Demand Response algorithms for building energy management through virtual power plant operators

Maria João Dias Machado
Supervisor: Prof. Doutor Carlos Augusto Santos Silva
Co-supervisor: Prof. Doutor Paulo Manuel Cadete Ferrão

Abstract

One of the big challenges that modern society must face consists of the decreasing of energy consumption or using energy more efficiently. It exist a high potential to increase energy efficiency and energy saving in the building sector. This energetic change must have into account the comfort of their occupants, so the use of energy management systems that adjust energy demand for their production, taking into account tariff, daily routines, comfort and other types of constraints, is an asset to satisfy these two conflicting demands.

The objective of this thesis is to design a demand-response algorithm to adjust the electricity consumption to the tariff, the users’ comfort and the availability of renewable electricity. These algorithm was implemented with the support of Matlab and EnergyPlus software and tested in the Energy in Buildings laboratory at Instituto Superior Técnico in Tagus Park campus. Besides the creation of a new algorithm, it is intended to implement an existing algorithm in the literature and make an analysis of results of these two models.

It was concluded that in all models, the percentage of comfort decreases and the percentage of cost increases when the emphasis given to the cost is increased. The model which uses dynamic programing is able to obtain an optimal solution. However, due to its limitations, the solution obtained with this model were less accurate when compared with the genetic algorithm.

1. Introduction

The demand for electricity has increased significantly throughout the world either in developed countries or in developing countries. IEA’s forecasts indicate that electricity demand in 2030 will be 50% higher than the current demand [1]. Despite the increase in demand, problems as dependence on fossil fuels, the negative impact of these fuels on the environment and the constant changes in prices; have led worldwide communities to invest in activities that promote energy efficiency and changing the production system and power management. Increase energy efficiency by 20% is one of the three main objectives of the European Union, according to the 2020 climate and energy package [2], especially in the building sector, whose potential to increase energy efficiency and energy saving is the highest [3].

One of the visible changes in production and electrical power management system consists of decentralizing the production, through the implementation of micro generation systems, working together with custom management systems for each building [4]. There has been more and more interest from consumers to produce locally the very energy they consume from renewable sources and control or register every energy consumption through domotic. Energy management systems that adjust energy demand for their production, taking into account tariff, daily routines, comfort and other types of constraints would be an added
advantage to maximize the return on the initial investment in micro-generation and domotic. So the use of a demand response algorithm could: manage the uses of energy in a dwelling in order to shape the power consumption and shave the peak of demand; manage the use of energy from sources of micro-generation, taking into account the state of the batteries and the tariffs; guide the use of energy in order to always maintain a level of comfort to the occupants; create conditions for the application of the smart grid; among other actions [5]. This system could replace humans in making difficult decisions at short time intervals during a day in order to make more efficient use of energy in housing.

The objective of this thesis is to design a demand-response algorithm to adjust the electricity demand to the tariff, the users’ comfort and preferences and the availability of renewable electricity. This algorithm was implemented with the support of Matlab software and tested in the Energy in Buildings laboratory at Instituto Superior Técnico in Tagus Park campus.

2. Literature Review

   • Energy Consumption in the Residential Sector

   In IE countries, the electricity consumption in the residential sector grew by about 48% between 1990 and 2004. More than half of this energy, 57%, is consumed by appliances [6]. There are several reasons that have contributed to the increase in consumption, such as: improvement of comfort; increasing the number of devices per household; Increasing the size of homes; among others [7]. However, there are already many countries promoting energy efficiency: establishing minimum standards for energy consumption and improving energy efficiency of these same devices. But to be able to reduce or control the consumption of electricity is necessary to understand, characterize and analyze patterns of consumption, [8]. Soares et al. [8, 9] analyzed and characterized the daily electricity consumption in the residential sector in Portugal, with the aim of applying autonomous systems power management. They concluded that it is possible to identify a pattern of a typical schedule consumption of different appliances. So the objective of minimizing the electricity costs without diminishing energetic comfort, goes through the following actions: advance or delay the work cycles of devices; restore comfort temperatures and creating small periods of interrupted load [8, 9].

   • Building Climate Control

   In Portugal, the second largest domestic electricity consumption is the energy that is used to heat or cool the dwelling. This represents about 16% of total electricity consumption [10]. This energy consumption can vary considerably over a day. There are numerous factors that influence energy losses in climate control: the house location – weather; solar radiation falling on the surrounding housing; thermal performance of the surrounding - solutions adopted for thermal insulation, volume vs. the surrounding area; thermal behavior of the occupants - degree of thermal comfort; etc. [11]. To predict the amount of energy that the occupants of a dwelling are willing to spend to improve their environmental comfort, it is necessary to know the general conditions that provide this comfort, since, from person to person the physiological and psychological needs make the comfort conditions vary. These conditions are usually evaluated in terms of thermal properties, light and air quality.

   There are several models and studies on thermal comfort and which parameters that provide comfort. Each model has its own definition of comfort and the parameters that they consider relevant. According to ASHRAE 55 thermal comfort is the condition of mind that expresses satisfaction with the thermal environment [12]. This satisfaction is related to the ease with which human beings can exchange heat with the environment, in order to maintain the internal temperature. The static equilibrium models of heat try to explain people’s satisfaction
with the thermal environment by transferring heat between the environment and the person. These models are the most used in the air conditioning of spaces [13]. ISO 7730 and ASHRAE standards 55 are examples of such methods. For ASHRAE 55 there are six factors that define comfort conditions: metabolic rate, clothing insulation, air temperature, radiant temperature, air speed and humidity [12]. For certain values of these factors, it is possible to determine a comfort zone and set this in a range of operating temperature. Through a thermal equilibrium between the occupants and their environment, it is possible to measure the degree of comfort of such persons based on physiological reactions. This measurement of comfort is presented on a scale of sensations: predicted mean vote, PMV. The large defect of these models is the need for a very specific basic data, such as the level of thermal insulation of clothing or the type of activity performed in each time. In addition, the occupants are analyzed as passive receivers of thermal stimulation, where cultural, psychological, social and contextual factors are neglected [13 and 14].

Unlike static models, the adaptive models attach an active role to their occupants and the fundamental assumption of the adaptive approach is expressed by the adaptive principle: if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort [14]. The adaptation can be understood as the progressive loss of the body's response to an environmental stimulation [13]. So in this way, the adaptive model relates the comfort temperatures with outside temperatures or external parameters.

A third model is based on the result of the statistical analysis and aims to find the temperature or combination of variables (temperature, humidity and air velocity) that providing thermal comfort. These figures relate to the thermal environment experienced by people with their satisfaction. This satisfaction is measured through questionnaires [12 and 13].

The visual comfort is associated with the lighting level required to perform a certain task, is measured in lux, and corresponds to the illumination incident per square meter. Knowing the type of activity that each person plays, it is possible to estimate the minimum amount of energy that is required for that task to be carried out under conditions of visual comfort.

- Optimization Algorithms

In the literature there are several types of optimization algorithms applied to energy management problems, but there are few algorithms that focus on energy management of a dwelling. D. Livengood e R. Larson [5] present a prototype of an optimization model in a dwelling, using dynamic programming. Dynamic programming is a mathematical technique used for determining a sequence of interrelated decisions. Through a systematic approach, it is possible to determine the best combination of decisions. In this kind of optimization algorithm, the process of obtaining the optimal value or path is achieved through an analysis of possible solutions at each stage. The analysis starts at the last instant to be optimized and the best solution of this stage is added to the solutions of the immediately previous instant. This procedure is done systematically to the current stage. Finally, a path is traced with the best solution, which is the optimal solution. Because of this characteristic of obtaining the optimal solution, in reverse order, from the end to beginning, the influence that recent decisions have on the evolution of future temperatures is not accounted for.

A. Gomes et al. [15] apply a genetic algorithm with a multi-objective function in order to identify control actions. It is said that genetic algorithms are well suited for multi-objective combinatory problems because they work with Populations.

The dynamic programming algorithm ensures the optimal value, but due to its reverse characteristic of obtaining the optimal can neglect their results. On the other hand, the
genetic algorithm does not ensure the optimal solution, but allows review several thermal changes inside the room

3. Study case description

The objective of this thesis is to design a demand-response algorithm to adjust the electricity demand to the tariff, the users’ comfort and preferences and the availability of renewable electricity. This algorithm was implemented with the support of Matlab software and tested in the Energy in Buildings laboratory at Instituto Superior Técnico in Tagus Park campus.

The outer envelope has a free facade, with a Southeast solar orientation. The internal surrounding faces four rooms and a common circulation area. To characterize the heat transfer through the opaque envelope and glazed areas is necessary to take into account the type of construction and the materials of the room. In this way an inventory of those materials was made to determine the overall heat transfer coefficient for each of the elements mentioned above.

Inside the room, the user has access to the illumination intensity and the operation speed of the air conditioner. In order to monitor and act on lighting and air conditioning system, there are four types of sensors inside the room: temperature sensor; relative humidity sensor and illumination sensor. Apart from these sensors is even possible to know in what state is the air conditioner (on / off status and fan speed) and the illumination intensity.

4. Methodology

For the optimization model obtain the best solution, it needs to test several solutions until it converges to the best result. Since these solutions are related to future events, it is necessary to know the time evolution of the climacteric conditions inside the room, depending on the different stimulations applied. Therefore, to simulate future climate conditions inside the room it was decided to use the EnergyPlus software to simulate the climate evolution. EnergyPlus model contains all the features listed in point 3. In addition to the physical characteristics of the room, the EnergyPlus software needs a weather file [16]. This file contains hourly data from several climate variables over a period of a year. To measure the thermal comfort, it was chosen the static models ASHRAE 55, since this indicates in the form of percentage the comfort experienced inside the room. For the measurement of visual comfort, it was assumed that the occupants inside the room are doing office activities, so the minimum Lux range required lies between 300 – 750 Lux. But since the sensor that measures the number of Lux is not on top of a desk, but in the upper part of a wall, the lower limit was defined as 100 Lux.

4.1. Input variables

The input variables are divided into three groups: the input variables of the EnergyPlus software, the input variables in the model of thermal comfort and the input variables of the optimization model. The input variables of the EnergyPlus software are related to the weather file and the fan speed of the air conditioner (speed 0, 1, 2 or 3). In the thermal comfort model, the input variables are: air temperature, radiant temperature [°C]; relative humidity [%]; metabolic rate [Met]; isolation of clothing [Clo] and air velocity [m / s]. The first three variables result from the simulation of EnergyPlus and the others corresponding to fixed values. Finally, the input variables of the optimization model are: percentage of thermal comfort from the thermal comfort model; value that corresponds to the importance to give comfort or monetary cost in each hour; price of the electricity in each hour; renewable energy production and the inside the room illuminance [Lux].
4.2. Objective function

The problem to be optimized is a multi-objective minimization problem: ensure the comfort inside the room (minimize discomfort), taking into account the monetary cost of that comfort.

The following equation 1, represents the objective function of the problem:

\[
\minimize_F = \left\{ \sum_{t=0}^{24} \lambda^\text{discomfort}_t \times u^\text{discomfort}_t(s_t, d_t) + \lambda^\text{cost}_t \times u^\text{cost}_t(s_t, d_t) \right\};
\]

wherein:

\[
\lambda^\text{discomfort}_t + \lambda^\text{cost}_t = 1. \tag{2}
\]

These variables, \(\lambda^\text{discomfort}_t\) and \(\lambda^\text{cost}_t\), represent the importance to give to comfort and the monetary cost. Functions \(u^\text{discomfort}_t\) and \(u^\text{cost}_t\) are the thermal discomfort and the monetary cost, respectively, in the instant \(t\). These two functions are given by the following expressions 4 and 5:

\[
u^\text{discomfort}_t(s_t, d_t) = 100 - \text{Model of Thermal Comfort} (s^\text{home.temp}_t) \tag{4}
\]

\[
\begin{align*}
\text{(6)} \quad & \text{se} \quad 100 - s^\text{price}_t \times \left[ s^\text{AC.energ}_t - \frac{C}{4} (s^\text{use.bat}_t - s^\text{use.bat}_{t+1}) \right] < 0; \\
\text{(7)} \quad & \text{se} \quad 100 - s^\text{price}_t \times \left[ s^\text{AC.energ}_t - \frac{C}{4} (s^\text{use.bat}_t - s^\text{use.bat}_{t+1}) \right] > 0 \quad e \quad s^\text{use.bat}_t < s^\text{use.bat}_{t+1} \\
\text{(8)} \quad & \text{se} \quad 100 - s^\text{price}_t \times \left[ s^\text{AC.energ}_t - \frac{C}{4} (s^\text{use.bat}_t - s^\text{use.bat}_{t+1}) \right] > 0 \quad e \quad s^\text{use.bat}_t > s^\text{use.bat}_{t+1}
\end{align*}
\]

\[
u^\text{cost}_t(s_t, d_t) = \begin{cases} s^\text{AC.energ}_t \times s^\text{price}_t & \text{if } s^\text{AC.energ}_t \times s^\text{price}_t < s^\text{AC.energ.max}_t \times s^\text{price.max}_t \\ 0 & \text{otherwise} \end{cases} \tag{6}
\]

\[
u^\text{cost}_t(s_t, d_t) = \frac{s^\text{AC.energ}_t \times s^\text{price}_t}{s^\text{AC.energ.max}_t \times s^\text{price.max}_t} \tag{7}
\]

Where \(s^\text{price}_t\) is the price of electricity at the instant \(t\), the variable \(C\) corresponds to the maximum charge capacity of the battery and the superscript max is the maximum tariff price and the maximum electricity consumption of air conditioner. \(s^\text{AC.energ}_t\) is the power consumed by air conditioner and \(s^\text{use.bat}_t\) is the battery states of charge.

4.3. Description of the model

The operation of this model can be divided into two distinct parts: allocation of variables and optimization. The Genetic Algorithm model was implemented in Matlab. The first part of the operation of this model is related to allocation of variables and data preparation.

The program starts with the gathering of data from the weather forecasting of the day. Next, these data are stored in the EnergyPlus weather file. The operational speeds of the air conditioner in the file are initialized to zero. After this, the EnergyPlus program begins with
the simulation of thermal evolution of the next 24 hours. Then, the simulation results are analyzed by the comfort model and this model calculates the percentage of discomfort at each instant.

The next step is related to optimization. In each iteration of the optimization, the EnergyPlus program and the model of thermal comfort are executed. After the optimization is finished, the values attributed to the speed of the fan-convector are collected. These values correspond to the best solution found by the generic algorithm.

5. Results

5.1. Genetic algorithm model (Simulation)

It was chosen a typical summer day to record data for simulation. It was record the weather forecasting of the day, the temperature, relative humidity and illuminance inside the room for 24 hours. The data was recorded without the presence of people inside the room and the speed of the fan-convector was set to zero. This ensures the same conditions for all simulations.

The following figure (Figure 1) represents the evolution of the temperature inside the room, for the previously conditions, and the simulated temperature with the software EnergyPlus.

![Figure 1 - Comparison between simulated and real temperature inside the room.](image)

There were perform five types of simulations where the parameter $\lambda_i^{cost}$ ranged from 0 to 1. Table 1 show in detail the five simulations performed.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>$\lambda_i^{cost}$</th>
<th>Schedule</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>9:00 – 12:00 and 13:00 – 19:00</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Remaining hours</td>
</tr>
<tr>
<td>2</td>
<td>0.3</td>
<td>9:00 – 12:00 and 13:00 – 19:00</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Remaining hours</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>9:00 – 12:00 and 13:00 – 19:00</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Remaining hours</td>
</tr>
<tr>
<td>4</td>
<td>0.7</td>
<td>9:00 – 12:00 and 13:00 – 19:00</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Remaining hours</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>Full time</td>
</tr>
</tbody>
</table>

Each simulation was repeated three times, and the numbers of populations and generations used in the genetic algorithm were 40 units. The next table shows the results for all performed simulations. The table shows, in each simulations the results for the objective function, comfort function, cost function and cost in euros.
Table 2 - The results for the objective function, comfort function, cost function and cost in euros for the five simulations.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OF [%]</td>
<td>Comfort [%]</td>
<td>Cost [%]</td>
<td>Cost [€]</td>
<td>OF [%]</td>
</tr>
<tr>
<td>Best solution</td>
<td>87.3</td>
<td>92.9</td>
<td>93.0</td>
<td>9.97</td>
<td>89.89</td>
</tr>
<tr>
<td>Mean value</td>
<td>85.9</td>
<td>89.9</td>
<td>95.7</td>
<td>10.31</td>
<td>88.1</td>
</tr>
</tbody>
</table>

It is possible to observe that for the five types of simulations the objective function increase with the increasing of the parameter $\lambda_i^{cost}$. The cost function, with one exception for simulation 1, increase with $\lambda_i^{cost}$, because is given more importance to the cost compared to the comfort. The simulation 1 have a higher value compared to what was expected because in the periods where the $\lambda_i^{cost}$ is zero, only the comfort matters, so the cost function assumes the maximum value. The following figures (2 to 4) compare the results of the comfort and cost function and the battery state of charge for the five simulation.

![Figure 2](image1.png)

Figure 2 – Comfort functions for the five simulations.

![Figure 3](image2.png)

Figure 3 – Cost functions for the five simulations.
In figure 2, it is possible to observe the evolution of comfort along 24 hours of optimization for the five simulations performed. In the first period of time (22:00 – 09:50), where $\lambda_1^{\text{cost}}=1$, all the cost functions are in the same range of values and when it reach 9:00 they disperse, where the functions which have lower $\lambda_i^{\text{cost}}$ values have higher comfort results. At lunch time, where $\lambda_1^{\text{cost}}=1$ the percentage of comfort for all five simulations decreased. When the time reach 13:00 the comfort functions with lower $\lambda_i^{\text{cost}}$ values have higher comfort results. Finally, at the last period, where $\lambda_1^{\text{cost}}=1$, the five comfort functions remains constant.

The figure 3 shows the evolutions of the battery state of charge along the 24 hours of optimization. It is possible to confirm, that in the night period, where there is no production of solar energy, the battery state of charge don’t charge and during the day, it is able to charge.

Comparing figure 3 with figure 4, which shows the evolution of the cost functions for the five simulations along 24 hours of optimization, all cost functions have inferior values when the battery is not fully charge. This means that when the air conditioner is used and the battery is not fully charge, it is necessary to use the energy from the grid to attempt to this demand. Another conclusions is that the battery state of charge for lower values of $\lambda_i^{\text{cost}}$, is more requested, because the comfort is more important than the cost, so the air conditioner is more used, that means a higher energy demand.

### 5.2. Genetic algorithm model (Real test)

There was an opportunity to implement the genetic algorithm model in real time in the Energy in Buildings laboratory with some limitations. It was necessary to start the optimization with this model 4 hours previous, because it is the time that the models take to obtain results with a numbers of populations and generations of 40 units. The values chosen for the $\lambda_i^{\text{cost}}$ are explained in the table 3.

<table>
<thead>
<tr>
<th>Schedule</th>
<th>Stage</th>
<th>$\lambda_i^{\text{cost}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>4:00 – 8:00</td>
<td>Optimization</td>
<td>1</td>
</tr>
<tr>
<td>8:00 – 9:00</td>
<td>fan-convector speed</td>
<td>0.5</td>
</tr>
<tr>
<td>9:00 – 12:00</td>
<td>implementation</td>
<td>1</td>
</tr>
<tr>
<td>12:00 – 13:00</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>13:00 – 19:00</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>19:00 – 22:30</td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Unfortunately it was not possible to control and record the battery usage and the record of energy demand. Only was possible to measure the evolution of the temperature inside the room. The next figures shows the evolution of the comfort function, the fan-convector speed and the temperature.
Throw the results shown in the figure 5 and 6 it is possible to confirm that the real influence of the air conditioner in the temperature inside the room is more remarkable than the results simulated by the model. Despite this difference, the absolute mean error between the real values and the simulated ones, is 0.5°C with a standard deviation 0.4 °C. The behavior of this model when implemented in real time corresponds with the behavior when is simulated.

6. Conclusions

It is possible to conclude that for the five types of simulations the objective function increase with the increasing of the parameter $\lambda_{iCost}$. The percentage of comfort decreases and the percentage of cost increases when the emphasis given to the cost is increased.

Throw the realization of all this simulations and real tests, it is possible to conclude that the EnergyPlus software allied to an energy optimization model has a great power of simulations energy demands problems.

References


EDP, “Viva a sua casa com uma energia mais sustentável.”


