any device has a change in schedule or Intensity, a message is sent to this device and the IDF file of E+ is updated.

Table 3. Description of Manager module attributes.

Attribute	Description
Day	Day that will be used in the E+ simulation
Month	Month that will be used in the E+ simulation
Operation mode	Without DSM, SREM-BS, SREM-EE or Comparative DSM (described on Section 6)
Peak economy	Percentage of savings during peak hours
Intermediate economy	Percentage of savings during intermediate hours

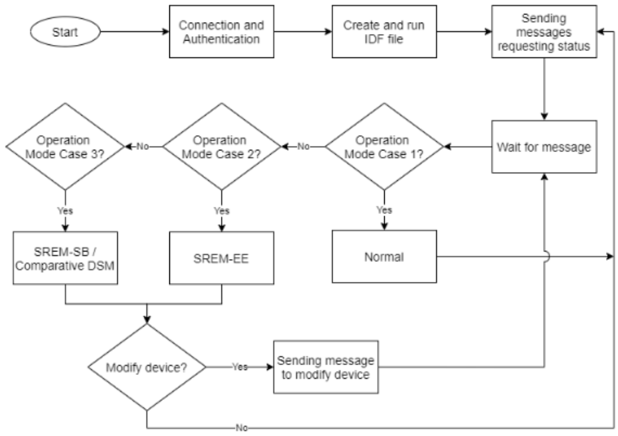

Fig. 8. Flowchart of the Manager module.

6. Results and Discussion

The proposed models were validated through simulation. For this purpose, we developed the ECNS described in Section 5. The first analysis aims to ensure the reliability of the simulator. Then, the performance of SREM-BS and SREM-EE are analyzed in relevant residential scenarios according to the Brazilian standards. We also implement a mechanism from Li and Zhang to compare with the SREM-BS [7].

6.1. Simulation tool validation

The simulation tool was validated through two tests. The first test verified the behavior of the electrical system by comparing simulated consumption with the theoretical formulation. Tab. 4 shows the consumption of some household appliances.

The results obtained with simulations were compared with the electrical consumption calculated by the theoretical formula defined in Eq. 5, where C is the consumption, P_average is the average power, and T_hours corresponds to the time in hours.

$$C = P\_average \ \times \ T\_hours \quad (5)$$

The simulation results were good. The obtained results corresponded to the value expected by the formula. The refrigerator power curve varies throughout the day, but the simulation program has limitations. Therefore, instead of varying the refrigerator power throughout the day, we used the average power during the 24 hours, as shown in Tab. 5.

The second experiment verified the compliance of message passing between the elements of the communication network. We performed this analysis by examining the NS-3 logs. In this respect, the messages exchanged in the simulation were following the logic of the proposed mechanisms.

Table 4. Consumption test for validation of the electrical system.

Appliances	Average electrical power (W)	Usage time (h)	Consumption (Wh)
Refrigerator	73	24	1752
Water filter	6	24	144
Refrigerator + Water filter	79	24	1896

6.2 Simulation scenarios

The analysis of the DSM models considers four residential simulation scenarios [38]. Usage habits were based on the public usage report called Procel [39]. The climatic file used in the E+ simulation was from the city of Niteroi, Rio de Janeiro, Brazil [40].

Some electrical devices have a power curve that varies throughout the day, however, due to the limitations of the simulation programs, the average operating power of each equipment was used as provided by the Brazilian Labeling Program, from Inmetro institute.

Tab. 5 shows the data considered for each energy family profile. The first profile considers a family that has energy-efficient equipment and low energy consumption. The second profile, on the other hand, contemplates the same consumption pattern but using energy-inefficient equipment. The third and fourth profiles consider families that have high energy consumption, with efficient and inefficient equipment, respectively.

For profiles 1 and 2, the HVAC system works between 24 and 26 C. For profiles 3 and 4, the HVAC system works between 22 and 24 C. It is important to note that the consumption of HVAC systems was dimensioned by E+, and these consumption are illustrated in Tab. 5 to give a notion of the expected consumption for each profile.

Table 5. Classification and consumption of household appliances for each profile (Hours × Watts)

Appliances	Classification	Daily average usage per profile			
		Profile 1	Profile 2	Profile 3	Profile 4
Refrigerator	Indispensable	24x51	24x73	24x51	24x73
Washing machine	Flexible	1x270	1x350	1x270	1x350
Microwave	Indispensable	0.1x800	0.1x800	0.25x800	0.25x800
Water filter	Dispensable	24x6	24x6	24x6	24x6
Vacuum Cleaner	Dispensable	2x876	2x876	2x876	2x876
Automatic electric iron	Indispensable	1x156	1x156	1x156	1x156
Computer	Indispensable	2x120	2x120	5x120	5x120
TV	Indispensable	2x100	2x100	5x100	5x100
Single Room Lighting	Adjustable	1x20	1x100	4x20	4x100
Double Room Lighting	Adjustable	1x20	1x100	4x20	4x100
Living room lighting	Adjustable	2x80	2x400	4x80	4x400
Dining room lighting	Adjustable	1x80	1x400	4x80	4x400
Bathroom lighting	Adjustable	1x40	1x200	3x40	3x200
Kitchen lighting	Adjustable	1x40	1x200	3x40	3x200
Service area lighting	Adjustable	1x40	1x200	3x40	3x200
External lighting	Adjustable	0.5x280	0.5x1400	2x280	2x1400
HVAC system	Adjustable	9x618	9x618	9x1149	9x1149
Electric shower	Adjustable	0.67x3700	0.67x5500	2x3700	2x5500

In E+, the simulation models a house with three thermal zones: a double bedroom with 20 m², a single bedroom with 12 m², and the rest of the house with 45 m², as shown in Fig. 9. The dimensions used for the house in E+ are an adaptation of the house simulated in [41].

6.3. SREM-BS results and analysis

The main objective of SREM-BS is to adjust the demand of the house to reach the percentage of consumption savings, configured by the user, during peak and intermediate hours. So, the SREM-BS model was analyzed and compared with one of the mechanisms presented in [7]. In this article, their mechanism was called Comparative DSM. It works similarly to SREM-BS, however, it only works in the thermostat control of air conditioning units. Note that the SREM-BS acts on any device that has variable power control or through scheduling loads at peak hours.

In SREM-BS, the variation of four parameters will be analyzed: α, Intensity, percentage of savings, and profiles. The parameter α is related to the calibration of the prediction mechanism. Intensity is the comfort parameter of adjustable devices. Percentage of savings is related to how much energy the user wants to save during peak hours. Profiles are the four simulation scenarios described in Tab. 5.

6.3.1. Calibration of the demand prediction mechanism

The first analysis involves only our mechanism to calibrate the α value used in the target calculation as shown in Eq. 3, in Section 4.2. The α is used to update the demand forecast in SREM-BS mechanism. The α defines the weight of the current average demand in the forecast update. The lower the α, the greater the historical weight in the update and the lower the current demand weight.

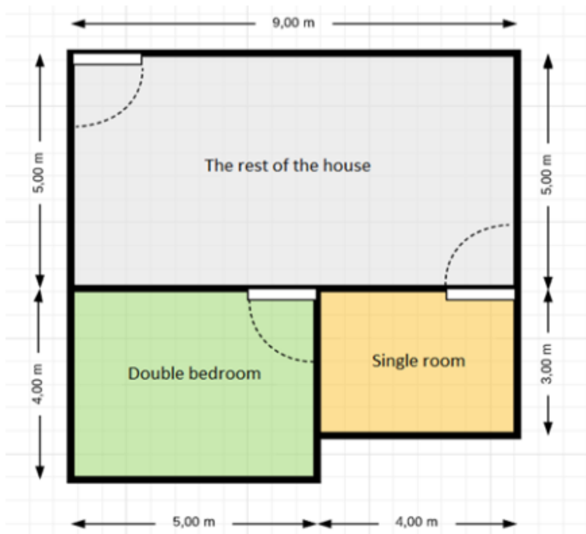

Fig. 9. House plan used in simulations.

To evaluate α, the mean quadratic error between forecast and demand is calculated as shown in Eq. 6. This analysis uses only profile 4 because this profile has the highest consumption, so it presents greater deviations when there is a forecast error. The α values used in the test were: 0.1, 0.3, 0.5, 0.7, 0.9 and 1.0.

$$SquaredError = \sqrt{((Prediction - Demand)^2\})}/Demand \qquad (6)$$

Fig. 10 shows the error percentage average of the estimator with the α variation, for 20 runs for each α value. The standard deviation is shown at the top of each bar. Note that α > 0.5 has the lowest error percentages. In the interval 0.5 < α <1, the error is random. So, to simplify the analysis we decided to use α = 1, which means disregarding the historical calculation of the demand forecast. With α = 1, the consumption forecast for each hour of the day is equal to the consumption of the previous day. This is because the usage time of the devices is turned on and off in a home is usually random. In a factory, for instance, the result could be different, as there is a determined operating time for each equipment. In this way, the demand curve is more stable, and the history has a greater weight (small α values) in the demand forecast.

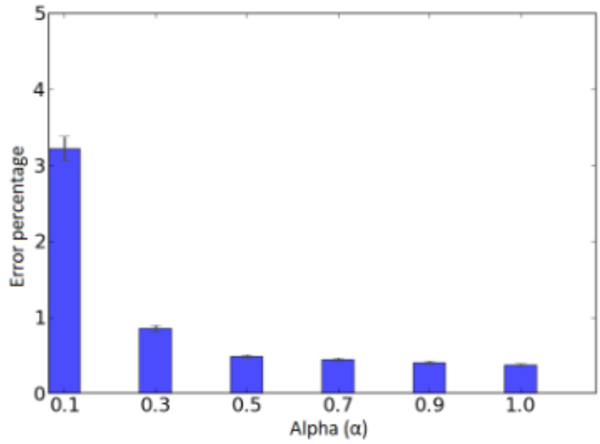

Fig. 10. Average quadratic error of demand forecast in the analysis of α.

6.3.2. Impact of Intensity variation

The second parameter evaluated is Intensity. Intensity is a parameter related to user comfort, as explained in Section 4. In this analysis, α =1 and we also use profile 4. Since it has the highest consumption, it also represents the best opportunity for energy savings. The percentage of savings used here is 5%, as it is a low percentage. The purpose of this analysis is to verify the behavior of the mechanism with the variation of the Intensity, without other restrictions of the system.

The Intensity varies in the integer range of 5 to 1. Fig. 11 shows the energy demand curve without DSM, with the Comparative DSM model, and with the SREM-BS. However, the objective is to analyze the mechanisms quantitatively. Therefore, we identify the percentage of savings achieved in a consolidated graph of the data, shown in Fig. 12.

SREM-BS runs during peak hours, so there are greater savings at this time compared to the total savings for the day. As expected, the lower the Intensity, the greater the savings, as can be seen in the graphic of the Fig. 12. For Intensity 5, the devices operate at maximum power, and the only technique used is load rescheduling, as described in Subsection 4.2. Only one device was rescheduled in this case, which was the washing machine. In this scenario, the user received an alert message stating that the savings energy percentage has not been reached.

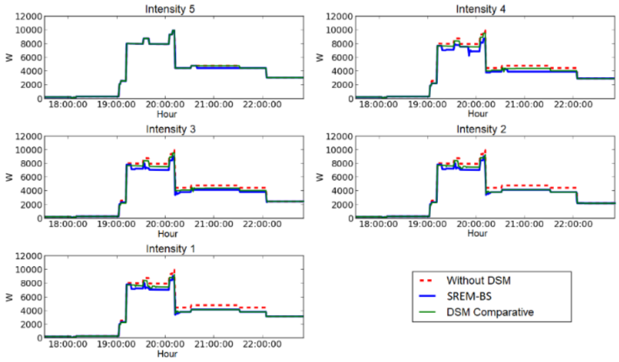

Fig. 11. Demand graph of SREM-BS over time varying the Intensity.

The lower the value of the Intensity variable, the greater the percentage of savings obtained. The SREM-BS achieved savings of 18% and the DSM Comparative saved up to 9%, despite the percentage of the 5% percentage pre-configured in the system. This occurred due to the anti-oscillation mechanism, described in Section 4. The algorithm reduces the power of the adjustable devices if the demand is above the target or increases the power if the demand is below the target. However, the power of a device may fluctuate between increasing and decreasing. When this happens, the mechanism no longer increases the Intensity, until the end of the peak period. As the savings target is variable, the anti-oscillation mechanism was activated at the beginning of the peak period, not allowing an increase in power if demand were below the target in the following hours. However, the comfort limits of each equipment are configurable by the user. Therefore, these greater savings should not have a major impact on user comfort.

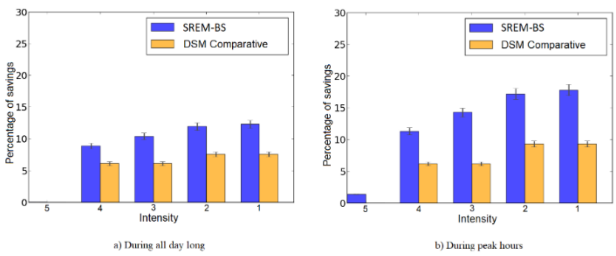

Fig. 12. SREM-BS efficiency by varying the Intensity.

6.3.3. Impact of the percentage of savings variation

The third experiment analyzes the variation in the percentage of savings. The percentage of savings ranges from 10% to 90%. We use α, profile 4, and Intensity=1, as the last two parameters represent greater savings potential.

Fig. 13 shows the results of this experiment. The savings obtained are directly proportional to the configured percentage of savings by the customer. It increases until the maximum limit is reached, that is, the limit of the user's comfort parameters, as described in Subsection 4.2.1. Therefore, peak hour savings remain at 40%, even if the setting is 90%, as can be seen in the graphic b) in Fig. 13. The system sends alert messages to the customer in the case where energy demand is greater than the savings target.

In this scenario, SREM-BS offers much greater savings than DSM Comparative. When the saving rate set by the user is higher than 10%, the effect of the anti-oscillation mechanism is not so evident. For saving rates higher than 10%, the proposed mechanism gets closer to the user saving demand, without interfering with user comfort, being more efficient than DSM Comparative. For the configured parameters, the comparative DSM savings limit is 11% for this scenario.

6.3.3. Impact on different profiles

In this subsection, we evaluated the four residence profiles (see Tab. 5). The idea is to check the percentage of energy savings during the day and at peak periods considering each profile. The analysis uses α =1, Intensity=1 and a target of 30% of energy savings. During the tests, some of the profiles did not reach the 30% savings target. Then, as a way to stress the mechanisms, we chose this target value.

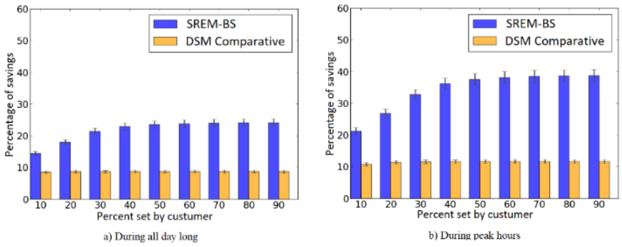

Fig. 13. SREM-BS efficiency by varying the percentage of savings set by customer.

Fig. 14 shows the percentage of energy savings a) during the day and b) at peak periods. Note that the higher the energy consumption for a profile (3 and 4), the greater the energy savings achieved by SREM-BS. Saving capacity for profiles 1 and 2 is around 25% on-peak hours, respecting user comfort parameters. So, they did not reach the target, and the system sent alert messages to these customers. Profiles 3 and 4 achieved the desired savings percentage just by varying the power of the adjustable devices.

SREM-EE outperformed Comparative DSM across all user profiles. For profiles 2 and 4, the savings made by our model were twice as large. The best performance of Comparative DSM was 20% for profile 3 at peak times, while the best results for SREM-EE were 34% for profiles 3 and 4.

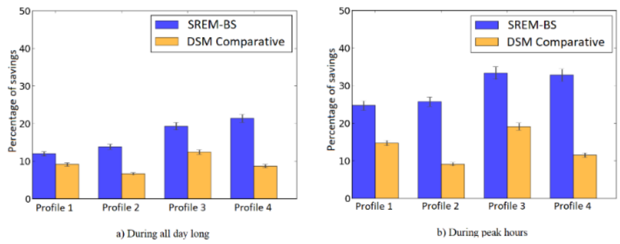

Fig. 14. SREM-BS efficiency for different profiles.

Impact on reducing consumption with the implementation

To conclude the analysis of the SREM-BS, we analyzed the impact on reducing consumption with its implementation on 20% of the Brazilian population. Based on [42] (IBGE, 2019), we classify Brazilian families within the four profiles used in this work. Tab. 6 shows the classification of families in profiles according to their income. The percentage of savings corresponds to the result obtained in Subsection 6.3.4.

Table 6. Percentage of savings by profile of Brazilian families.

Profile	Family Income (equivalent in dollar)	Percentage of Families	Percentage of Savings
1	Up to US$ 539.53	42.50	0.12
2	More than US$ 539.53 to R$ 1079.06	30.50	0.15
3	More than US$ 1079.06 to R$ 2697.66	20.40	0.20
4	More than US$ 2697.66	6.60	0.23

Based on the public data from the Ministry of Mines and Energy of Brazil [4] (EPE, 2020), Tab. 7 presents the 2020 annual energy consumption balance for each region of Brazil. The economy column is a multiplication of consumption by the percentage of the population that participates in the program (20%) and by the weighted average of the percentage of savings in Tab. 6.

Table 7. Residential consumption and economy by Brazilian region.

Region of Brazil	Consumption (Twh)	Economy (Twh)
North	9.489	0.289
North East	29.078	0.888
Southeast	68.413	2.089
South	22.871	0.698
Midwest	12.720	0.388
Total	142.571	4.354

Fig. 15 illustrates the energy saved for the participation of 20% of the population. The Southeast has the greatest potential for savings, as it is the region with the highest energy consumption. The total energy saved represents almost 50% of the energy consumed by the North region. So, the implementation of the SREM-BS can generate great savings in the expansion of the electricity grid and offer a more intelligent use of residential electricity.

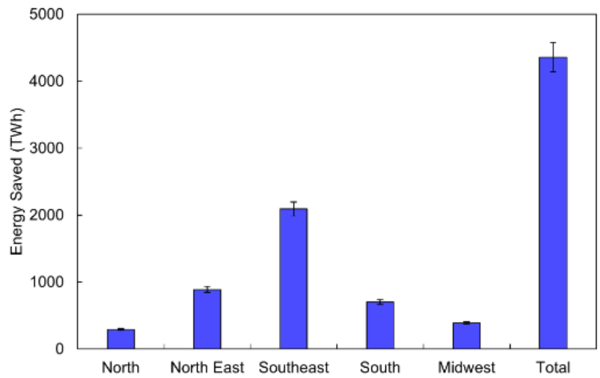

Fig. 15. SREM-BS - Residential energy savings by region.

6.4. SREM-EE results and analysis

The main objective of SREM-EE is to adjust residential demand during emergency events, guaranteeing that the demand does not exceed the target. In this scenario, we analyze the variation of three parameters: Intensity, percentage of reduction, and profiles. The emergency target is calculated based on the current demand, as described in Subsection 4.3. So, there is no α in this model. In these tests, the emergency period happens between 9:20 pm and 10:20 pm.

We use two metrics to evaluate the performance of the mechanisms: Severity and Error. Severity is described by Eq. 7. It indicates the reduction deviation, that is, how much the mechanism has reduced the energy demand more than necessary. The error is described by Eq. 8. It represents how far the mechanism has exceeded the limit of energy demand during the emergency period. In other words, if at any point the mechanism does not respect the target. Demands above the target in the convergence period were disregarded.

$$Severity = \begin{cases} \frac{D_{without\_DSM} - D_{emergency}}{D_{without\_DSM}} \text{, if } Trg\_emer > D_{without\_DSM} \\ \frac{Trg\_emer - D_{emergency}}{Trg\_emer} \text{, if } Trg\_emer < D_{without\_DSM} \end{cases} \quad (7)$$

$$Error = \begin{cases} \frac{D_{without\_DSM} - D_{emergency}}{D_{without\_DSM}} \text{, if } D_{emergency} > Trg\_emer \\ 0 \quad \text{, if } D_{emergency} < Trg\_emer \end{cases} \quad (8)$$

D_(without_DSM) is the demand without using DSM. D_emergency is the demand using SREM-EE. Trg_emer is the demand target during the emergency event.

6.4.1. Impact of Intensity Variation

In the first analysis of SREM-EE, we vary the Intensity chosen by the consumer, the reduction percentage is set to 5%, and we use profile 4. Fig. 16 presents five graphics for each value of Intensity, each representing the demand of energy consumption over time.

The first action of SREM-EE is to reduce the intensities to the minimum set by the consumer. The lower the Intensity, the greater the demand reduction. As the SREM-EE operates only during the emergency event, outside of this period the energy demand of the SREM-EE and "without DSM" is usually the same. However, for the Intensity 5 graphic, the SREM-EE curve is greater than the "without DSM" curve after the end of the emergency event. This is caused by load rescheduling, which was necessary due to the impossibility of readjusting the device's intensity during the emergency event.

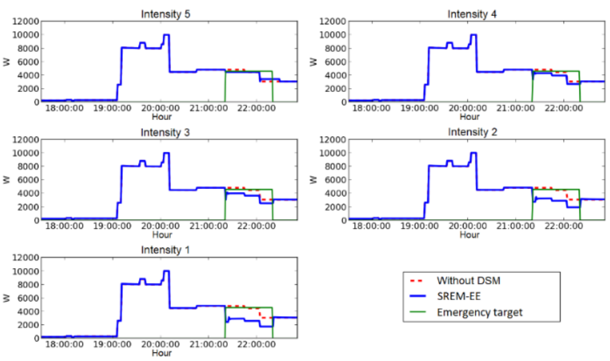

Fig. 16. SREM-EE by varying the Intensity.

Fig. 17 shows the severity graph for Intensity variation. For Intensity 1, there was a high deviation in demand reduction, reducing on average 30% more than necessary. This deviation occurs during the regulation of the Adjustable. In this step, the Intensity of the adjustable is regulated to the minimum allowed by the user. Therefore, this deviation does not have a major impact on user comfort.

The values of the error (Eq. 8) in these tests are equal to zero. After the convergence period, there was no record of any demand above the target. Severity corresponds to how far the demand was below the target. The Error corresponds to how much the demand was above the target. That is, large Severity values are linked to Errors closer to zero.

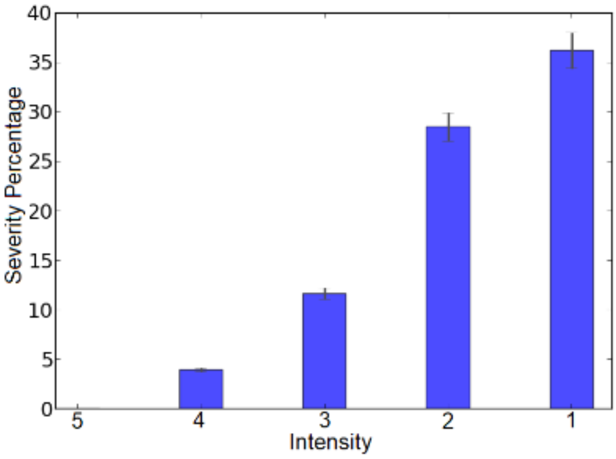

Fig. 17. SREM-EE - Severity by Intensity graph.

6.4.2. Impact of the percentage of reduction

In the second analysis, the percentage of reduction varied was varied (10%, 30%, 50%, 70% and 90%), with Intensity 1 and profile 4. Fig. 18 shows the results of the variation in the reduction percentage.

This test analyzed the evolution of the load reduction groups. On the 50%, 70% and 90% charts, demand was above target for a period. This occurred during the convergence period, as the mechanism has an action delay due to HVAC adjustment. Analyzing the experiment data, the maximum convergence period was seven minutes. In other words, after receiving the emergency message, SREM-EE took up to seven minutes to reach its target.

In all cases, SREM-EE was able to guarantee demand below the target. For a reduction of 10% and 30%, the target was reached by decreasing the power of the adjustable devices. For 50%, there was load rescheduling. That can be seen with the increase in demand after the end of the emergency period. Also, the HVAC system was shut down. For 70% and 90%, after trying to reduce the power, there is a reduction so great that the algorithm is forced to turn off the entire house. And then restart the devices that can be switched on again, respecting the target.

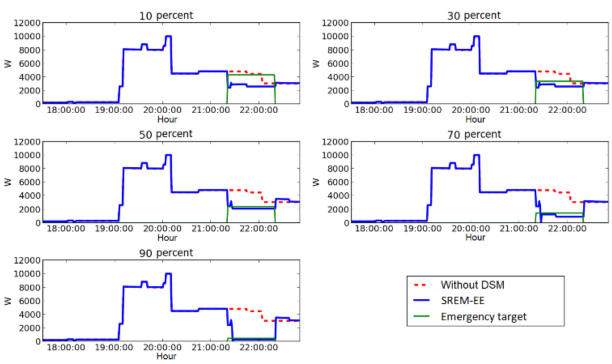

Fig. 18. SREM-EE by varying the percentage of savings.

Fig. 19 shows the severity graph for the variation in the reduction percentage. There were deviations of up to 35% in the reduction of demand. For the 10% reduction graphic, the deviation occurs during the regulation of the Adjustable. In this step, the Intensity of the adjustable is regulated to the minimum allowed by the user. Therefore, this deviation does not have a major impact on user comfort. For 70% and 90% reduction requests, there were large percentage deviations, but these deviations do not represent a large amount of energy. Analyzing their curves in Fig. 18, demand is very close to the target.The values of the error (Eq. 8) in these tests are equal to zero.

6.4.3. Impact of different consumer profiles

The third analysis of the SREM-EE is performed on the four residence consumer profiles, with a reduction request of 30% and Intensity=5. Fig. 20 shows the energy demand curves for each of the profiles.

All profiles respected the reduction target during the emergency period. To achieve this objective, profile 1 shut down the HVAC system to reach the target, while profile 2 reached the target with adjustable Intensity reduction and load rescheduling. Profiles 3 and 4, reached the target only with the reduction of Intensity of the adjustable.

Fig. 21 shows the severity values for each profile. For profile 3, there was a large percentage deviation, but these deviations do not represent a large amount of energy. Analyzing its curves in Fig. 20, demand is very close to the target. Also, profile 3 achieved the target by reducing the power of the adjustable devices, respecting the user's comfort parameters. In other words, this deviation does not cause great discomfort to the user.

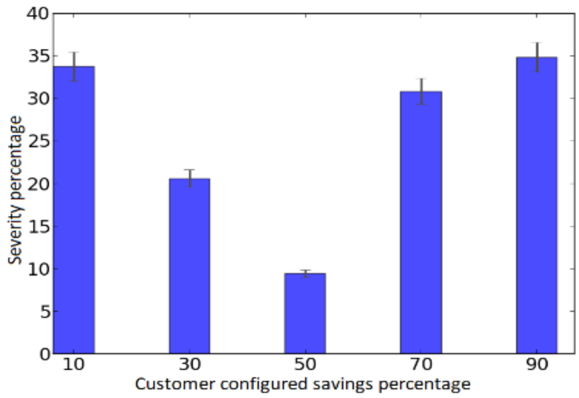

Fig. 19. Severity of SREM-EE according to the percentage of savings.

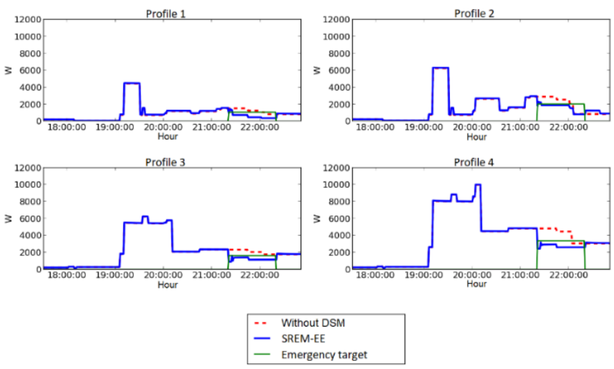

Fig. 20. Energy demand curves of profiles.

Once again, the error values in this experiment are zero. After the convergence period, no demand exceeded the target.

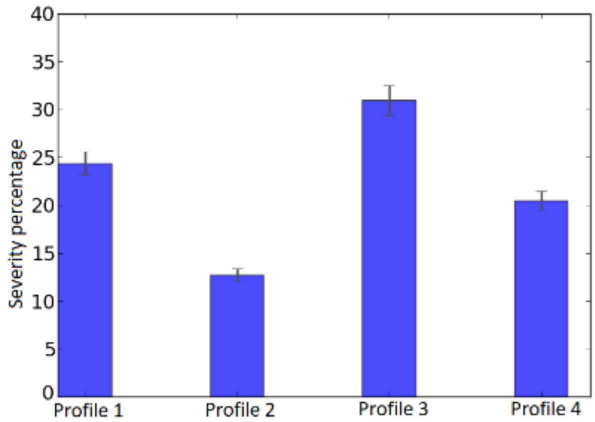

Fig. 21. SREM-EE - Severity by profile graph.

Impact on demand reduction with the implementation

To calculate the impact on demand reduction with the implementation of the SREM-EE, we used a scenario of 1000 houses. The distribution of user-profiles corresponded to the proportion shown in Tab. 7. The total power demand of these houses during emergency hours was 2354 kW. The percentage of reduction sent by the utility to the participants was 30%.

Tab. 8 and Fig. 22 show the reduction in demand achieved for different percentages of population participation in the program (10, 15, 20, 25, and 30% - membership). The SREM-EE guarantees reduced demand below the target. Therefore, the demand reduction can vary between the target (30%) and the power reduction made by the SREM-EE, considering the severity percentage of each profile as shown in Fig. 21. The third column of the table represents the percentage of reduction in total demand.

Table 8. Demand reduction by the percentage of population membership.

Membership (%)	Target - SREM-EE (kW)	Demand reduction (%)
10	71-107	3-5
15	106-161	5-7
20	141-215	6-9
25	176-268	8-11
30	212-322	9-14

As shown in Fig. 22, the higher the percentage of the population affiliated with the program, the greater the power reduction demand the SREM-EE achieves. With a 30% membership, we reached a power reduction of 322 kW.

The SREM-EE proved to be an excellent tool for reducing energy demand. It reached the target in a maximum of seven minutes. And was able to reduce until 14% of the total energy demand, with only the participation of 30% of the houses in a region.

This work presents two efficient DSM mechanisms that respect users' comfort parameters. They perform saving actions automatically, allowing users to save energy without major changes in their habits. Its heuristic logic depends on low computational power. In this way, making the system cheaper and easier to deploy on a large scale. These mechanisms are powerful tools for utilities. They allow the reduction of energy consumption during peak hours and the demand reduction during emergency network events. The SREM-BS allows its users to save energy and benefit from the use of variable energy charging. And the SREM-EE users receive a discount on their bills to reduce their demands during emergencies.

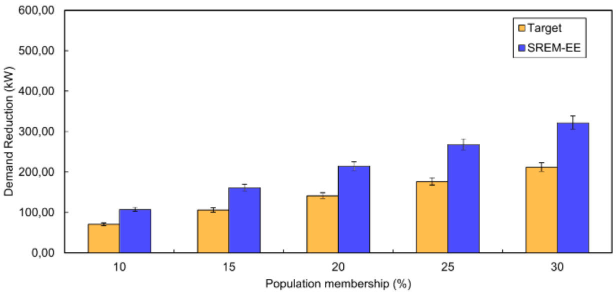

Fig. 22. SREM-EE - Demand reduction by the percentage of population membership.

Most DSM in literature proposals save energy only by adjusting the HVAC system or by rescheduling the home appliances. Our models use both strategies, adjusting the HVAC system, and rescheduling loads at the same time. In addition, it also regulates the power variation of some devices, dynamically adapting the service to different user profiles. Another important issue for DSM programs is the population adoption to the program. DSM programs that cause discomfort or uncertainty will not be hired by consumers. Hence, we classified devices according to their impact on user habits. The idea is to ensure that DSM will not be a disturbing routine and incentivizing a higher number of clients to adhere to the system. With the proposed programs, even a more modest user can achieve satisfactory savings.

We also developed the ECNS, a simulator to analyze different DSM control logic algorithms. This simulator is the result of the integration of the E+, an energy system simulator, and the NS-3, a communications network simulator. ECNS was used in the simulations of the SREM-BS and SREM-EE. It simplifies the evaluation of new mechanisms, considering the power system characteristics, the control logic, and the communication network scenario.

7. Conclusion

Demand Side Management (DSM) mechanisms are fundamental for residential energy consumption automation, not only for the balance generation and demand of energy, but also because they present an excellent opportunity to save costs and provide more efficient energy use.

We proposed two demand-side management mechanisms for residential users, SREM-BS (for billing savings) and SREM-EE (for emergency events). To test the mechanisms, we developed a simulator for electrical and telecommunications systems, the ECNS.

About the development of the simulator, the E+ and NS-3 integration was a success. And the ECNS proved to be an excellent tool to simulate the scenarios studied. Its downside is that it only works on Linux operating systems.

The SREM-BS showed excellent performance in saving different user profiles, achieving energy savings of up to 40%. We also compared SREM-BS with other proposal [7] and our program outperforms the Li and Zhang mechanism, often saving twice without causing higher discomfort to the user. Our emergency model, SREM-EE also performed well in our tests. It reached the target in a maximum of seven minutes and kept demand below the target during the emergency period. It was tested in different profiles, and with different percentages of reduction. We showed that it was able to reduce residential energy demand even in the most critical cases, with a 90% reduction in energy.

We analyzed the implementation of SREM-BS in the Brazilian scenario, Subsection 6.3.5. With 20% of the population joining the program, the total energy saved represents almost 50% of the energy consumed by the North region. Therefore, it represents an excellent opportunity to reduce grid expansion and to reduce expenses with power generation.

For SREM-EE, we evaluated a scenario of 1000 houses with the participation of 30% of users, Subsection 6.4.4. For the 30% reduction target, we achieved a total demand reduction of 14% within a maximum time of seven minutes. Therefore, proving the mechanism's ability to guarantee demand reduction during emergency events.

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