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An Agent-Based Simulator to Estimate Domestic Energy Use

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To my family and girlfriend.

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ABSTRACT

Throughout recent years, there has been an increase in the population size, as well as a fast economic growth, which has led to an increase of the energy demand that comes mainly from fossil fuels. In order to reduce the ecological footprint, governments have implemented sustainable measures and it is expected that by 2035 the energy produced from renewable energy sources, such as wind and solar would be responsible for one-third of the energy produced globally. However, since the energy produced from renewable sources is governed by the availability of the respective primary energy source there is often a mismatch between production and demand, which could be solved by adding flexibility on the demand side through demand response (DR). DR programs influence the end-user electricity usage by changing its cost along the time. Under this scenario the user needs to estimate the energy demand and on-site production in advance to plan its energy demand according to the energy price. This work focuses on the development of an agent-based electrical simulator, capable of:

(a) estimating the energy demand and on-site generation with a 1-min time resolution for a 24-h period,

(b) calculating the energy price for a given scenario,

(c) making suggestions on how to maximize the usage of renewable energy produced on-site and to lower the electricity costs by rescheduling the use of certain appliances.

The results show that this simulator allows reducing the energy bill by 11% and almost doubling the use of renewable energy produced on-site.

Keywords: Residential electricity simulation; Demand response; Multi-agent systems; Flexible energy demand.

Resumo

Nos últimos anos tem-se verificado um aumento populacional e um rápido crescimento económico, o que levou a um aumento da energia consumida globalmente tendo a sua maioria proveniência em combustíveis fósseis. De forma a reduzir a pegada ecológica, vários governos têm implementado medidas de sustentabilidade e é expectável que em 2035 a energia produzida através de fontes renováveis, tais como o vento e o sol, sejam responsáveis por um-terço da energia produzida globalmente. Contudo, uma vez que a energia produzida através de fontes renováveis é dependente da disponibilidade do respectivo recurso energético existe frequentemente um desfasamento entre a produção e o consumo. Este problema pode ser resolvido introduzindo maior flexibilidade do lado do utilizador através de técnicas de *demand response* (DR), cujo funcionamento se baseia na alteração dos comportamentos do utilizador através da alteração do preço da energia ao longo do tempo. Assim, é importante para o utilizador ter um conhecimento prévio do seu consumo e da energia produzida na sua habitação, para poder planear o seu consumo de acordo com os preços da energia. Este trabalho foca-se no desenvolvimento de um simulador elétrico baseado em agentes, que é capaz de:

(a) estimar o consumo energético e energia produzida na habitação, com uma resolução temporal de 1 min e para o período de 24 h,

(b) calcular o preço da energia para um dado cenário,

(c) fazer sugestões sobre como maximizar o uso da energia produzida na habitação e como reduzir o custo da energia utilizada, reorganizando o período em que certos electrodomésticos funcionam.

Os resultados mostram que este simulador permite uma redução de 11% na factura energética e quase duplicar a utilização da energia produzida no local.

Palavras-chave: Simulação energética em habitações; *Demand response*; Sistemas multi-agentes; Flexibilização da procura energética.

Contents

List of Figures

List of Tables

ACRONYMS

AC air conditioning.

CDA conditional demand analysis.

CHREM Canadian Hybrid Residential End-use Energy and Emission Model.

DR demand response.

EM engineering methods.

FIPA-ACL Foundation for Intelligent Physical Agents Communication Language.

GA genetic algorithms.

GDP gross domestic product.

GHG greenhouse gas.

IDE Integrated Development Environment.

JADE Java Agent DEvelopment Framework.

NN neural network.

SM statistical methods.

Chapter 1

Introduction

This chapter will introduce the background of the developed work, as well as the respective motivation, which will be followed by the goals that are responsible for guiding the development of the agent-based simulator. In the end, it will be presented the organization of the present document.

1.1 Background and motivation

Throughout recent years, there has been an increase in the population size. This fact together with a fast economic growth in regions, such as Asia, Africa and Latin America has led to an increase in the energy demand, as it can be seen in Figure 1.1. The majority of this energy comes from the combustion of fossil fuels, which contributes for 57% of the greenhouse gas (GHG) generated globally [1]. Therefore, for a more sustainable future new policies have started to be implemented by governments worldwide in order to reduce the ecological footprint on the planet.

The existing commitment with a sustainable development has resulted in the introduction of regulation that considers emission limits of GHG, carbon taxes and ambitious renewable energy targets. As a consequence, it is expected that by 2035 the energy produced from renewable energy sources, such as wind and solar will be responsible for one-third of the globally produced energy [2]. However, since the energy production from renewable sources is governed by the availability of the respective primary energy source, there is often no correlation between production and demand [1]. This mismatch between renewable production and demand is nowadays being solved by introducing flexibility on the supply side (e.g. adding carbon intensive generators). But, in order to meet sustainable development targets [2], cleaner solutions must be employed. For instance, adding flexibility on the demand side through demand response (DR) measures is pointed out as one of the solutions to the referred problem [3].

DR is not a new concept and it regards the ability of consumers to modify their usual consumption profiles as a reaction to different electricity prices [4]. Under this scenario, residential building tenants might have to make some decisions in order to reduce their electricity bills as a reaction to different tariffs throughout the day. However, certain knowledge on the user's energy demand and on-site generation is needed in advance so the user can plan its energy consumption. As a consequence, building energy estimation tools are an important component for implementing load management strategies in buildings. These estimations should include the shape of the load curve and the influence that each device has on it so the user can be aware of the devices that have the most impact on their energy profile, as well as the correspondent energy costs.

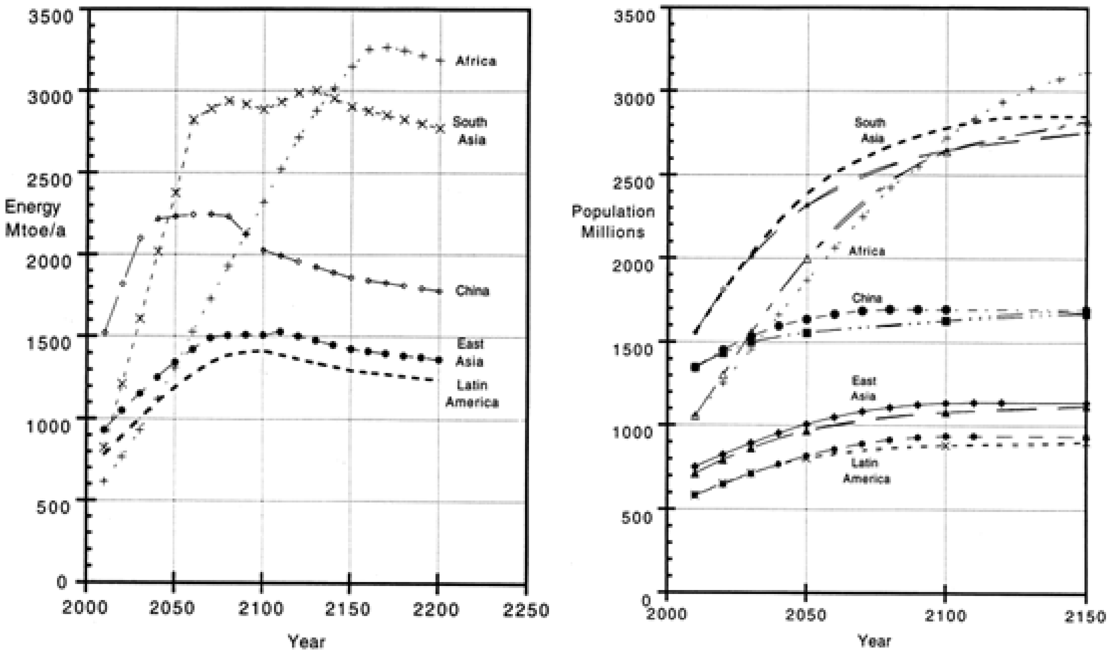


Figure 1.1: Population growth and energy demand [2].

1.2 Objective

This thesis has the goal of providing the domestic users with a tool to improve the flexibility and control over the demand side, allowing the implementation of demand response measures. Therefore, an agent-based simulator has been designed to help consumers making detailed estimations of the energy demand and on-site production for a residential building, which includes not only the energy consumed/produced by each device, but also the impact that external factors, such as the climate have on their behavior. Moreover, it should also provide suggestions on how to maximize the use of the renewable energy produced on site and how to reduce the energy bill by time-shifting the working period of some appliances. Each simulation will represent a 24-h period of any month chosen by the user with a time resolution of one minute. To make these estimates possible the simulator uses a hybrid bottom-up approach that combines the model developed by Richardson et al. [5] with physical characteristics of the building and some devices. Furthermore, it also considers meteorological data and user-given specifications.

1.3 Contributions

This thesis presents a simulator capable of making estimates on the energy consumption and on-site generation of a residential building for a 24-h period with a 1-min time resolution. Due to the fact that it has been used an agent-based modular architecture it is possible for the user to adjust the simulation's conditions in real time, which will instantly affect the output results. The presented simulator also makes use of genetic algorithms to provide suggestions on load optimization by time-shifting the use of certain appliances, such as the washing machine, the washer dryer and the dish washer. As a consequence, it makes possible to maximize the use of the energy produced in the building and to reduce the energy bill.

1.4 Structure of the document

Apart from the present chapter (Chapter 1) this document has five more, namely:

- **Chapter 2 – Literature review**

  This chapter presents the literature review on the possible approaches and methods for estimating the energy demand/on-site generation of a building.

- **Chapter 3 – Modeling the simulator**

  The third chapter introduces the architecture used in order to make possible the implementation of the agent-based simulator, as well as the features it has available to the user.

- **Chapter 4 – Simulator design**

  This chapter presents the technology used when implementing this system and the input data, as well as the physical models that have been used.

- **Chapter 5 – Results and analysis**

  The fifth chapter introduces a case study where the different results given by the simulator (with and without the optimization algorithms) are compared.

- **Chapter 6 – Conclusion**

  Here a general synthesis will be made regarding the presented thesis and the correspondent contribution to the scientific community. In the end of this chapter it is also presented the future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Bottom-up and top-down approaches

In order to develop an energy estimation tool one of the following approaches shall be considered: a "bottom-up" or a "top-down" approach. A top-down approach relies on the estimates of total residential sector energy consumption to attribute the energy consumption to characteristics of the entire housing sector and it is commonly used to express the inter-relationship between the energy sector and the economy in general. Therefore, this methodology is able to acknowledge the effect on energy consumption due to ongoing long-term changes or transactions within the residential sector, primarily for the purpose of determining supply requirements. For that purpose variables such as macroeconomic indicators (e.g. gross domestic product (GDP), employment rates and price index), climatic conditions, estimates of appliance ownership and house construction or demolition data are commonly used to estimate the energy consumption [6]. Since it relies on macroeconomic trends and historical data, this approach often lack in details regarding the energy consumption of end-users, which eliminates the ability of identifying the individual contribution of single devices on the energy consumption of a residential building. Additionally it is difficult to identify areas of improvement and harder the job of implementing techniques to improve the energy consumption. In conclusion, this approach would not be the more accurate when designing a solution that could help consumers to implement demand response techniques, because it is required a deeper knowledge on the contribution that each device has on the building's energy profile. On the other hand, the bottom-up approach relies on a hierarchy of disaggregated components that can then be extrapolated to represent a city or a bigger region. In this way it is easier to measure the contribution of end-users for the energy profile of a given area and it is also possible for consumers to acknowledge the influence that each device has on the energy profile of their homes. Often the energy estimates depend on factors, such as the characteristics of the building (e.g. geometry, insulation materials), appliances, occupancy, climate and billing data. As a consequence, these models are seen as a way to evaluate the most cost-effective options to achieve given carbon dioxide targets and to identify areas of improvement. However, this approach makes use of much more data than the top-down models and the energy estimates can be more complex [2]. Since the presented work as the goal of providing consumers with a tool to estimate the energy consumed/generated at their homes, a bottom-up approach provides more accurate information and helps the user implementing techniques of demand response. Therefore, the simulator presented in this document relies on a bottom-up approach.

2.2 Bottom-up models

In order to implement a bottom-up approach there are two main distinct methods that can be used to estimate energy consumption:

1. Statistical methods (SM);

2. Engineering methods (EM).

These models are capable of estimating the contribution of each device towards the aggregate energy balance of a residential building using different data inputs and methods.

The SM are based on historical consumption data, such as billing information, which is then used to regress the energy consumed as a function of a house's characteristics. Even though this method can be used to model residential energy consumption, it does not take into consideration physical characteristics of the building, such as geometry, the insulation materials used and thermodynamic principles (e.g. heat transfer) and it is not capable of providing information regarding the energy generated by domestic renewable energy generators, such as wind turbines and photovoltaic panels. For that purpose other techniques, such as EM must be considered. However, SM are able to discern the effect of occupant behavior, which has been found to vary widely [6].

EM are based on physical characteristics, such as building's geometry, insulation, thermodynamics and heat transfer analysis. Therefore, they are able to estimate energy demand/on-site generation without any historical energy information, which makes possible to adapt each estimate to a certain household. As a result, this method is more flexible than SM since it makes it easier to model new devices in which there is very little or no historical consumption data. However, this model cannot provide information regarding occupancy. Each one of the presented models, SM and EM can use different methods to estimate the energy consumption and on-site generation. Figure 2.1 presents the most well documented methods that are commonly used [6].

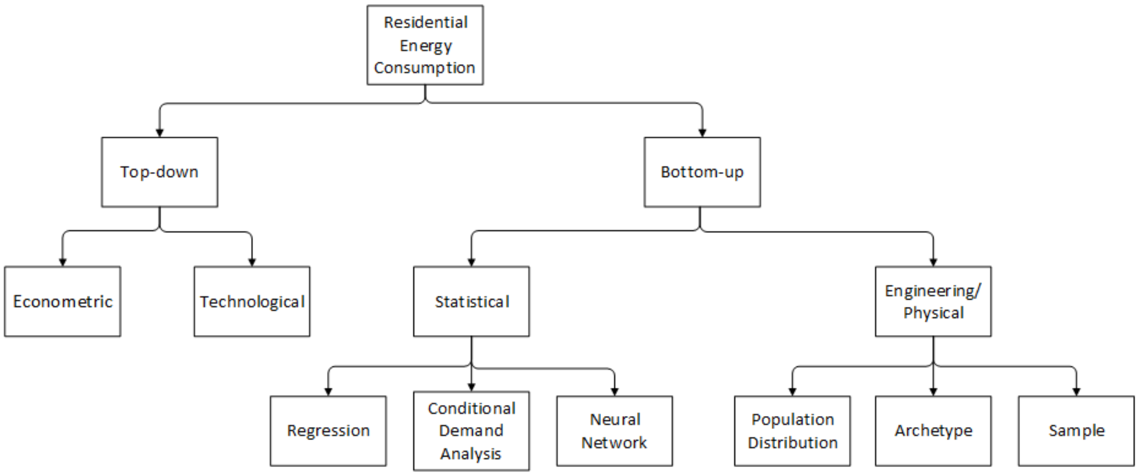


Figure 2.1: Possible modeling techniques to estimate the residential energy consumption. Adapted from [6].

2.2.1 Statistical methods

Statistical methods rely on information, such as energy bills, weather records and energy price to make it possible to estimate the energy consumption as a function of house characteristics. So it is possible to relate the collected information with a particular residential building in which the energy balance is intended to be estimated. Moreover, based on the collected information these methods are also capable of estimating the building's occupant behavior. Bellow, there will be presented three of the best well-documented methods.

2.2.1.1 Regression

This method uses regression analysis to estimate the aggregate energy consumption of the building as a function of some parameters that can affect the energy consumption. The model is evaluated on goodness of fit using the correlation coefficient. Regression analysis can be used both for estimating the use of appliances and to estimate the correlation between energy consumption and other factors (e.g. socio-economical). Therefore, through the years a variety of authors have done studies that not only estimate the energy consumption of a household but also estimate the impact of climate, demographics and energy price (Fung et. al [7]) to detect opportunities for energy improvement (Raffio et al. [8]) or to better understand the relationship between them and the energy consumption (Chen et al. [9]).

By using multivariate regression analysis, Chen et al. [9] have performed correlation analysis among household variables and energy consumption. Moreover, they have also explored the effect that socio-economic and behavioral variables have on residential energy consumption in China. To do so, data from 642 households has been collected through the winter and from 838 households through the summer. With this study the authors were able to measure the impact that each factor has on the energy consumption, which is mainly influenced by socio-economic patterns (up to 28.8%), income (18%) and floor area (44%).

Min et al. [10] have used a regression-based statistical analysis for modeling residential energy consumption in the United States (US). For that purpose, data collected from the US Energy Information Administration on the Residential Energy Consumption Survey have been used. By using an ordinary least square method it was possible to find linear and log-linear models for estimating the energy consumption of space heating/cooling, water heating and other appliances. The proposed models have been tested using data from the U.S. Census 2000 and the correlation coefficients for linear/log-linear models were the following 0.594/0.825 (heating), 0.490/0.703 (cooling), 0.295/0.343 (water heating) and 0.409/0.518 (other appliances).

However, in both above mentioned studies authors claimed the need for more data in order to better estimate the power consumed by each appliance. For instance, Chen et al. were not able to isolate the heating/cooling energy consumption from other end-uses. Min et al. have stated that the major limitation was the fact that it was not possible to access a dataset with the tracks of monthly energy end uses.

2.2.1.2 Conditional demand analysis

Conditional demand analysis (CDA) performs regression based on the presence of end-use appliances, by regressing total energy consumption onto the list of owned appliances. One of the biggest advantages of this method is that it only needs information from the user regarding the respective appliances and the energy billing data. On the down side, it requires a huge amount of data from different houses in order to produce reliable results, since it relies on the differences in ownership to determine each appliance's component of the total dwelling consumption. According to [6] conditional demand analysis was pioneered by Parti and Parti on a study made in 1980 [11]. In that study information from more than 5000 households in San Diego including appliances, occupancy and the billing data was collected. Based on that information Parti and Parti were able to propose a conditional demand regression that considers appliance ownership and the interrelation between those and the building's characteristics (e.g. floor area) and demographic factors, as shown in Table 2.1.

During the development of this study, authors have specified some conditions in order to limit the use of certain appliances with the intent of determining the regression coefficient. As a consequence, some appliances, such as the air conditioning (AC) and space heating have been disallowed during the periods November - March (for the cooling air conditioning) and July – August (in the case of space heating). The authors have also identified that some appliances have more impact on the energy consumption. For instance: the air conditioning, space heating, water heating, dishwasher, cooking range, dryer, refrigerators and freezers play a big role in the load profile of the residential sector. To evaluate the goodness of fitness of this model, the correlation coefficient has been calculated, which has resulted in values ranging from 0.58 to 0.65.

Table 2.1: Interrelation between appliances and the building's characteristics [11].

Appliances and equipment	**Interaction variables**				
	Number of occupants	Electricity price	Household income	Floor area	Heating/cooling per unit area
Common appliances	✓	✓	✓		
Refrigerator	✓				
Hot water	✓	✓	✓		
Space heating and cooling		✓	✓	✓	✓

When comparing this method to EM the authors have realized that the presented model is capable of estimating occupant behavior more accurately than the estimates made by the EM, which uses theoretical considerations. Moreover, through this study, the authors have also stated that the use of CDA is beneficial when disaggregating the energy consumption by end-use without sub-metering and the inclusion of behavioral aspects within the coefficients.

Therefore, it is possible to conclude that CDA methods do offer a certain level of detail, which allows not only to estimate the energy consumption of an end-user but also to relate economic and demographic factors with the energy use. However, due to the lack of information regarding the use of new devices it is not capable of modeling more recent technologies, such as solar and wind based generation devices.

Since then, researchers have tried to make improvements so that estimations would be more accurate. Some authors have raised the number of samples; for instance LaFrance and Perron [12] have increased the amount of samples to 100000 homes over the period of 3 years. This increase has resulted in a correlation coefficient value ranging between 0.55 and 0.70. Moreover, they were also capable of identifying strong relationships between incentive activities and appliance penetration. However, the authors weren't able to separate the energy consumed for refrigeration from that consumed by small appliances, due to lack of information regarding the technical characteristics of the devices used in each home.

2.2.1.3 Neural network

Similar to the other regression methods the neural network (NN) has as main goal estimate the energy consumption based on a data sample. This method is a non-linear computing system consisting of a large number of interconnected processing units (neurons), which simulate the human brain's learning process. Contrarily to the other statistical methods previously presented, this one is self-adaptive, which means it learns from examples and captures functional relationships among the data. Therefore, it does not need as much information in the beginning and can be easily adaptable to the addition of new information. According to [13] the use of NN to model the energy consumption of a building has started in the 1990s, beginning with commercial buildings and progressing in complexity.

It has been reported by Krarti et al. [14] that Kreider [15] were the first to apply a NN model to predict the energy consumption of a building, in 1991. This model was built in order to estimate the electricity consumption of a commercial building and the results showed that the predictions of the NN model were accurate. The authors indicated that NN were easier to use than classical regression methods since it learns from fact patterns and there was no requirement for an a priori statistical analysis.

However, the use of NN based methods to model residential energy have been historically limited, possibly due to the computational and data requirements or the lack of physical significance of the coefficients relating dwelling characteristics to total energy consumption [6]. On the other hand, they are highly suitable for determining relationships amongst a large number of parameters. Therefore, and because of their simplicity, accuracy and ability to model nonlinear processes (e.g. energy building loads) NN are used for prediction problems as a substitute for other statistical approaches for estimating national end-use energy consumption and the impact of socio-economic factors in the residential sector. But, when compared to other SM, NN are not flexible evaluating the impact of energy conservation measures [15]. Mihalakakou et al. [16] have created an energy model for a residential building in Greece in which they have used a feedforward backpropagation NN. The developed model considers the atmospheric conditions, including air temperature and solar radiation. This model has been trained using information regarding energy consumption data that has been collected for the period of five years. Final results were excellent on hourly basis, due to the amount of data used to calibrate the model. The correlation coefficients vary from 0.96 to 0.94, depending on the tested month. Therefore, it is possible to consider that the presented approach can be used to simulate and estimate the energy consumption time series with sufficient accuracy. However, it is not always possible to predict future values of ambient air temperature and total solar radiation. As a consequence, authors have concentrated the estimations in summer months since during this period the Mediterranean has a more predictable weather.

2.2.1.4 Richardson's model

When designing the simulator it has been adopted a model to generate the data that was not possible to express by using EM, such as occupancy and human habits related with energy consumption. In [5] it is presented a model developed by Richardson et al. that generates synthetic active occupancy data and appliance usage data (including mean power consumption and working period) with a 1min time resolution for a 24-h period, based upon survey data on how people spend their time at home in the United Kingdom (UK) [17] and nationwide ownership statistics. The survey data has been made by using many thousands of 1-day diaries recorded at a 10-min resolution.

By integrating the UK statistics with a first order Markov-Chain technique authors were able to make a model that generates synthetic demand data that is only dependent on the tasks performed previously by the user together with the probabilities of the user performing a different task. These probabilities are calculated considering the number of active occupants (inhabitants that are at home and awake), month of the year, type of day (weekend day or week day), the time of the day and meteorological conditions. Therefore, in order to better adjust the simulation to a certain dwelling the user must provide information regarding the number of inhabitants and month, as well as type of the day. Moreover, it considers the sharing of appliances, such as lighting. For example, doubling the number of active occupants in a house is unlikely to double the lighting demand, since occupants will share lighting in common rooms. Although this fact might be true, the model considers that sharing is dependent on the number of active occupants in a house at a given time but also on the appliance type in question. In the case of lightning this model not only considers the human habits and occupancy but also the level of solar radiation, which means that as the solar radiation decreases the lights tend to be switched on (unless there is not any active occupant).

When generating the data the start state is chosen by picking a random number of active occupants from a probability distribution (according to the number of inhabitants set by the user). Subsequent states in the chain are determined by picking a random number for each time step and using this with the appropriate transition probability matrix (given the type of day and the total number of residents in the house). Therefore, each run of this model is different because of the random numbers used in the stochastic generation but all runs are based on the same transition probability matrices and thus exhibit similar characteristics. To validate this model, the authors have recorded data from 22 dwellings around the town of Loughborough (UK) with a time resolution of 1min, in 2008. After comparing both the synthetic and the recorded data it has been found that results were very similar.

2.2.2 Engineering methods

EM are based on physical characteristics, such as building's geometry, insulation materials, thermodynamics and heat transfer analysis. Methods that can be used in order to estimate energy consumption and on-site generation of renewable energy generators are presented below.

2.2.2.1 Distribution

The distribution method uses the distribution of device ownership and use with common appliance ratings and, in some cases, historic data to calculate the energy consumption of each end-use. Since end-uses are usually calculated separately, it does not consider the interaction between appliances. After calculating the energy consumption of each appliance it is possible to aggregate those consumptions in order to estimate the residential energy consumption of a bigger region (e.g. city, country). Despite the fact that this method relies on national balance of appliance penetration and might use historical information, it can be considered a bottom-up approach due to its level of disaggregation, as the number of houses and appliance distributions are known. The distribution method has been used in order to model the energy consumption of the residential sector in a variety of countries, such as Italy (Capaso et al. [18]), Canada (Jaccard and Baille [19]), Malaysia (Saidur et al. [20]).

The study made by Capaso et al. has allowed modeling the residential sector based on distributions, which have been determined by using surveys. This data allowed to combine demographic and lifestyle information with engineering models of a wide range of appliances. The developed model was then applied to that region and compared with load recordings.

Saidur et al. created a residential energy model to represent the energy consumption in Malaysia. The presented model is designed based on the distribution estimates of appliances' ownership made by different researchers, as well as appliances' power rate and efficiency and appliance use. Due to the Malaysia's climate, space heating equipment does not need to be considered. The national energy estimate was then calculated by summing the energy of each device. With this model they were also able to measure the overall efficiency of appliances, which was 70%.

2.2.2.2 Sample

Sample methods make use of real house samples, which makes it more accurate when it comes to model a region's energy consumption since it can realistically reflect the high degree of variety found in actual housing stock, but on the other hand, there is more data to be processed.

Larsen and Nesbakken [21] developed a model of the Norway's housing stock using information collected from 2013 dwellings. By doing so, they were able to account for every end-use. When compared to CDA, it has been pointed out as a main advantage the fact that this method is more accurate in considering the impact of new technologies. Griffith and Crawley [22] have done a similar study using 5430 buildings, however in both studies the authors have stated that one of the disadvantages of this method was the amount of input data, which requires a significant computing capability.

2.2.2.3 Archetypes

The archetypes are considered to be a restricted number of residential buildings which together represent the different classes of houses found in the residential sector. To generate these archetypes certain characteristics must be considered, such as geometry, thermal characteristics and operating parameters. Although, this methods can be more accurate than statistical ones when estimating the energy consumption of each device, its lack of information regarding occupancy can lead to misleading estimations [2].

Shimoda et al. [23] developed a residential end-use energy consumption model on the city scale for Osaka, Japan. They developed 20 dwelling types and 23 occupant types to represent the variety of houses within the city. For each type of building conductive heat transfer analysis were considered when modeling. However, it has been considered that insulation materials were identical to the materials available in 1997. The occupants' model types were developed based on the number of family members, appliance ownership levels and appliance ratings.

MacGregor et al. [24] developed a residential model using a total of 27 archetypes. In order to estimate the energy consumption of each archetype, they used typical values of occupancy, appliances and lightning to run an hourly analysis program. Energy consumption values were then extrapolated to provincial levels based on the total number of dwellings represented by each archetype. Final results were then compared to top-down estimates and were found to be in agreement.

During the analysis of these two studies it was possible to identify that the use of archetypes has some advantages when compared to other EM. For instance, when compared to the distribution method, this model allows capturing the interconnectivity between appliances and end-uses. Secondly, when compared to the sample method archetypes reduce the simulation time, since the number of archetypes is limited. However, this method provides a more limited representation of the housing sector and, similar to the other EM, it requires the assumption of occupancy values.

2.2.3 Hybrid models

Hybrid models are a combination of both engineering and statistical methods and can use any of the different methods of each model. This approach makes possible to correlate the data that is better estimated by each one of those methods, as shown in the examples mentioned next. For instance, it is possible to improve the information provided when using EM by adding information regarding the building's occupancy, which can only be estimated using SM otherwise a constant value would have to be assumed.

The Canadian Hybrid Residential End-use Energy and Emission Model (CHREM) is based on two modeling components, statistical and physical that are used to make estimates on the energy consumption of the major end-use groups: domestic appliances and lightning, domestic hot water and space heating/cooling. The statistical part of the model is employed by using NN to estimate the annual energy consumption for appliances, lightning and domestic hot water, since these devices are predominantly influenced by occupant behavior. On the other hand, estimates on space heating/cooling are made possible through the use of a building performance simulation package, which makes possible to consider the use of new technologies [25].

Another hybrid model, developed by Caves et al. [26], integrates CDA with EM estimates. In this study, the authors have treated the information from the engineering approach as prior evidence on usage patterns for specific appliances, and by using Bayesian analysis, engineering estimates were integrated into CDA model to estimate hourly appliance consumption. The sample data contained daily electric consumption information (excluding weekends) and appliance ownership information from 129 households that had been collected for two summer months in 1977, in Los Angeles. The engineering estimates were generated from a simulation program and include estimates of occupant behavior. This simulation program includes twelve scenarios, which represented three types of buildings (single family detached, single family attached and multifamily), two weather districts, and two building sizes. Average loads for each of these appliances of the sample data were constructed using a weighted average of the twelve scenarios, where the weights reflected the housing type and size characteristics of the sample, and the distribution of the sample households between the weather districts. For central air conditioning, both methods provided similar estimates, but for dishwasher the estimates differed considerably, since dishwasher consumption was more dependent on consumer behavior, which is more difficult to predict using EM.

In this thesis an agent-based simulator based on a hybrid bottom-up approach, combines a synthetic data generator (to represent statistical methods) with engineering methods. The fact that the presented work is not a model itself, but a simulator that allows the users to estimate the energy demand and on-site generation of their homes, makes it a more extensible and operable tool for the end-user. The synthetic data generator that has been used was designed by Richardson et al. [5] and provides information regarding occupancy and power consumption of each electrical device, including lightning, which are more dependent on the user interaction. EM were considered to model the physical behavior of some devices, i.e. the electric water heater, air-conditioning, refrigerator, photovoltaic panel and wind turbine.

CHAPTER 3

MODELING THE SIMULATOR

This chapter presents the modeling techniques used to provide to the user estimates regarding the demand and on-site generation of its residential building. Apart from these estimates, the developed simulator should also feature the following characteristics: add/remove devices in real time (during the simulation period), adjust each simulation to the user's necessities and suggest ways of maximizing the use of the energy produced on site and reduce the cost of the energy imported from the grid.

To accommodate these specifications this simulator has been made using an agent-based modular architecture, allowing therefore the user to change the simulation's conditions in real time and making possible the exchange of information between the different devices. Moreover, it allows the integration of different data sources, such as meteorological data and energy prices. To module the behavior of each device it has been used either, thermal/electric models or Richardson's model, depending on the device. At last, this simulator uses genetic algorithms to provide suggestions on load optimization. The user interaction as been made possible through the use of a graphical interface that enables the user to adjust each simulation and beware of the estimates made, which are displayed through the use of charts.

3.1 Functional model

As mentioned in section 3, the designed simulator has available features that make possible to the user to access information regarding estimates of the energy demand/on-site generation of its residential building, all of which are summarized in Figure 3.1.

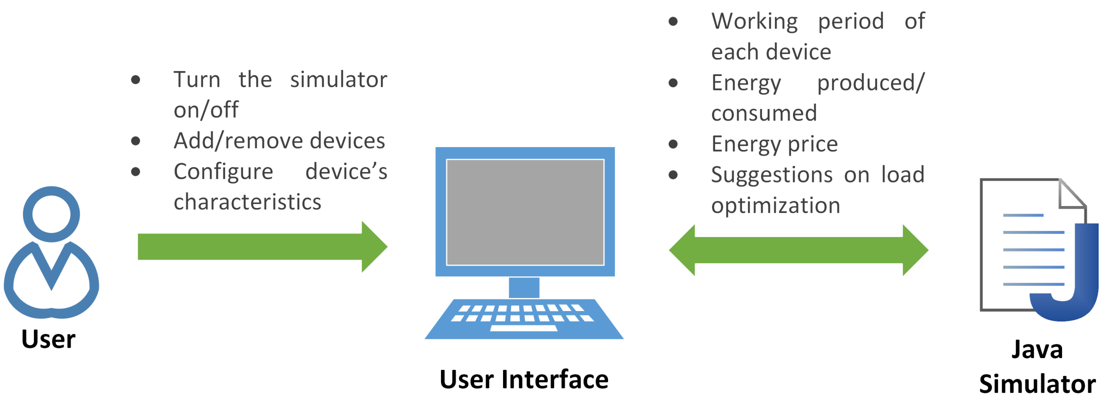


Figure 3.1: Features the simulator has available to the user.

After initiating the simulation process the user has the ability of adding/removing any device, as well as configuring any of them with the intended specifications. It is important to mention that any of these changes to the device's characteristics can be made in real time, during the simulation process. Despite the fact that the simulation represents a 24-h period, it is possible for the user to adjust the time scale in order to make the simulation run at the desired speed. For instance, the user can set that 1min in the simulation represents 0.3 s in the real world, which means that the 24-h period will take 7 min and 12 seconds to be simulated.

On the output, this simulator provides information about the energy consumption/-generation, including the working period and the energy produced/consumed by each device, as well as the total energy balance of the home. Moreover, information regarding the energy cost is provided at the end of the simulation period, as well as suggestions on how to maximize the use of the renewable energy produced in the building and on how to lower the energy cost.

3.2 Architecture

In order to implement the features presented in section 3.1 an architecture containing five major entities has been designed. Each one of them is composed of at least one module that is responsible for implementing the functionalities of the entity it is associated with. Moreover, it is also important to assure the interoperability between modules, to enable the exchange of information among entities. Figure 3.2 represents these entities, as well as the data flux (symbolized by the arrows).

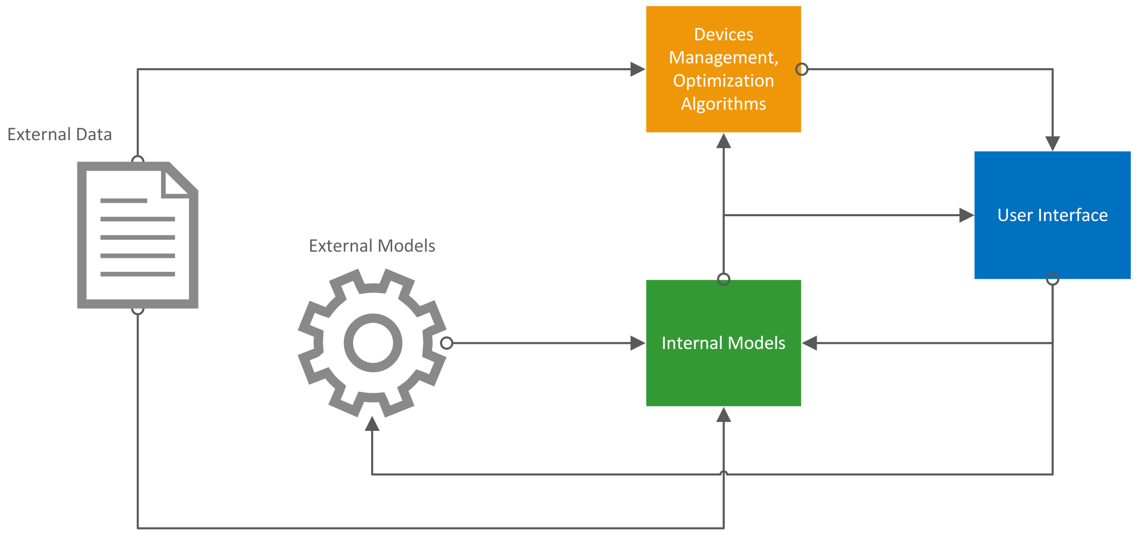


Figure 3.2: System's architecture.

The "External Data" entity is composed by two modules, including the Microsoft Excel work book with the meteorological data and another one with the energy prices (as shown in Figure 3.3). Meteorological data is important not only to estimate the power generated by the renewable energy generators (photovoltaic panel and wind turbine) but also to estimate the power consumption of the thermostat-controlled appliances (e.g. refrigerator). Therefore, it is important to make this information available to the entities in which it is estimated the power consumed/produced by each device. The energy price is used to estimate the cost of each simulation.

"External Models" incorporates the Richardson's model, which is responsible for providing estimates of the occupancy schedules and the power consumed by the event-driven appliances (household appliances that are only dependent on the human interaction to change their status, e.g. washing machine). Since these estimates depend on information provided by the user, it should receive data from the "User Interface" and send the estimates made to the "Internal Models" entity so they can be interpreted.

The "Internal Models" entity is composed of three kinds of modules representing the different types of devices that integrate this simulator; energy generation devices (e.g. photovoltaic panel), event-driven appliances and thermostat-controlled appliances (household appliances that are dependent on a thermostat to change their status, e.g. refrigerator). This last group is then composed by two other modules; one representing the thermal component and another one representing the electrical component of a given device (as presented in Figure 3.3). In this entity, estimates on the power consumed by the thermostat-controlled appliances and on the power produced on-site are made and are incorporated with the estimates made in the "External Models" for the event-driven appliances. Due to the fact that it is possible to change the specifications of the devices added to each simulation it is important that this entity is connected to the "User Interface" to receive the data set by the user.

"User Interface" entity is composed of just one module capable of providing the user a way of adjusting the simulation to the respective needs. Thus, it is possible to provide a good level of abstraction so that a deep knowledge on the devices is not required when setting up a new simulation. On the output, the user interface displays charts with the variation of power consumption and on-site generation, as well as the temperature variance of the thermostat-controlled appliances, the estimated occupancy schedules and the total cost of the energy consumed from the grid.

All of the information, regarding energy demand/on-site generation is then saved on the entity named "Devices Management, Optimization Algorithms", which is also responsible for calculating the energy cost of each simulation and provide suggestions on load optimization, so it would be possible to maximize the use of the energy produced on site and lower the energy bill.

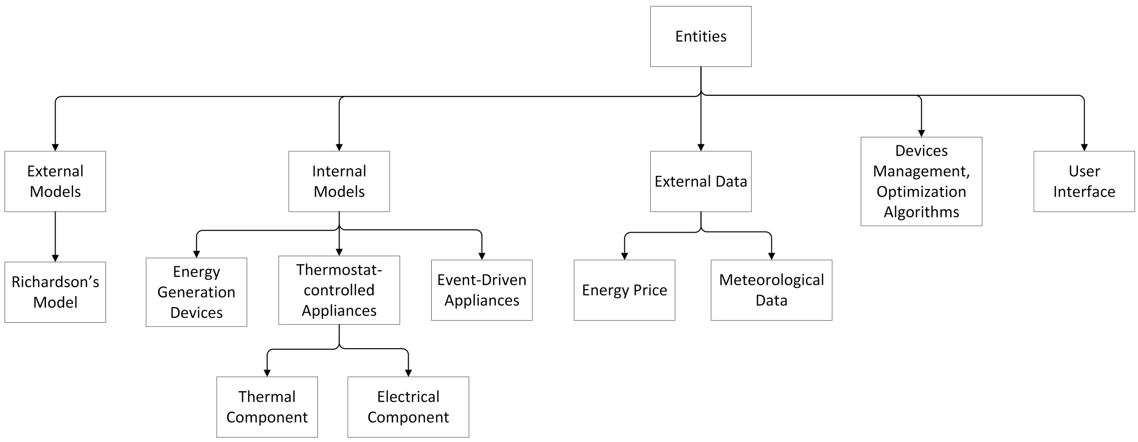


Figure 3.3: Modules that integrate the different entities.

To make possible the implementation of the system presented in Figure 3.2 and the interaction between the different modules in Figure 3.3 this simulator has been designed using an agent-based modular architecture. This approach not only allows the creation of various independent modules (agents) but it also makes their interaction possible through the exchange of messages. Therefore, modularity offers some characteristics that this simulator can benefit from. For instance, it is possible to divide the data that needs to be processed among the existing modules, it is easily scalable (more agents can be add without compromising the existing architecture) and it is adaptable to changes. This makes possible to separate the various algorithms that estimate the behavior of the devices, making a certain agent responsible for estimating the behavior of just one device. Even though the algorithms are separated, it is possible for one device to react to another one change in behavior through the messages exchanged. Moreover, due to the fact that each module is independent from the others it is possible, during the simulation process, to add/remove devices in real time without compromising the rest of the estimates that are being made for other devices. It is also possible to add various instances of the same device enabling, for example, to have more than one television or air-conditioning.

3.3 Optimization algorithms

Optimization algorithms were added to the system so it would be possible to provide suggestions to the user on how to maximize the use of the energy produced on site and lower the energy cost, by rescheduling the use of certain appliances. For this purpose genetic algorithms (GA) were implemented due to the fact they can handle complicated optimization problems with nonlinear, discrete and constrained search spaces [27], providing good solutions using few computational resources.

GA provide a method of solving optimization problems by imitating the evolutionary process based on the mechanics of Darwin's natural selection. To the group of existing individuals it is given the name of "population" (i.e. possible solutions). As in the evolution of organisms, each individual's information is described by sign rows called "chromosomes". Each of these chromosomes has then a number of "genes" containing a possible solution, as shown in Figure 3.4. It is important to mention that different chromosomes can have equal genes in their constitution.

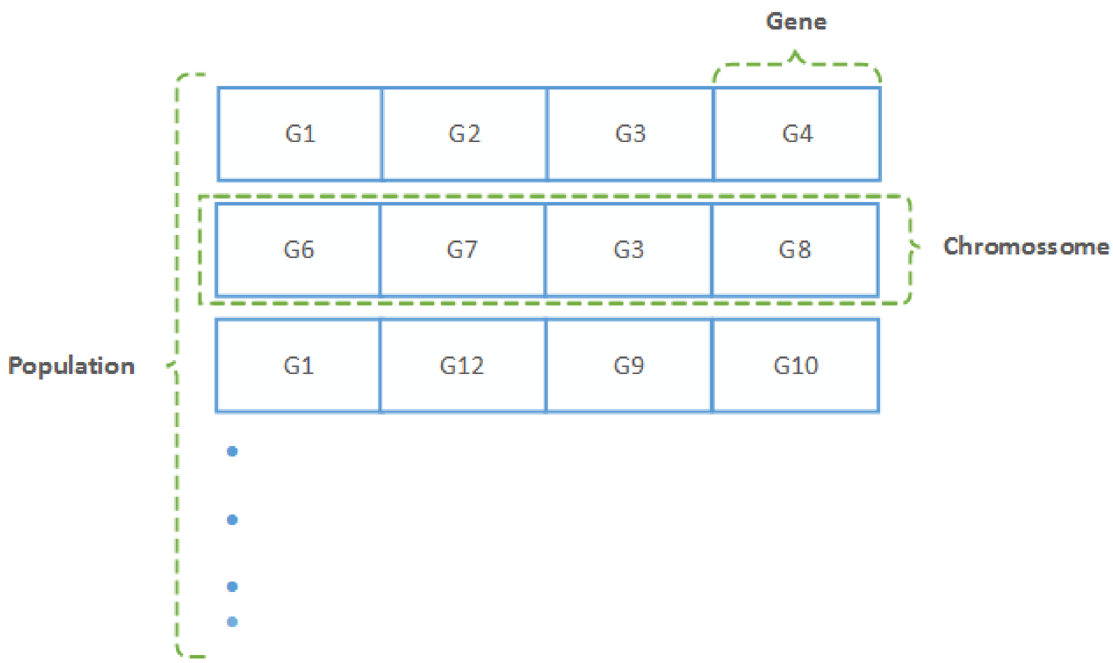


Figure 3.4: Illustration of the constitution of a GA's population.

Genetic algorithms perform genetic operations similar to the ones in the evolutionary process such as selection, crossover, and mutations to each individual within the population and the subsequent fitness (objective function) of each individual is calculated for evaluation. The individual with the highest fitness value of all the enquired individuals becomes the optimum individual. However, because the size of the population and the number of possible generations is restricted the final solution presented by the algorithm might not be the optimal solution, since that restriction comprises the capability of evaluating all the possible cases.

3.3.1 Energy consumption optimization

The optimization of the energy consumption has been built so that the user can maximize the use of the renewable energy produced in the building. Consequently, by using this algorithm it is possible to know how to shift the working period of the controllable appliances to the times where there is more energy available. To make it possible, this algorithm must find a solution that reduces as much as possible the difference between the power generated and consumed in every minute of the 24-h period, as it is expressed in equation (3.1).

$$Min \left\{ \sum_{t=0}^{N} |P_{prod}(t) - P_{cons}(t)| \right\} \tag{3.1}$$

In (3.1), N is the number of minutes of a day, 1440 min. P_{prod} and P_{cons} are the produced and consumed power, respectively, at time t. To implement this fitness function, information regarding the working period and power demand/on-site generation of each device must be known.

3.3.2 Energy cost optimization

The optimization of the energy cost has been built so that the user could not only maximize the use of the renewable energy produced in the building but also reduce the energy cost. This optimization algorithm is similar to the one in section 3.3.1 but it also considers the price of the energy that needs to be consumed from the grid when the amount of renewable energy available is not enough to satisfy the building's demand. In those cases it suggests shifting the use of controllable appliances to the times the user can save more money, as expressed in equation (3.2).

$$Min \left\{ \sum_{t=0}^{N} C(t) \right\}, \quad \text{where}$$
$$C(t) = \begin{cases} E_{price}(t) * (P_{cons}(t) - P_{prod}(t)), & \text{if} \quad P_{cons}(t) > P_{prod}(t) \\ 0, & \text{if} \quad P_{cons}(t) \leq P_{prod}(t) \end{cases} \tag{3.2}$$

In (3.2), N is the number of minutes of a day, 1440 min. P_{prod} and P_{cons} are the produced and consumed power, respectively, at time t. To implement this fitness function, information regarding the working period and power consumption/ on-site generation of each device must be known, as well as the energy price (E_{price}).

3.3.3 Adaptation of the genetic algorithms to the simulator

For this simulator it has been considered that in order to have the least interference on the user's comfort only the washing machine, washer dryer and the dish washer could be time-shifted. Moreover, it has been assumed that these devices would not work more than once a day, which results in having just three genes per chromosome (each one representing a different controllable appliance). These genes contain information on the time at which each appliance could start working, which can be at any time between $t = 0$ min and $t = 1440 - \Delta_{work}$ (where Δ_{work} is the working period of the device).

When running the optimization algorithms mentioned in section 3.3.1 and 3.3.2 an initial population is randomly constituted by generating a hundred individuals each one containing three genes, representing the number of controllable appliances that can be shifted (washing machine, washer dryer and dishwasher). After setting the initial population, the fitness value of each individual is calculated using either equation (3.2) or (3.1) (depending on the type of optimization that it is being performed). The individual with the best fitness is kept to the next generation and a new population is created using cross over or mutation processes. Figure 3.5 presents the flowchart that describes the functioning of both optimization algorithms (section 3.3.1 and 3.3.2). Since it has been established that the number of possible generations was a hundred the selection process presented in the flowchart is repeated several times, at the end of which is presented the best found solution.

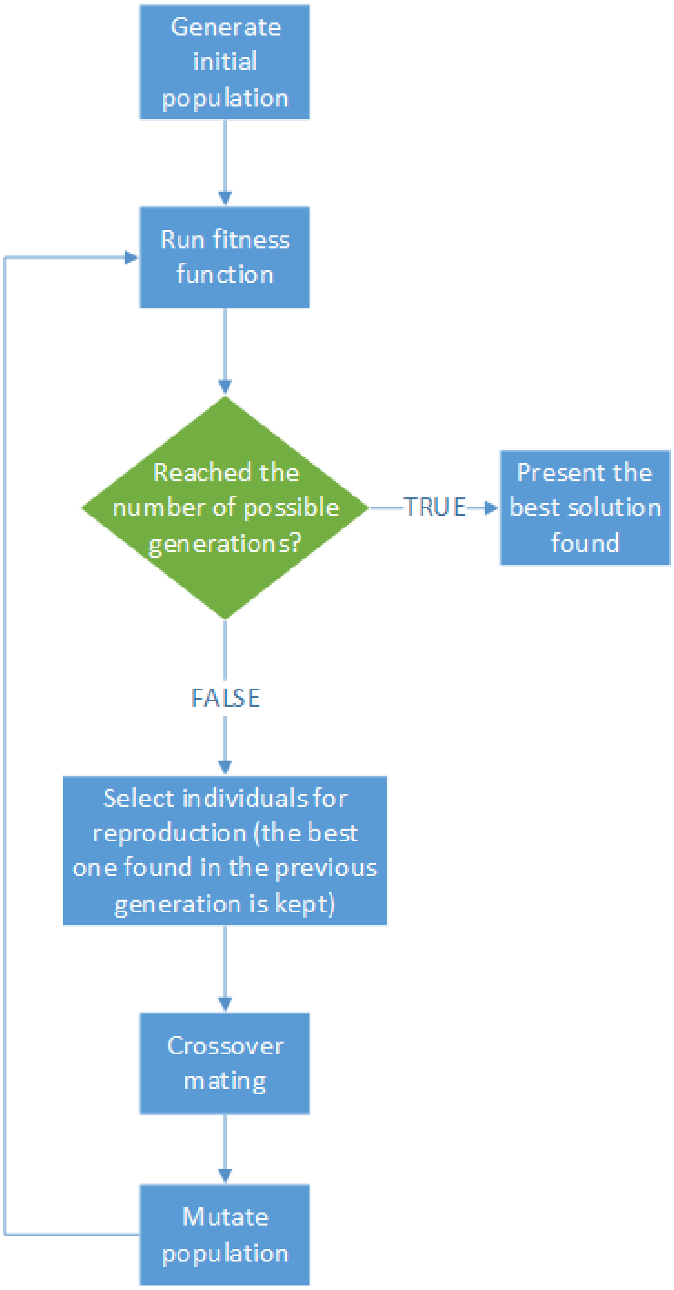


Figure 3.5: Flowchart of the GA's operation.

CHAPTER 4

IMPLEMENTING THE SIMULATOR

4.1 Technology used

In order to implement an agent-based modular architecture, the Java Agent DEvelopment Framework (JADE) has been used and the communication between agents was made possible thanks to Foundation for Intelligent Physical Agents Communication Language (FIPA-ACL). As a consequence, the majority of the simulator was designed in Java, using NetBeans Integrated Development Environment (IDE). This IDE has been selected due to the fact that it is open-source, supports Java and provides tools that allow the design of a user interface.

To integrate the simulator with Richardson's model it has been built a Visual Basic program to run the existing macros in the Microsoft Excel work book. For this purpose Notepad++ has been used. The thermal and electric models presented in section 4.4 were tested before used in this simulator by using Matlab software.

4.2 Detailed architecture

This section aims to provide a more detailed view of the various modules (agents) presented in section 3.2 and their interaction. Figure 4.1 comprehends the different kinds of agents, as well as the content of the exchanged messages (represented by the dashed lines). In this scheme, the agent containing the thermal component of the air conditioning, which in reality corresponds to the thermal model of the residential building, has been represented separately, since it is responsible for providing information regarding the temperature inside the building to the other thermal models. Throughout this chapter, the operating principle of the different kinds of appliances in Figure 4.1 are presented in more detail, as well as how meteorological data, energy prices and the Richardson's model have been integrated with the simulator.

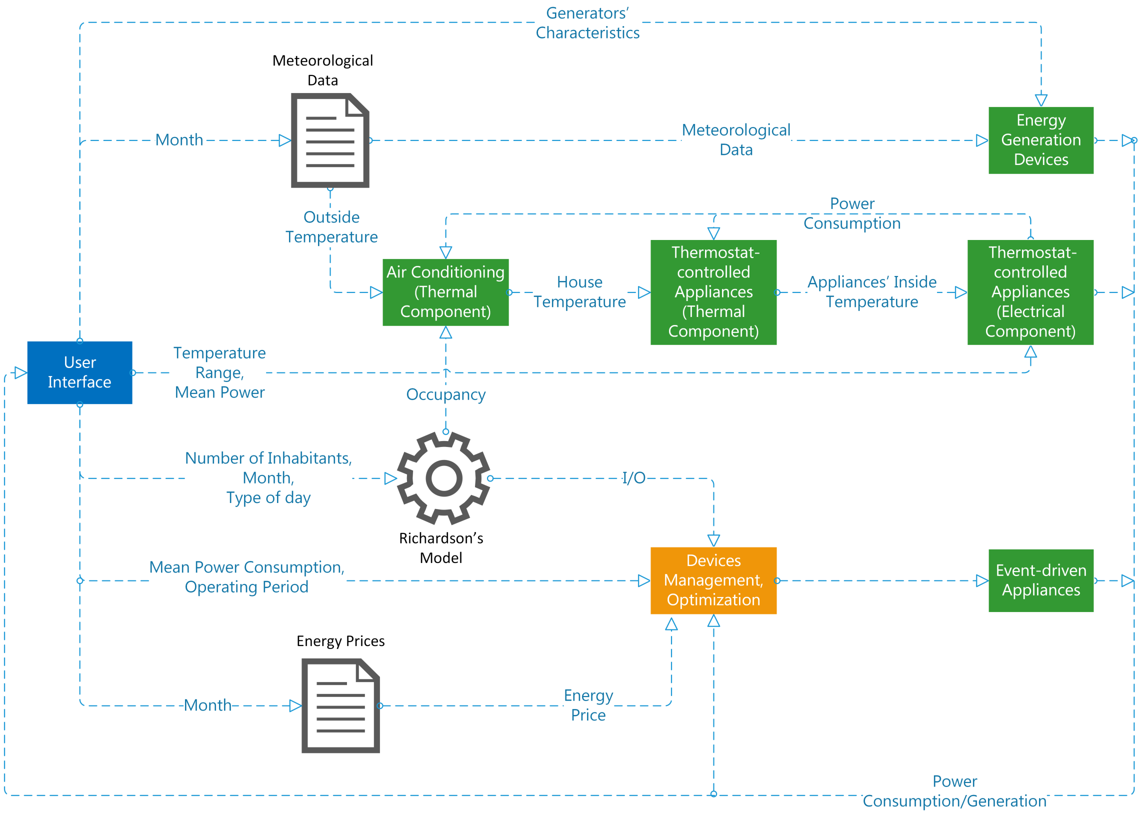


Figure 4.1: Detailed architecture of the simulator.

4.3 Input data

The simulator was designed so that data from different sources could be used. In this specific case, data sources include: meteorological data (saved on a Microsoft Excel document), energy price, Richardson's model and the data provided by the user using the graphical interface. However, due to the modular structure of the simulator this data sources could be replaced. For instance the simulator could collect data directly from a meteorological station instead of using data previously measured and Richardson's model could be replaced by a similar model.

4.3.1 Information set by the user

Through the user interface it is possible to add different types of devices with different specifications. Table 4.1 presents the different devices' types that the simulator has available for the user, as well as the data that must be provided when adding new appliances or energy generators to the simulation.

The appliances listed in Table 4.1 were chosen due to the fact that according to [28], some of the devices that have more impact on the energy demand of the Portuguese residential sector are the refrigerator, washing machine, clothes dryer, dishwasher, lightning, hot water heating, air heating/cooling systems and oven, as shown in Figure 4.2.

Table 4.1: Types of devices the simulator has available.

Type of devices	**Input data**
Photovoltaic panel	Area of the panel
Wind turbine	Diameter of the turbine
Refrigerator	Mean power Temperature range
Water heater	Mean power Temperature range Water flow Temperature of the inlet water
Air conditioning	Mean power Temperature range
Oven and television	Mean power
Washing machine Washer dryer and Dishwasher	Mean power Duration of the washing period

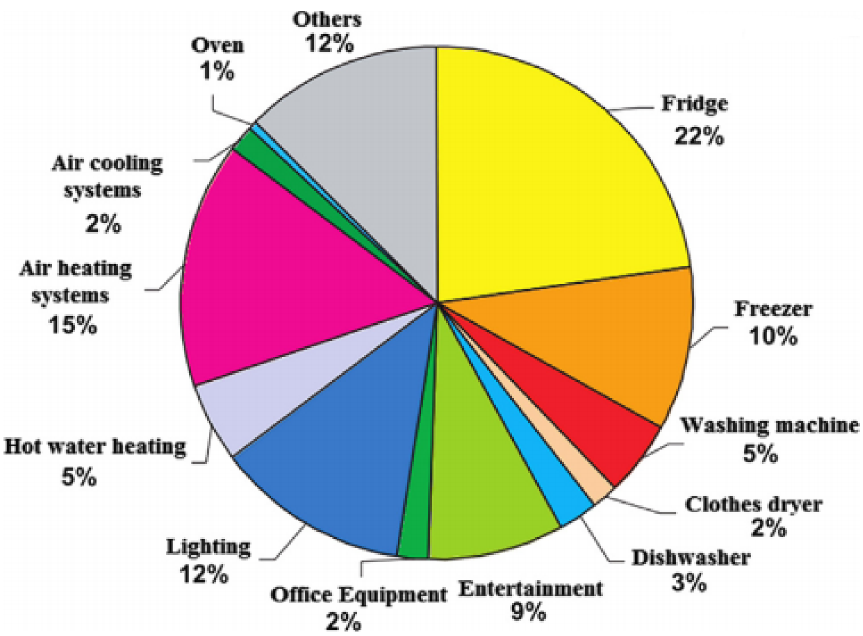


Figure 4.2: Devices that have the most impact on the Portuguese energy demand of the residential sector [28].

However, it is important to mention that because this simulator follows a modular approach, it would have been possible to make different types of devices available to the user without changing the simulator's architecture. Due to this modular architecture, the system also allows the user to add as many instances of the same device with different specifications as needed. Moreover, when setting a new simulation the user is also able to make configurations regarding the number of inhabitants, month of the year, type of day and the simulation speed.

4.3.2 Meteorological data

Due to the fact that electricity consumption and generation in residential households varies significantly depending on seasonality [29], when simulating the behavior of both the thermostat-controlled appliances and the renewable energy generators, the simulator makes use of meteorological data that has been acquired using a meteorological station installed on the Department of Electrical Engineering at New University of Lisbon (38°39'38.2"N 9°12'17.6"W) during a one year period with a time resolution of 1-min. These measurements include the outside temperature, solar radiation and wind speed averaged during a 1-month period to produce a typical day for each of the 12 months considered. As a result, when setting up a new simulation, the user can choose the month of interest.

Since, the meteorological data has been saved on a Microsoft Excel work book a Java agent is used to enable the interaction between the simulator and the data file. Therefore, after the user has set the month of interest (using the user interface) that information is sent to the Java agent so that it can then read the meteorological data of the correspondent month from the Microsoft Excel work book. This interaction is presented in Figure 4.3.

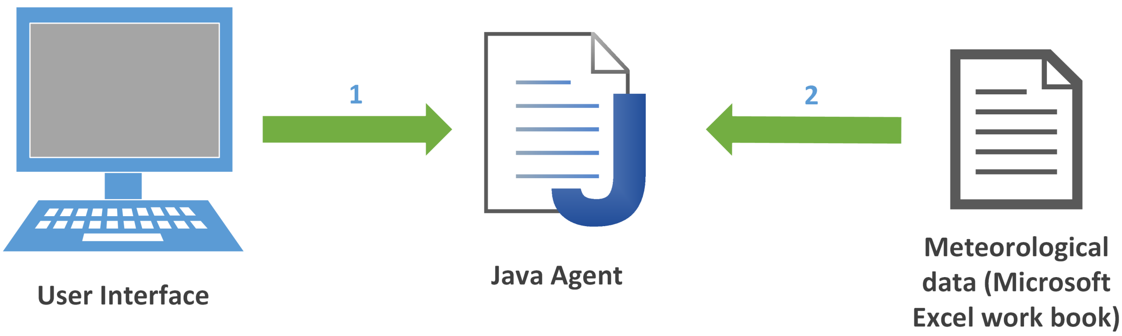


Figure 4.3: Interaction between the meteorological-data's file and the simulator.

4.3.3 Energy price

The total cost of the imported energy, purchased from the electrical grid when the energy produced on-site is not sufficient to satisfy the building's demand, is calculated at the end of each simulation by using the prices of the tri-hourly tariff for a low special tension on a diary cycle of a Portuguese electricity supplier (Energias De Portugal). The energy price within this tariff varies depending on the time of the day and the season of the year, as it is depicted in Figure 4.4 and 4.5.

This information together with the estimation of the energy demand and on-site generation makes possible to introduce more control and flexibility on the demand side (i.e. the user is now aware of the impact that each device has on the load curve and the cost associated with it). Therefore, it is possible for the user to implement demand response techniques, by rescheduling the time at which a specific device operates, in order to reduce the energy cost and maximize the use of renewable energy, as suggested by the optimization algorithms (sections 3.3.1 and 3.3.2).

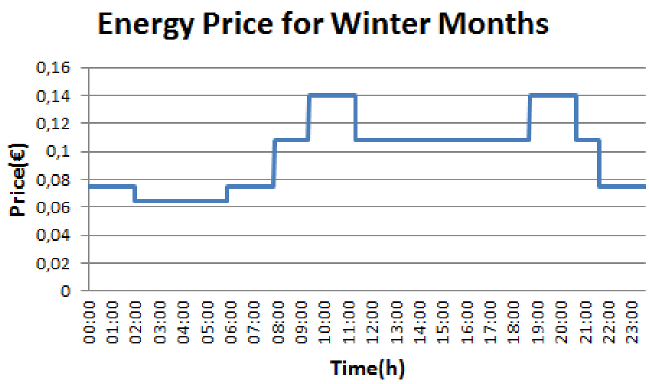


Figure 4.4: Energy prices for winter months (from October to March).

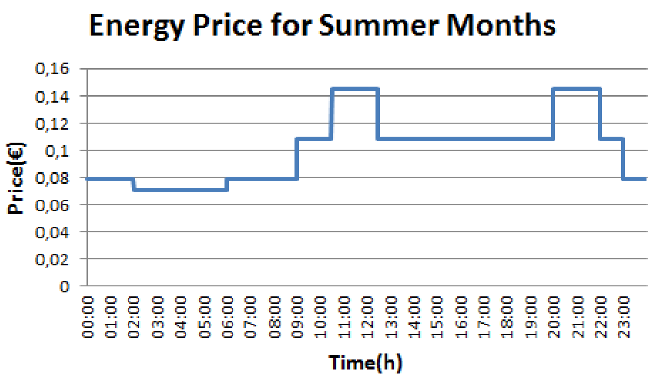


Figure 4.5: Energy prices for summer months (from April to September).

Since, the energy prices have been saved on a Microsoft Excel work book a Java agent is used to make possible the interaction between the simulator and the data file. Therefore, after the user has set the month of interest (using the user interface) that information is sent to the Java agent so that it can then read the energy prices of the correspondent period (winter or summer) from the Microsoft Excel work book. This interaction is presented in Figure 4.6.

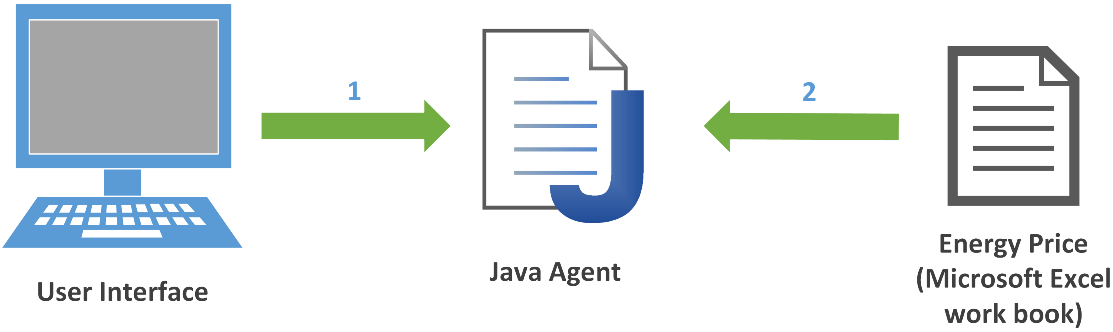


Figure 4.6: Interaction between the energy-price's file and the simulator.

4.4 Used models

The implementation of the EM has been made by using both thermal and electrical models to describe the behavior of the thermostat-controlled appliances and the energy generators, respectively.

4.4.1 Thermal models

4.4.1.1 Building

When studying the thermodynamics of a residential building certain assumptions have been made. For instance, it has been considered that only the outside temperature and the air conditioning are capable of altering the inside temperature of the house. Consequently, the house's thermal mass is limited to the thermal mass of the air. Secondly, in this model the building is viewed as a single space where the circulation effects are neglected and it is assumed that the inside temperature is uniform. The model used to calculate the building's inside temperature (T_{i+1}) is based on the one proposed by [30] and has the mathematical formula shown in (4.1).

$$T_{i+1} = \varepsilon T_i + (1+\varepsilon)\left(T^0 \pm \eta \frac{q_i}{A}\right)(+ : heating, - : cooling) \tag{4.1}$$

In (4.1), T_i is the temperature inside the residential building at the instant t_i. At the instant $t_i = 0$ min the inside temperature is considered to be equal to the value of the outside temperature (for that same time). T^0 varies according to the data in the data base, which has the measured meteorological information. η represents the thermal conversion efficiency when the air conditioning is heating. On the other hand, when cooling it represents the coefficient of performance. And q_i is the power delivered by the air conditioning to the building. Insulation (A), as well as the inertia factor (ϵ) are calculated through the formulas presented in (4.2) and (4.3), respectively.

In equation (4.2), m_c is the average thermal mass, τ is the time interval between t_i and t_{i+1} and A is the insulation which is determined using equation (4.3). In (4.3), S represents the surface area, x is the width of the insulation layer and k is the thermal conductivity of the material used to isolate.

$$\varepsilon = e^{\frac{-\tau A}{mc}} \tag{4.2}$$

$$A = \frac{Sk}{x} \tag{4.3}$$

When starting a new simulation a building with the characteristics presented in Table 4.2 is assumed by default. These characteristics were given as an example, but could have been defined differently.

Table 4.2: Characteristics of the building used in the simulator.

Building's characteristics	
Volume of the building	1247 m^3
Walls' area	320 m^2
Roof's area	601 m^2
Number of windows	6
Windows' size	1(m)x1(m)
Windows' glass thickness	0.015 m
Walls' thickness	0.2 m
Windows' thermal conductivity	0.780 W/(m°C)
Walls' thermal conductivity	0.038 W/(m°C)
Roof's thermal conductivity	0.038 W/(m°C)

Before implementing the model described in (4.1) in the simulator it has been tested using Matlab software. For that purpose a script has been built to represent the thermal behavior of the building. This script considers the characteristics presented in Table 4.2. However, it has been considered a constant outside temperature of 15 °C and a mean power of 3.5kW for the air conditioning. Moreover, it has been set that the temperature inside the building should not exceed the 23 °C nor be lower than 18 °C. The results obtained are presented below in Figure 4.7, where it is possible so see the variation of the temperature inside the building according to the air conditioning status (on or off).

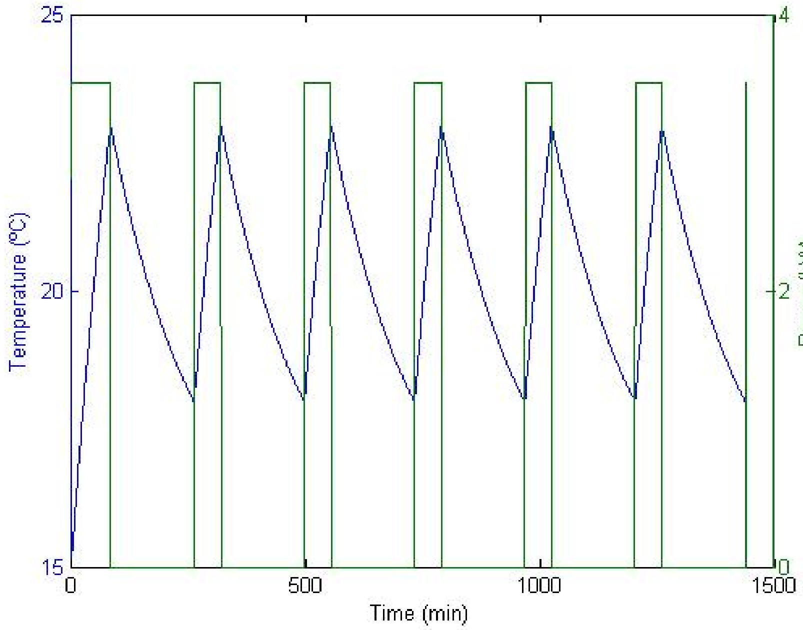


Figure 4.7: Variation of the temperature inside the house with the status of the air conditioning.

4.4.1.2 Refrigerator

The model used to calculate the refrigerator's inner temperature (T_{i+1}) is based on the one proposed by [31] and has the mathematical formula shown in (4.4):

$$T_{i+1} = \varepsilon T_i + (1+\varepsilon)\left(T^0 - \eta\frac{q_i}{A}\right) \tag{4.4}$$

In (4.4), T_i is the refrigerator/freezer inner temperature at time t_i. Parameter q_i denotes the electrical power required to turn on the compressor and η is the efficiency of the cooling device. T^0 describes the ambient temperature, which varies according to the house's inner temperature and it is calculated using the formula presented in (4.1). The system's inertia (ϵ) depends upon the insulation (A), whose equations are both presented in (4.2) and (4.3), respectively. S represents the surface area and x is the width of the insulation layer. k is the thermal conductivity of the material used to isolate. Equation (4.4) could also be used to model the temperature of a freezer. To model the refrigerator's behavior the following assumptions have been made, according to [31]: the thermal conductivity is always constant and has the value of 3.21 W/(m°C), the coefficient of performance (η) is 3.0 and the thermal mass is equally distributed along the refrigerator/freezer's inner compartment and is equal to 19.95 kWh/°C.

The model presented in (4.4) was implemented using Matlab software, considering the assumptions presented before. Moreover, it has been considered a constant outside temperature of 20 °C and a mean power of 70 W. It has also been defined that the temperature of the refrigerator's inner compartment should not exceed 8 °C nor be lower than 4 °C. The results obtained are presented in Figure 4.8, where it is possible to see the variation of the temperature inside the refrigerator together with the power consumption.

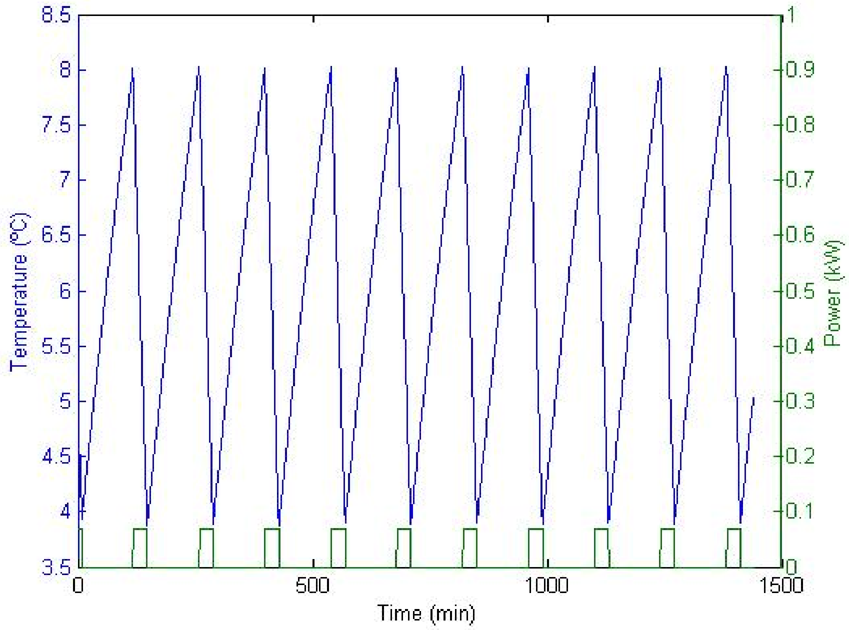


Figure 4.8: Variation of the temperature inside the refrigerator with the status of the compressor.

4.4.1.3 Electrical water heater

According to [32] the electric water heater can be modeled based on energy flow analysis and the temperature of the water inside the tank can be obtained as a function of time, as shown in (4.5).

$$Th(t) = Th(\tau)\left\{GR'T_{out} + BR'T_{in} + QR'\right\}\left[1 - e^{\frac{-1}{RC}(t-\tau)}\right] \tag{4.5}$$

In (4.5), $Th(t)$ is the water's temperature inside the tank at time t. T_{in} is the incoming cold water temperature and T_{out} is the ambient temperature of the house, as shown in Figure 4.9). The temperature of the house is not considered constant and is given by the equation in (4.1). τ is the initial time and $Th(\tau)$ is the temperature of the water in that instant. However, each time that Q or F changes τ is restarted. As a result, τ gets the value of the time at which that change happened.

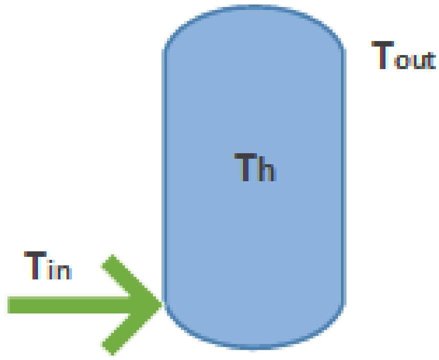


Figure 4.9: Representation of the water tank.

The insulation characteristics of the water heater are given by R (tank insulation thermal resistance). P is the heating element power and must be set in kW. The electric energy input (Q) is calculated trough (4.6).

$$Q = 3,4121.10^3 P \tag{4.6}$$

The constant C is calculated using the formula in (4.7).

$$C = \rho V C_p \tag{4.7}$$

In (4.7), V is the volume of the water tank, C_p is the specific heat of water and ρ the density of water. G, B and R' are defined according to the formulas shown in (4.8), (4.9) and (4.10), respectively. In (4.8), SA is the surface are of the water tank and in (4.9) F is the water flow rate.

$$G = \frac{SA}{R} \tag{4.8}$$

$$B = F \rho C_p \tag{4.9}$$

$$R^{'} = \frac{1}{G + B} \tag{4.10}$$

When the user adds an electrical water heater to its simulation it has the characteristics presented in Table 4.3 by default. These characteristics were given as an example, but could have been defined differently.

Before implementing the model described by equation (4.5) in the simulator it has been tested using Matlab software. For that purpose a script has been built to represent the behavior of the electrical water heater. This script considers the characteristics in Table 4.3. However, it has been considered a constant outside temperature of 20 °C, a water flow of 0.0016 m^3/h and 15 °C as the temperature of the incoming cold water. Moreover, it has been defined that the temperature of the water inside the tank should not exceed 55 °C and nor be lower than 50 °C. The results obtained are presented below in Figure

4.10, where it is possible so see the variation of the temperature inside the water tank as a function of the power consumed by the device. In this example it has been considered a mean power of 4.5 kW.

Table 4.3: Characteristics of the water tank used in the simulator.

Water-tank's characteristics	
Volume	1.13 m^3
High	1.79 m^2
Radius	0.45 m
Area	2.01 m
Insulation thermal resistance	2.642 (°C.m^2)/W

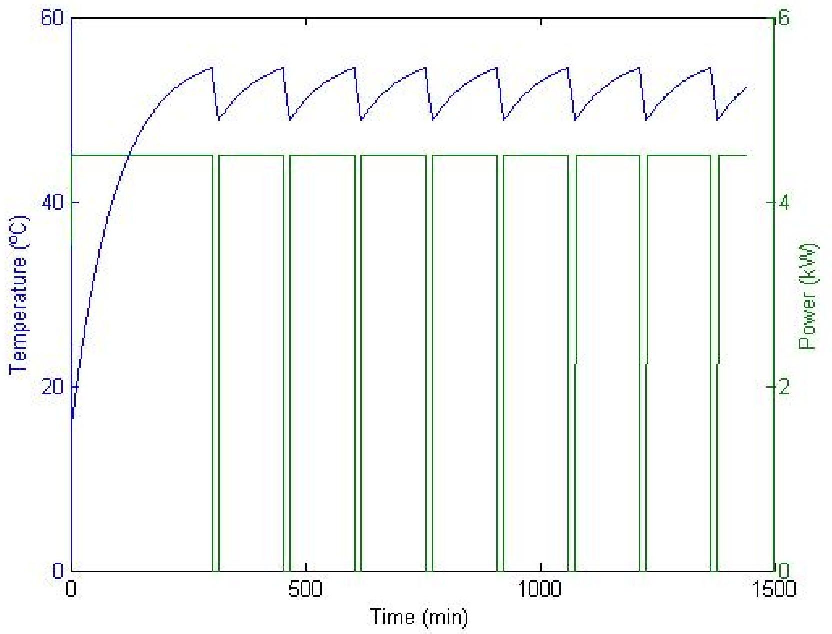


Figure 4.10: Variation of the water's temperature inside the water tank with the power consumption.

4.4.2 Electric models

4.4.2.1 Photovoltaic panel

To calculate the power generated by the solar panel a temperature dependent model presented in [33] has been chosen. The temperature dependence affects the cells' efficiency (4.12) and as a consequence, the power generated by the panel (4.11). Therefore, the model will be more realistic when estimating the power generated, than a model that does not consider the effect of the ambient temperature.

$$P_{real} = S\eta A \frac{S}{1000} \left(1 + \left(T_{cell} - 25\right)\gamma\right) \tag{4.11}$$

In (4.11), S represents the solar radiation and A is the photovoltaic panel area, which can be set by the user during the simulation period. The efficiency of the photovoltaic panel is given by η and γ is the temperature factor for power (-0.005 °C^{-1} $< \gamma <$ -0.003 °C^{-1}) [33]. T_{cell} is the cell's temperature and can be calculated using the formula shown in (4.12).

$$T_{cell} = T_{amb} + \frac{NOCT - 20}{800} S \tag{4.12}$$

In 4.12, T_{amb} is the ambient temperature and $NOCT$ is the Normal Operating Cell Temperature which is a characteristic of the solar panel. The ambient temperature, as well as the solar radiation are not constant and depend upon the data in the meteorological data base.

When the user adds a photovoltaic panel to the simulation it has the characteristics presented in Table 4.4 by default. These characteristics were given as an example, but could have been defined differently.

Table 4.4: Characteristics of the photovoltaic panel used in the simulator.

Photovoltaic-panel's characteristics	
NOCT	45 °C
η	15%
γ	-0.0035 °C^{-1}

4.4.2.2 Wind generator

According to [34], the amount of power that can be absorbed by a wind turbine is given by the model in (4.13).

$$P = \frac{1}{2} C_p \rho_{air} A v^3 \tag{4.13}$$

In (4.13), C_p is the power coefficient and is calculated using the formula shown in (4.14). The power coefficient represents the aerodynamic efficiency of the wind turbine. Because of the Betz limit, the C_p value cannot be higher than 16/27 [35]. ρ_{air} is the air density, A is the swept area of the turbine and v is the wind velocity, which is not constant and varies according to the data on the meteorological data base.

$$C_p = 0,5176 \left[\frac{116}{\frac{1}{\lambda - 0,08\beta} - \frac{0,035}{\beta^3+1}} - 0,4\beta - 5 \right] e^{\frac{-21}{\frac{1}{\lambda-0,08\beta} - \frac{0,035}{\beta^3}}} + 0,068\lambda \tag{4.14}$$

For this kind of turbine (horizontal axis wind turbine), C_p has a value between 0.2 and 0.5 [36]. β is the incident blade angle and is the tip speed ratio, which is given by (4.15).

$$\lambda = \frac{r\Omega_r}{v} \tag{4.15}$$

The turbine radius is given by r and can be set by the user during the simulation period. Ω_r is the rotational frequency of the turbine and v is the wind speed.

When the user adds a wind turbine to the simulation it has the characteristics presented in Table 4.5 by default. These characteristics were given as an example, but could have been defined differently.

Table 4.5: Characteristics of the wind turbine used in the simulator.

Wind-turbine's characteristics	
Ω_r	45 °C
C_p	0.4

4.4.3 Richardson's model

In the case of event-driven appliances (e.g. electrical oven) their status are dependent on the user's interaction along the day, turning them on and off. As a consequence, the behavior of these appliances is associated with occupancy schedules and human habits, which cannot be estimated using EM. By integrating Richardson's model in the simulator it makes possible to provide estimates regarding occupancy schedules and human habits, thereby enabling the working time and power consumption of the event-driven appliances to be estimated. Additionally, occupancy schedules are also used to help estimating the status of the air conditioning, since it is considered that it only works when the building has at least one active occupant (an individual that is at home and awake) and the temperature is out of the comfort range, defined previously by the user. However, in order to make this estimates possible the user must provide information regarding the month of the year, number of inhabitants, type of day and the appliances which consumption is intended to be estimated. Figure 4.11 illustrates the data input and output of the Richardson's model.

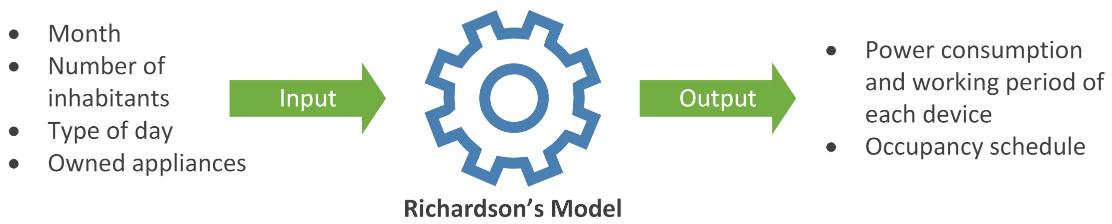


Figure 4.11: Information provided by the Richardson's model.

This model has been chosen due to the fact that it provides estimates for a single residential building for a 24-h period, with a time resolution of 1 min (according to [37] longer periods under-estimate the power demand). Moreover, Richardson's model requires very little input data and provides a Microsoft Excel work book, containing Visual Basic macros so that it would be possible to be incorporated into other models. Therefore, it could be easily integrated with the simulator presented in this thesis.

Next it will be presented the interaction between the simulator and the Richardson's model (illustrated in Figure 4.12). This interaction has been divided in four steps, which are represented in the same figure by the numbers 1 to 4. First, an agent has been created to make the connection between the user interface and the Microsoft Excel work book. This agent is therefore responsible for collecting the information set by the user in the user interface (step 1), regarding the number of inhabitants, month, type of day (weekend day or week day) and the list of owned appliances. After collecting this information the agent updates the Excel file with those parameters (step 2). Consequently a VBScript file is executed in order to run the macros in the Excel file (step 3). When the macros finish running the agent will read the updated information in the Excel file (step 4). This information regards estimates of the energy demand/on-site generation and working period of each device.

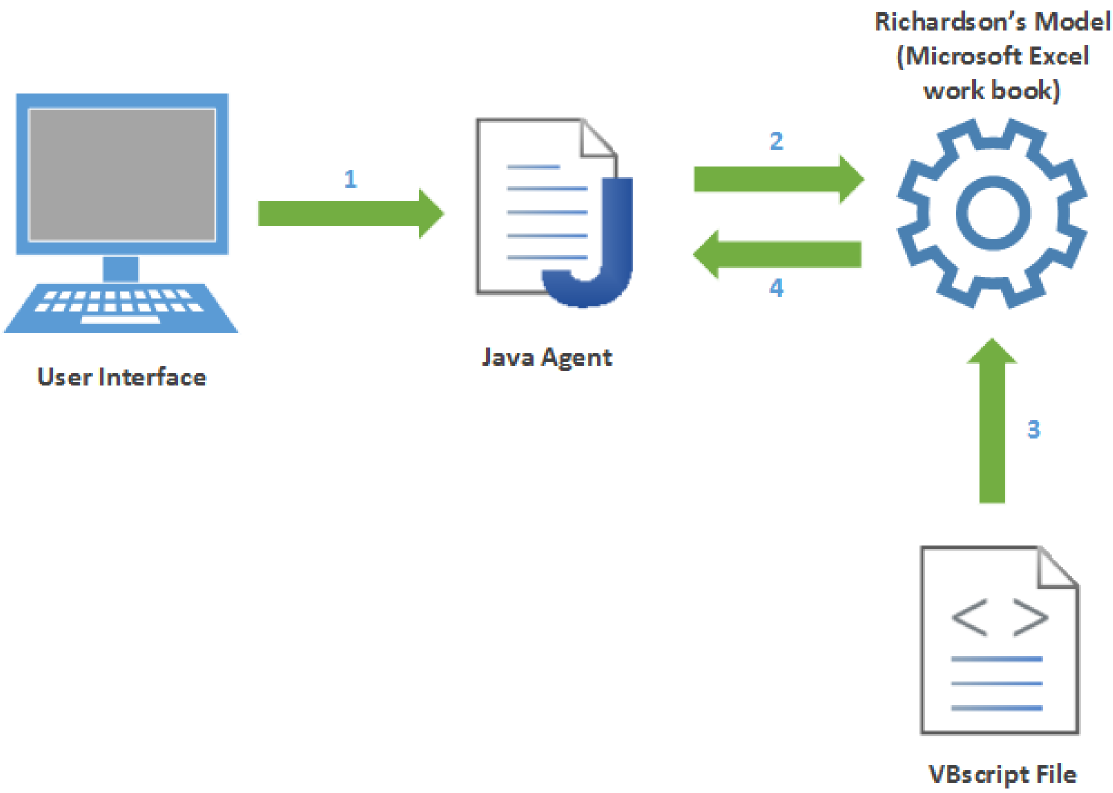


Figure 4.12: Interaction between the Richardson's model and the simulator.

CHAPTER 5

RESULTS AND ANALYSIS

This chapter presents a case study to show how the simulator works. Section 5.1 introduces the user interface and its features, in order to make possible for the user to start and configure a new simulation. Subsequently, in section 5.2, the devices used and the correspondent specifications of the case study are shown, together with the obtained results. This section does not include any optimization algorithm, so it would be possible to identify the effect of each device on the building's energy balance. Finally, in section 5.3 the optimization algorithms will present suggestions on how to maximize the use of the renewable energy produced on-site and to reduce the cost of the energy consumed from the grid.

5.1 Setting a simulation

When starting a new simulation the user must set information regarding the time scale and add a "House" device, using the graphical interface (Figure 5.1). By doing so, a new window will pop up so it would be possible to configure information regarding the month, number of inhabitants and type of day, as shown in Figure 5.2. After creating this first agent it is possible to add and configure any of the devices presented in Table 4.1. During the simulation period these devices can be removed or new ones can be added with different specifications. As the user does so, combo box are updated not only on the "Managing Devices" tab but also on the "Monitoring" tab (Figure 5.3), so devices can then be removed or their charts plotted (including the total amount of energy demand/generation). The user interface also provides the list of the active devices (on the "Managing Devices" tab) with the correspondent power consumption/generation, which is updated in real time, as shown in Figure 5.4.

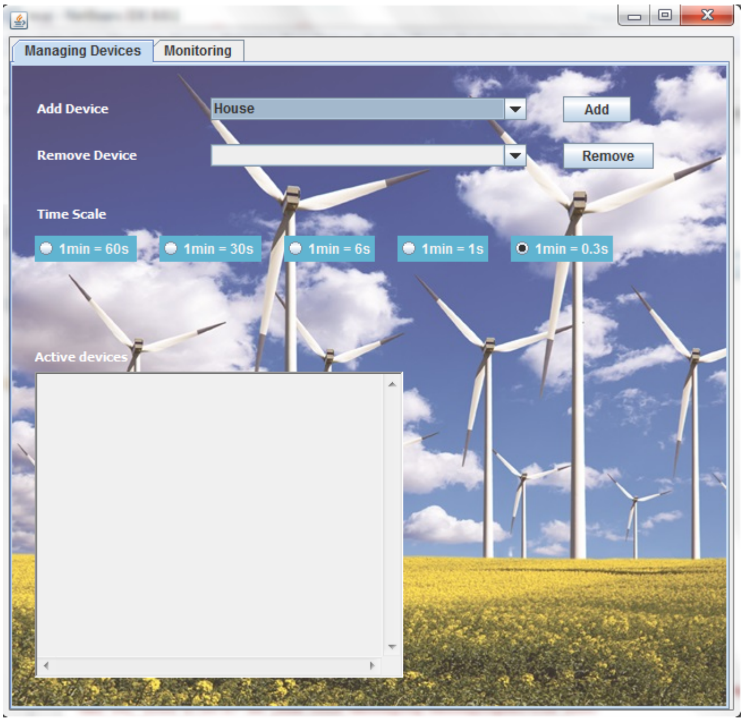


Figure 5.1: User interface.

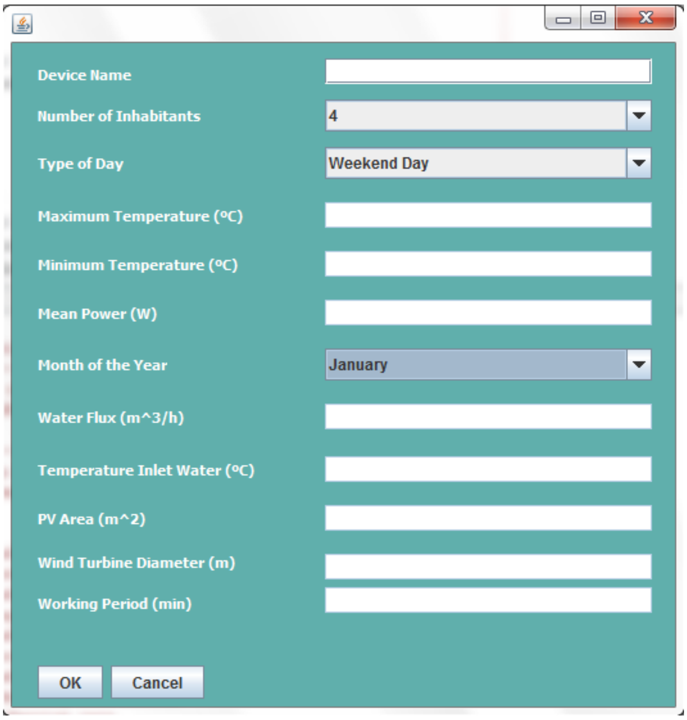


Figure 5.2: User interface (setting specifications of the simulation).

Figure 5.3: User interface ("Monitoring" tab).

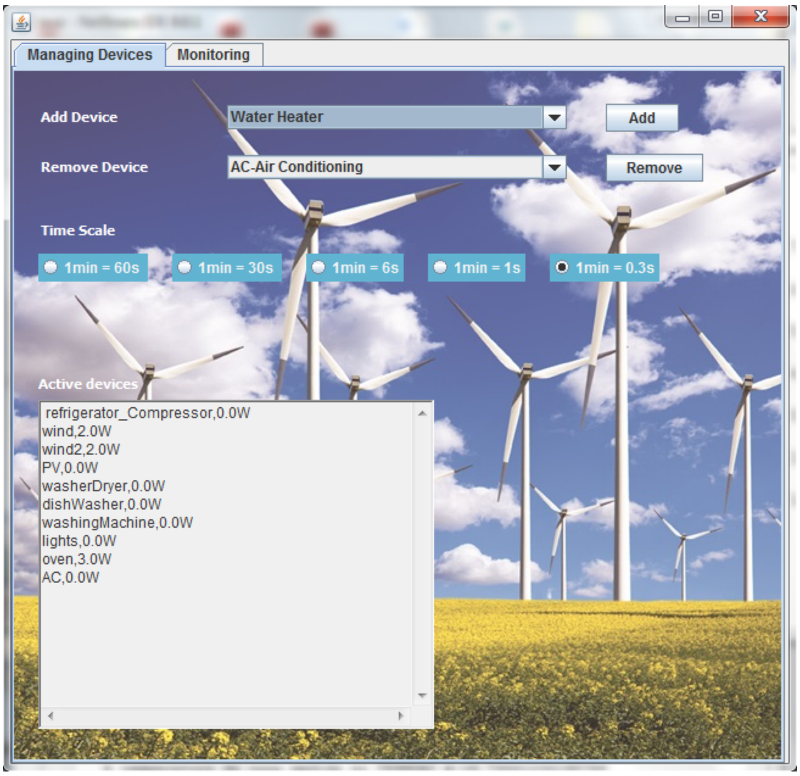


Figure 5.4: User interface (list of active devices).

5.2 Estimating energy demand/on-site generation

Without considering any of the optimization algorithms, the case study presented in this section estimates the energy demand/on-site generation of a house containing four inhabitants, during a weekend day on January. Since January is part of the winter months, it is going to be used the correspondent energy prices (Figure 4.4) for estimating the total cost of the used energy. Moreover, it has been defined that this house has the following appliances: a refrigerator, an air conditioning, a dishwasher, a washer dryer, a water heater, lightning and an oven. On-site generation is made possible through photovoltaic panels and two wind turbines. The specifications of all the used devices are presented in Table 5.1.

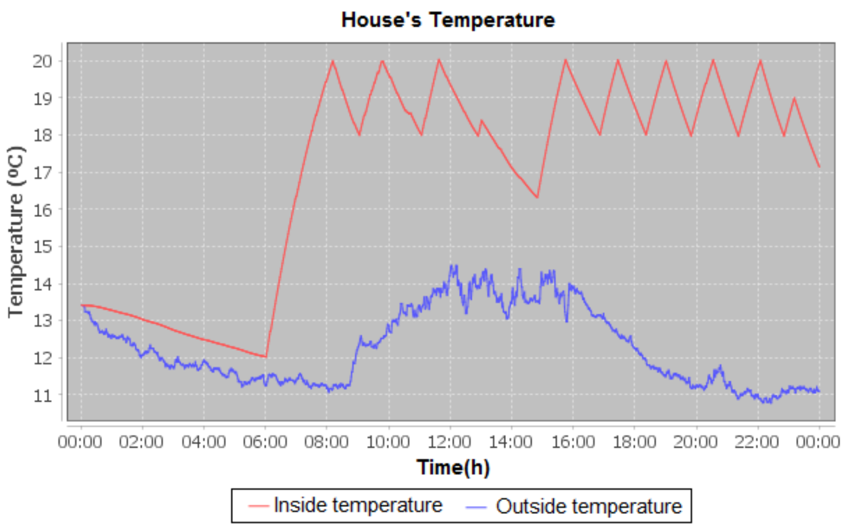
Table 5.1: List of the devices used during this case study.

Type of devices	**Specifications**
Photovoltaic panel	Installation area: 25 m^2
Two Wind turbines	Wind turbine diameter: 3 m
Refrigerator	Mean power: 150 W Desired temperature range: [4; 8] °C
Air conditioning	Mean power: 2700 W Comfort temperature: [18; 20] °C
Washing machine	Mean power: 2500 W Working period: 60 min
Dishwasher	Mean power: 2000 W Working period: 50 min
Washer dryer	Mean power: 3000 W Working period: 90 min
Water heater	Mean power: 4500 W Water temperature: [50; 55] °C Water flux: 0.0016 m^3/h Temperature of the inlet water: 15 °C
Lightning	Not applicable
Oven	Mean power: 3500 W

During the simulation period, charts containing the power consumption/on-site generation of these devices were collected (Figure 5.5). By analyzing those charts it is perceptible the impact that each device has on the building's energy demand/on-site generation (Figure 5.6), as well as the interference of external influences, such as temperature, solar radiation, wind speed and occupancy (in the case of the air conditioning). For instance, by comparing Figure 5.5a and 5.5b it is noticeable the effect of outside temperature on the working cycle of the air conditioning, which operates for longer periods when it is colder outside. It is also perceptible that this appliance is dependent on presence of at least one active occupant to work (Figure 5.5b).

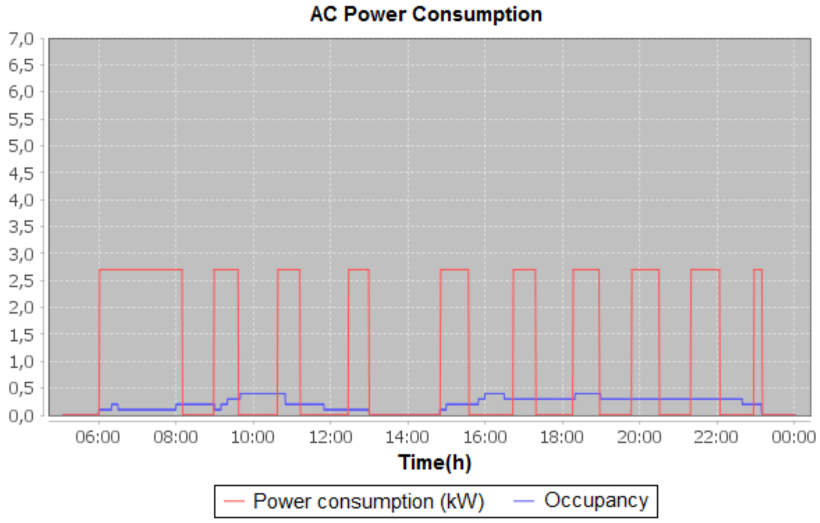
Figure 5.5c shows that the refrigerator's behavior is affected by the house's temperature, meaning that an increase in the temperature inside the house causes an increase on the refrigerator's inside temperature. Consequently, the refrigerator's compressor has to work more frequently to keep the temperature within the range previously defined. Although it cannot be noticed, the temperature inside the water tank is also dependent on the house's temperature (Figure 5.5d).

Sustained by the analysis of Figure 5.5g and Figure 5.5f it is possible to confirm that, as expected, lightning is influenced by the solar radiation, resulting in a bigger amount of switched-on lights when there is less solar radiation. On the generation side, it is perceptible that the amount of energy produced by the photovoltaic panel and wind generator is proportional to the solar radiation (Figure 5.5f) and wind speed (Figure 5.5e), respectively.

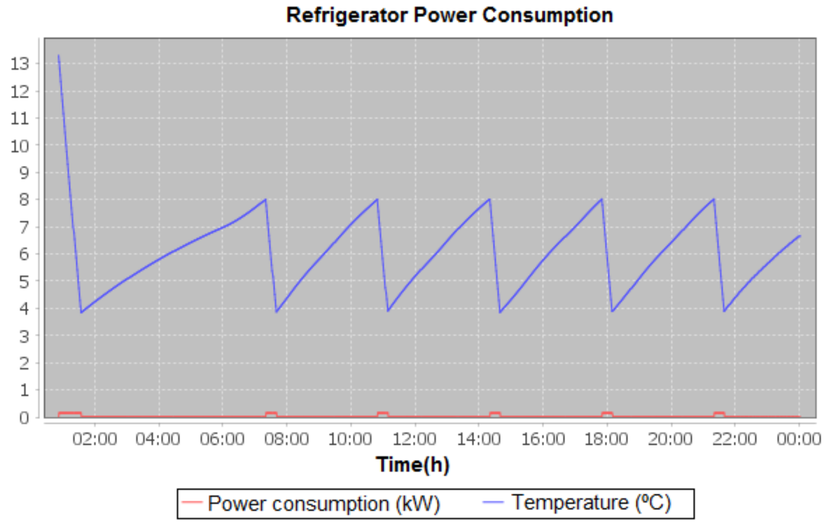


(a) Variation of the house's inside and outside temperature.

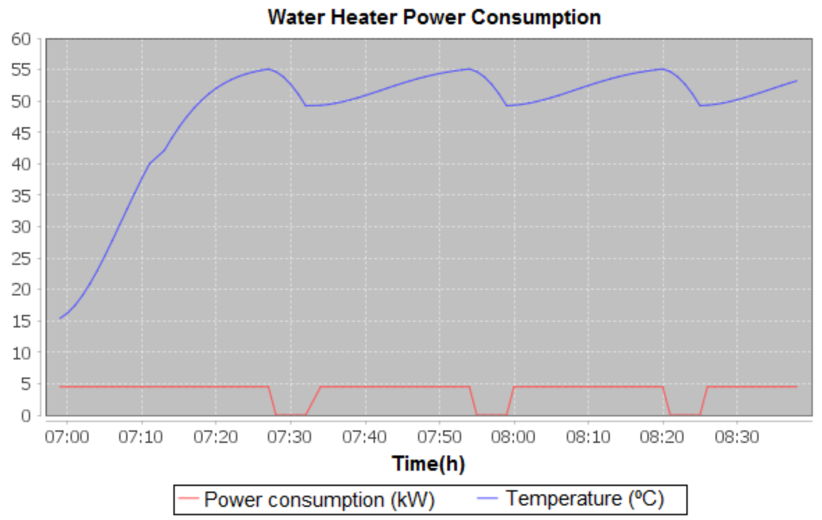
Figure 5.5: Power consumed/generated per device.



(b) Power consumption of the AC and number of active occupants.

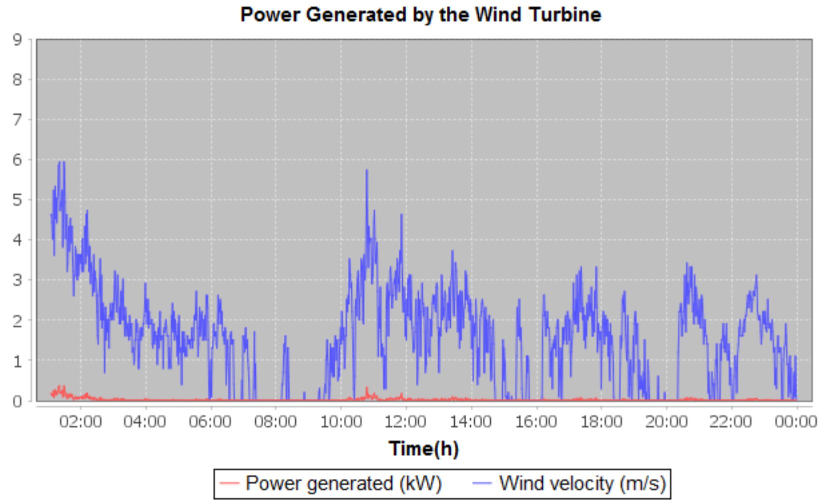


(c) Refrigerator's power consumption and inside temperature.

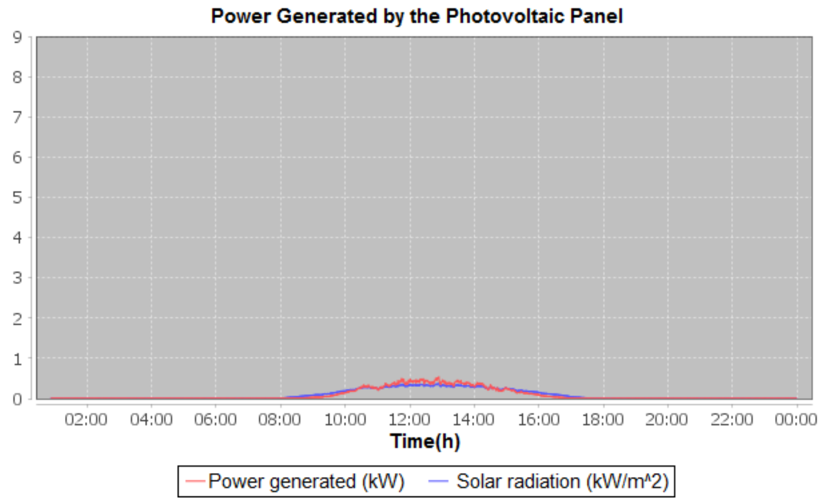


(d) Power consumption of the water heater and water's temperature variation.

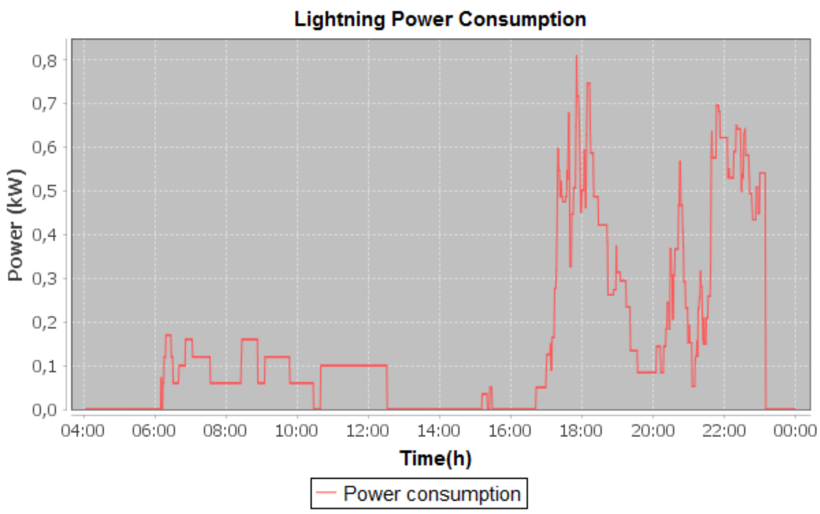
Figure 5.5: Power consumed/generated per device (continuation).



(e) Power generated by the wind turbine according to the wind speed.

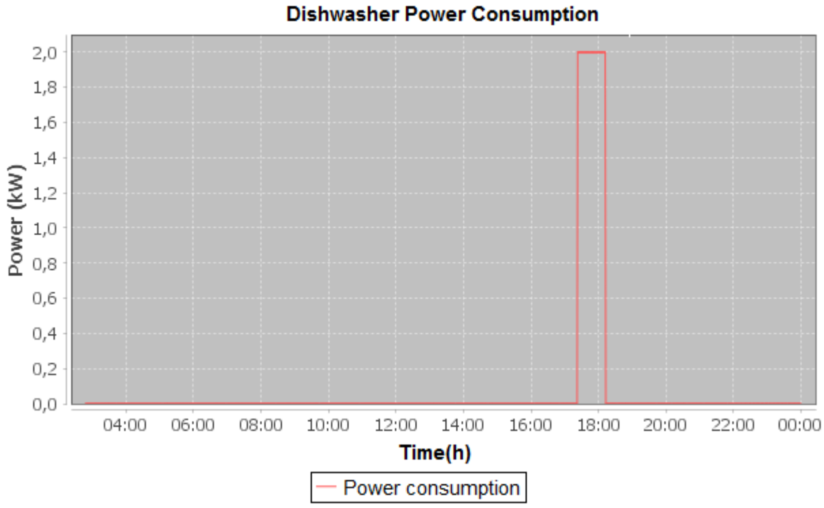


(f) Power generated by the PV panel and variation of the solar radiation.

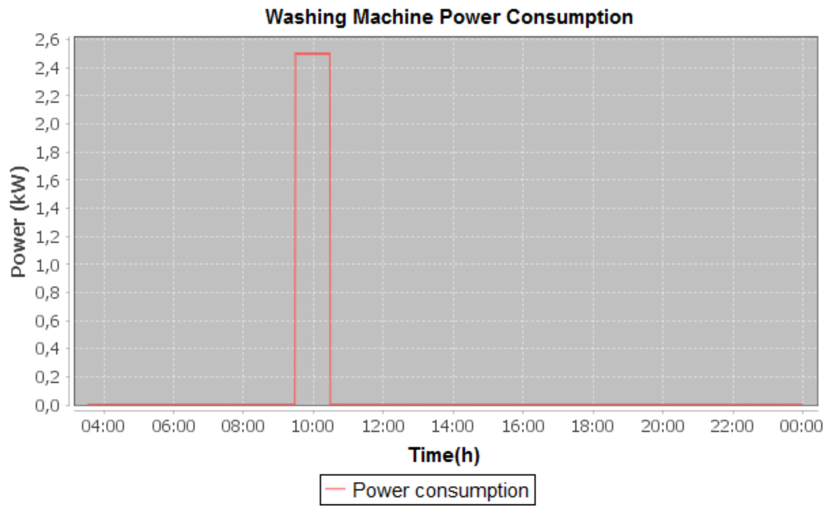


(g) Lightning power consumption.

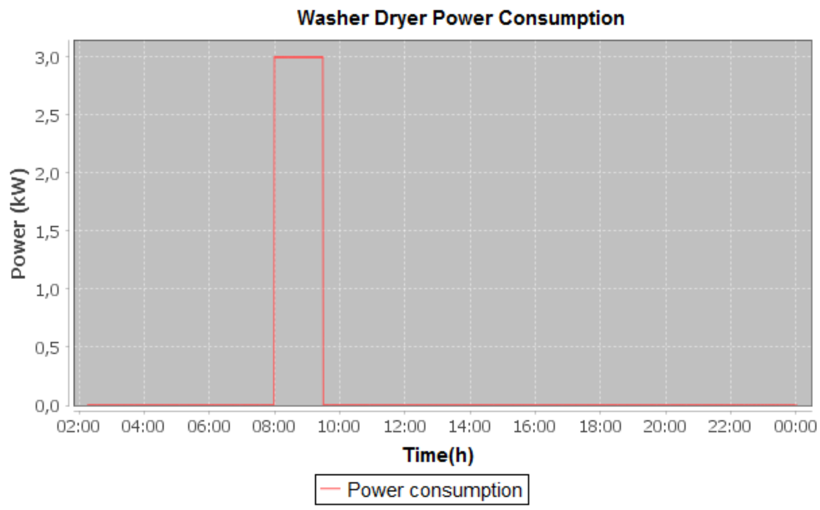
Figure 5.5: Power consumed/generated per device (continuation).



(h) Power consumed by the dishwasher.

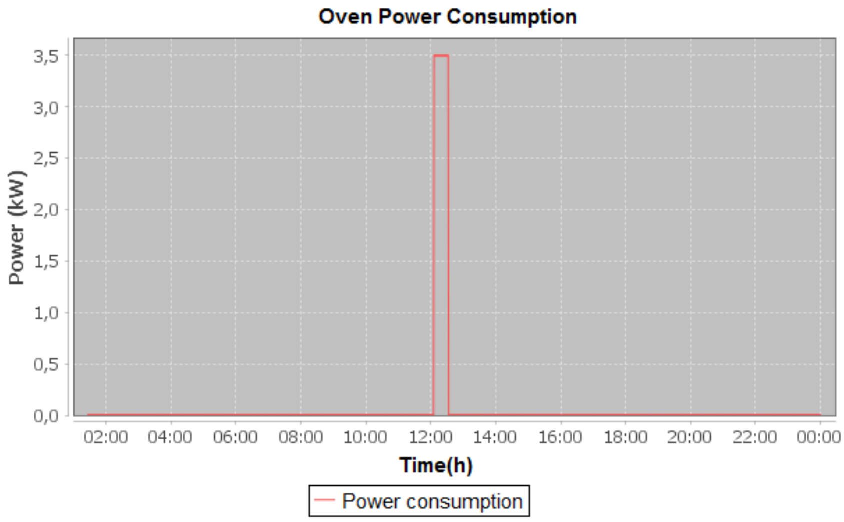


(i) Power consumed by the washing machine.



(j) Power consumed by the washer dryer.

Figure 5.5: Power consumed/generated per device (continuation).



(k) Power consumed by the oven.

Figure 5.5: Power consumed/generated per device (continuation).

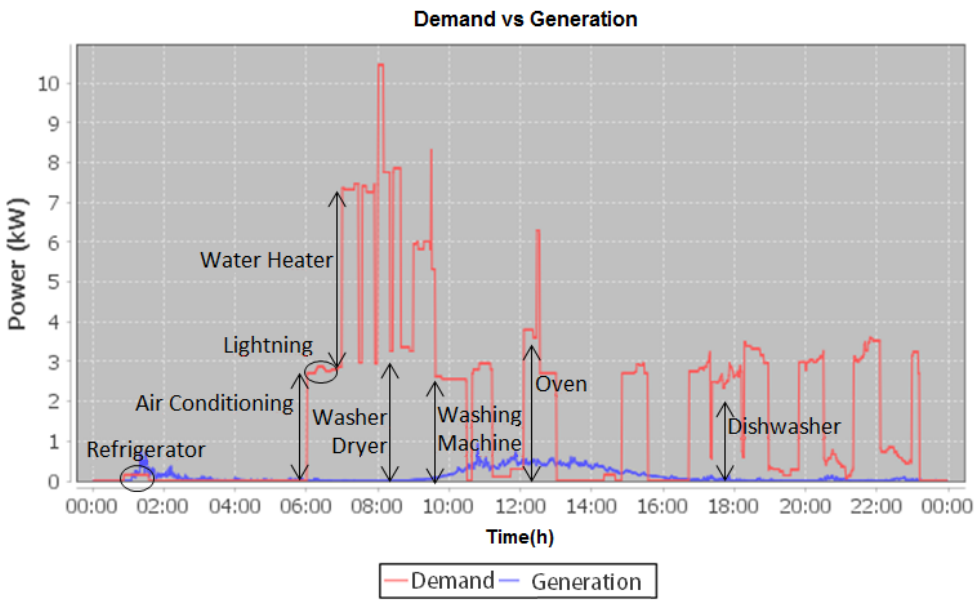


Figure 5.6: Power demand/on-site generation of the residential building.

The fact that a given device can, in real time, react to another one change in behavior or a change in the meteorological conditions is made possible due to the messages exchanged. This feature results in a simulation that better estimates the behavior of real devices. Figure 5.7 was taken from JADE's interface while the simulation was running and presents the messages sent by the agent representing the thermal component of the air conditioning to the other agents, such as the refrigerator, the water tank and the electrical component of the air conditioning. These messages, containing information regarding the ambient temperature of the house, enable devices to measure the impact it has on their functioning. On one hand, the electrical component of the AC needs to know the temperature of the building so it can keep its temperature within the temperature range defined by the user. On the other hand, the refrigerator and the water tank must know the surrounding temperature so they can measure the effect that it might have on the temperature of their inner compartments.

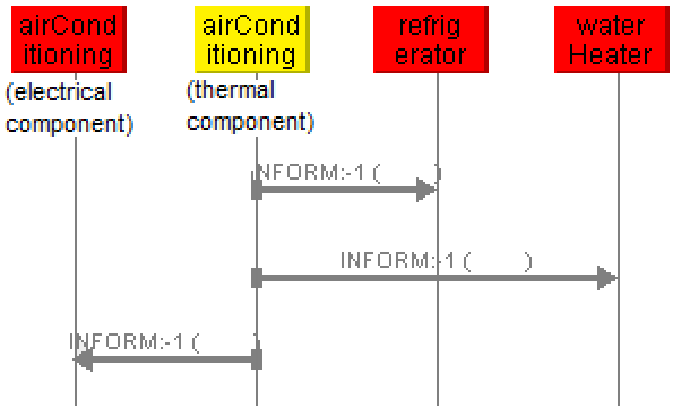


Figure 5.7: Messages exchanged between the air-conditioning's thermal component and all the thermostat-controlled agents.

Considering the electricity prices presented in section 4.3.3, at the end of this simulation it has been estimated that the energy consumed had the cost of 4.15 €and that it has been consumed approximately 2.80 kWh of on-site produced energy. This price does not reflect any taxes or fixed costs. Further in this document, these results will be compared with the ones provided by the use of optimization algorithms.

5.3 Planner

After the 24-h period, that this platform simulates, suggestions on how to maximize the use of renewable energy and on how to reduce the cost of energy consumed from the grid are made. In order to calculate the energy cost it has been assumed that the house only consumes energy from the grid when on-site generation is not enough. The energy price is the same as in section 5.2. Moreover, it has also been considered that this infrastructure never sells energy back to the grid.

5.3.1 Energy consumption optimization

As explained before in section 3.3.1 this algorithm as the purpose of maximizing the use of the renewable energy produced. Therefore, the main goal is to fit the washing machine, dish washer and washer dryer working in periods where less energy is going to be consumed from the grid.

By analyzing Figure 5.6 it is possible to see that the peak hours of energy demand did not always match the peak hours of energy generation. As a consequence, part of the energy produced is not being used. Figure 5.8 shows the improvements made in the use of renewable energy, which resulted in an increase of the renewable energy used. In addition, it is also visible that the consumption peak has been flattened and the load is now more equally distributed along the day. It has been estimated that by arranging the appliances this way, the cost of the energy consumed from the grid would be 3.92 €and that it has been consumed approximately 5.54 kWh of on-site produced energy.

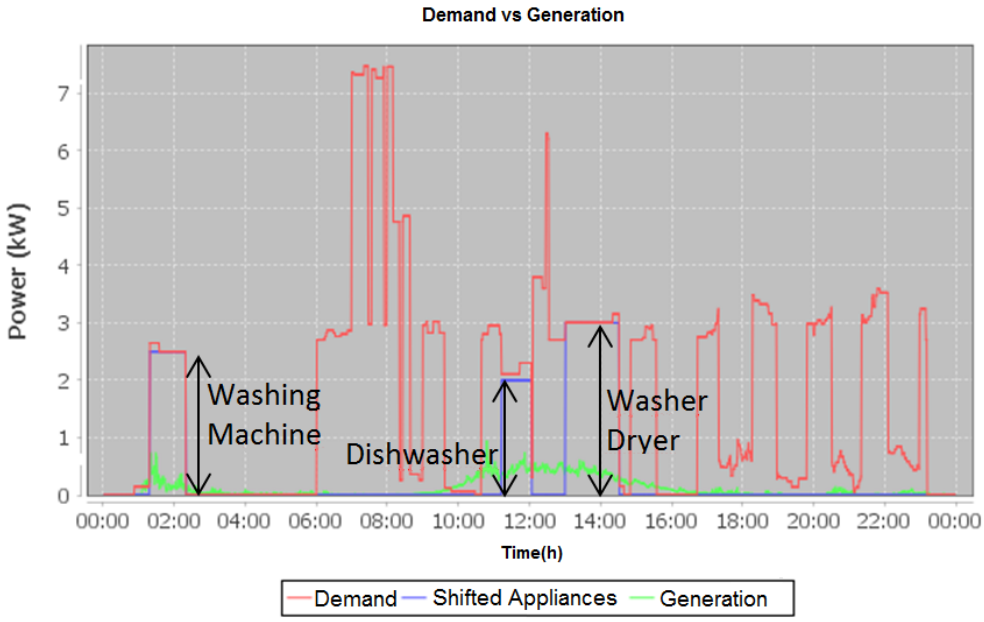


Figure 5.8: Power demand/on-site generation of the residential building after running the energy optimization algorithm.

5.3.2 Energy cost optimization

The algorithm for optimizing the energy cost is made so that the user can make greater use of the energy generated on site and at the same time save as much money as possible, as explained in section 3.3.2. For the conditions set in section 5.1 the amount of energy produced is not enough to cover up the demand of the washing machine, dish washer or washer dryer. Furthermore, by analyzing Figure 5.6 and Figure 4.4 it is possible to confirm that during the hours of more energy production (from 10 a.m. to 4 p.m.) the energy price is higher (from 2.17 to 1.64 times higher) than at the beginning of the day (2 a.m. to 6 a.m.). As a consequence, this algorithm suggested shifting those appliances to the time period of 2 a.m. to 6 a.m. (Figure 5.9), where energy is cheaper. It has been estimated that the total amount of energy consumed would have the cost of approximately 3.70 €and that it has been consumed approximately 4.45 kWh of on-site produced energy.

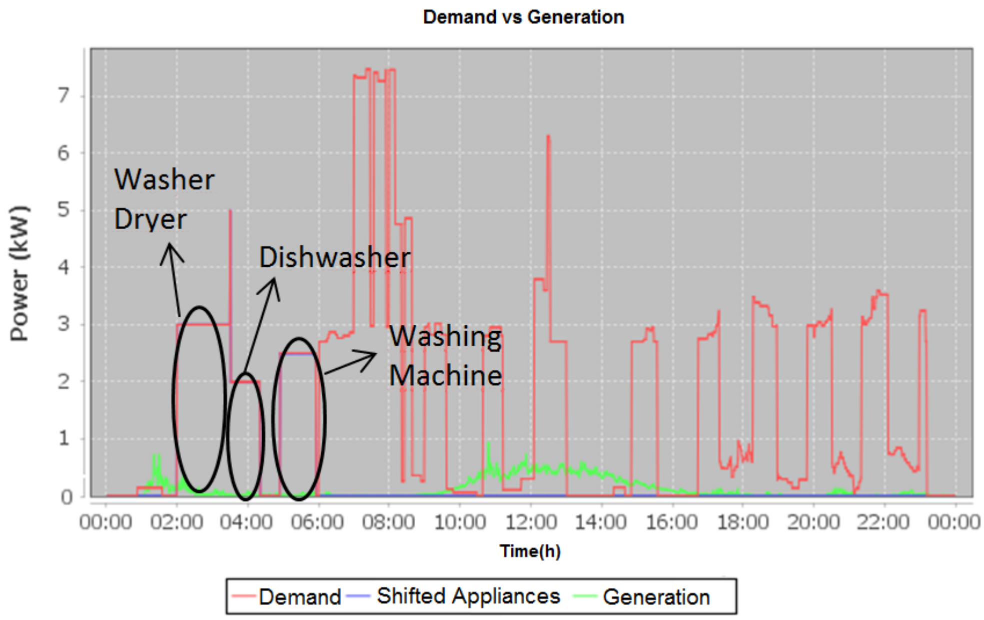


Figure 5.9: Power demand/on-site generation of the residential building after running the energy cost optimization algorithm.

5.4 Analysis

The results of the simulations made in sections 5.2, 5.3.1 and 5.3.2 are presented in Table 5.2 and show differences both in the amount of renewable energy used and in the energy cost. By analyzing it, it is possible to conclude that the optimization algorithms do present an alternative in which the user makes more use of the renewable energy produced on-site and is able to save money on the energy bill. Even though the total amount of power consumption along the day was kept, the implementation of these algorithms provide a different way of distributing the operating time of appliances, which has resulted in almost doubling the use of renewable energy and a decrease of approximately 11% in the energy bill.

Table 5.2: Results achieved by using optimization algorithms

	Simulation without optimization	**Energy consumption optimization**	**Energy cost optimization**
Energy cost	4.15 €	3.92 €	3.70 €
Renewable energy used	2.80 kWh	5.54 kWh	4.45 kWh

In conclusion, this simulator provides a tool to introduce more control and flexibility on the demand side allowing the user to implement techniques of demand response.

Moreover, in the suggestions made by both algorithms it was visible that they also made possible to flatten the load peak. As a result, the load is now more equally distributed along the day, which can be beneficial for the electricity supplier, since there is less power being consumed at the morning peak hours (from 9 a.m. to 10:30 a.m. according to the selected tariff).

CHAPTER 6

CONCLUSIONS

6.1 Conclusions

This thesis presents a simulator that is capable of estimating in real time the energy consumption and on-site production using renewable energy sources. As a consequence, the user can estimate in advance the energy demand/on-site generation for a 24-h period in any given month, with a time resolution of 1 min. Moreover, this simulator also provides suggestions on how to better schedule the working period of certain appliances in order to reduce the energy bill and maximize the use of the renewable energy produced on site. This has been made possible through the use of a hybrid "bottom-up" approach that combines Richardson's model with physical characteristics of the renewable energy generators, thermostat-controlled appliances and the building in order to estimate the energy demand/on-site generation.

In the experiments presented in Chapter 5, it has been found that by using this tool the user can save approximately 11% on the energy bill and almost doubling the use of renewable energy, by just time-shifting the washing machine, washer dryer and the dishwasher.

When compared to the studies presented in the second chapter the simulator designed during this thesis presents a tool that not only provides estimates regarding the energy consumed/produced, but it also provides suggestions on how the user can reschedule the working period of certain appliances in order to maximize the use of renewable energy and save on the energy bill, making therefore possible the application of demand response techniques.

Finally, this simulator is based on a modular architecture that allows the user to change the simulation conditions in real time, which will instantly affect the output results. On the contrary, the studies presented in Chapter 2 do not allow real time interaction with the user while the simulation is running. These output results are displayed to the user through the use of charts where it is presented the energy demand/generation of the entire building, as well as the individual impact of each device and the external factors that influence their behavior. This graphical interface allows the user to have a more instant visual perception of the building's energy balance. The fact that the presented work is a simulator and not just a model makes it more flexible and more easily adaptable to the user's reality. The presented study made possible the submission of the paper named below to the "IECON 2015 - 41st Annual Conference of the IEEE Industrial Electronics Society" conference, taking place in Yokohama (Japan), from 9 to 12 of November.

- António Sá, Rui Amaral Lopes, J. F. Martins; "Design of an Agent-Based Simulator for Real-Time Estimation of Power Consumption/Generation in Residential Buildings".

This paper can be found attached to this document (Appendix A).

6.2 Future work

When designing this simulator thermal models have been considered to make possible to estimate the behavior of devices that are controlled by a thermostat. However, in the used models some assumptions have been made. For instance, the thermal model of the residential building neglects the influence that appliances, as well as inhabitants could have on temperature. On the other hand, in this model the building is viewed as a single space where the circulation effects are not considered. In the case of the refrigerator it has been assumed a constant thermal mass value. As a consequence, these assumptions can produce misleading results. Therefore, it would be beneficial if more complex mathematical models were used in which these variables could be incorporated.

Secondly, it has been assumed a fix size for the building, the refrigerator and the water tank, which makes it difficult for the user to adjust this characteristic. By making possible to adjust it using the graphical interface it would enable to better recreate the existing conditions.

At last, it is important to mention that even though it has been proved the concept of creating a simulator that estimates the power demand/on-site generation of a residential building, this simulator has not been validated using real-life cases. Thus, it would be interesting to make these measurements and compare them with the ones estimated by the simulator presented in this thesis.

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APPENDIX A

WRITTEN SCIENTIFIC PAPERS

Design of an Agent-Based Simulator for Real-Time Estimation of Power Consumption/Generation in Residential Buildings

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Abstract—**Demand Response programs influence the end-user electricity usage by changing its cost along the time. In this scenario, to better manage the building's energy demand and consequently the electricity related costs, the user needs to estimate the energy demand and on-site production of the building in function of the electrical devices that are present on the building boundary. This paper presents an agent-based electrical simulator that has been built with the main objective of providing those tools to the consumer. The proposed simulator uses a hybrid "bottom-up" approach, with both statistical and physical models. The referred software is capable of estimating the energy demand and on-site generation with a 1-min time resolution for the period of 24h and calculates the energy price for each scenario. Therefore more control over the demand side is given to the end-user, allowing an easy response to changes in the electricity costs along the day. Such techniques could help the user to maximize the usage of renewable energy and to lower the electricity costs. On the other hand it is also beneficial for the energy provider since it is more likely to reduce the demand at peak hours.**

Keywords—Residential electricity simulation; demand response; multi-agent systems; flexible demand.

I. Introduction

Cyber-physical systems and industrial agents are not exclusively industry-based disciplines. These areas of knowledge are spreading throughout other application fields such as Smart Grids, Demand Response and user energy awareness. Electronics, personal computers, Internet-based solutions, advanced materials, are deeply changing the world as we know it and, in most cases, for the better. Even at our homes, tenants no longer deal just with the physical world/equipment but also with the cyber-part of complex energy usage patterns. The existing commitment with a sustainable development has resulted in the introduction of emissions limits, carbon taxes and ambitious renewable energy targets [1]. However, once the production from renewable sources is governed by the availability of the respective primary energy source there is often no correlation between production and consumption [2]. The mismatch between renewable production and consumption is nowadays solved by introducing flexibility on the supply side (e.g. adding carbon intensive generators). However, in order to meet sustainable development targets [1], cleaner solutions must be employed. Adding flexibility on the demand side through Demand Response (DR) measures is pointed out as one of the solutions to the referred problem [2]. Demand Response is not a new concept and it regards the ability of customers to modify their usual consumption profiles as a reaction to different electricity prices ([3], [4], [5], [6], [7]). On this scenario, residential building costumers might have to make some decisions to reduce their electricity bills as a reaction to different tariffs throughout the day. Having this into consideration, this paper presents a dynamic electrical simulator where customers can understand in real time the impact of bringing forward or delaying the use of certain appliances (e.g. washing machines) on their demand profile and consequently on their electricity bills. Moreover this simulator considers a real-time management of the electrical devices chosen by the costumer and the use of electrical devices responsible for on-site renewable energy production (e.g. PV systems). The dynamic electrical simulator presented in this paper follows a hybrid "bottom-up" approach, since it considers both statistics and physical models to estimate the energy produced and consumed on the building. Moreover, this simulator is based on a Multi Agent System (MAS). Comparing to existing "bottom-up" electricity models (e.g.[10], [11], [12], [13], [14]), the simulator described here presents as the main advantage the possibility of real-time interaction with the costumer, through a graphical interface, offering an opportunity of a better response to changes in the electricity tariff when demand response programs are implemented by electricity suppliers.

II. An Agent Based Electrical Simulator

Researchers worldwide do not agree on a single definition for what an Agent is. It is clear the lack of consensus on the several publications found in the literature, as pointed out by McArthur et al. [9]. However, one of the most popular definitions was stated by Michael Wooldridge et al. [8], defining an Agent as "a software and/or hardware entity that is situated in some environment and is able to autonomously react to changes in that environment". To further distinguish agents from other existing technologies, Wooldridge also stated that an agent must have the three following characteristics: reactivity, pro-activeness and Social ability. In this specific case, an Agent is a piece of software and its characteristics are used to provide a modular structure and a real-time response operation to the developed simulator, which has been implemented by using JAVA/JADE development platform. The simulator comprises the following three different types of electrical devices: appliances that are controlled by thermostat (e.g. refrigerator), appliances which are event driven (e.g. washing machine), and renewable energy generation devices as shown in Fig. 1. The event driven appliances use a statistical energy modeling component developed by Richardson et al. [15] to establish the respective operation times. Thermostat-controlled appliances on the other hand, use physical energy modeling components. This same principle is applied to the renewable energy generation devices. However, the thermostat-controlled appliances are represented by two different agents; one that is responsible for estimating the inner temperature and another one that is responsible for turning the device on and off, as a function of the temperature operation range, and for estimating the power needed.

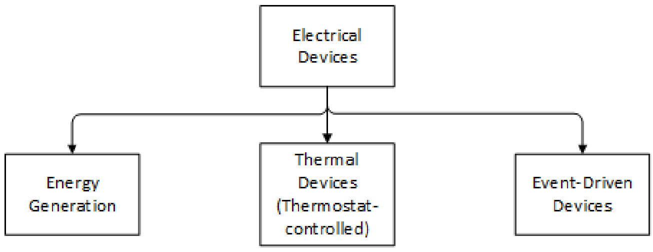

Fig. 1. Different types of agents.

A. Architecture and Operation

Fig. 2 presents the architecture that has been designed in order to make possible a “bottom-up” approach, allowing the user to easily identify the impact of each device on the building’s energy profile. This architecture comprises all the different types of agents named earlier in Section II. However, it has been considered that it would be important to represent the house’s agent separately from the other thermal models, since it is responsible for providing information regarding the temperature inside the building to the other thermal models.

One of the key features of this architecture is that it has a user interface, which provides the user with a good level of abstraction so that it is possible to interact with the simulator without having a deep knowledge on the devices when setting up a new simulation. Therefore, it is possible for the user to easily add or remove devices with different characteristics at any given time before or during the simulation. The fact that the simulator is agent-based allows the simulation to adapt its behavior in real time to any changes made. On the output, the interface displays charts with the variation of power consumption and generation, the temperature variance of the thermostat-controlled appliances and the total cost of the energy consumed from the grid. Each simulation represents a 24 hour period, starting at 0:00h and finishing at 23:59h.

1) Meteorological Data: Due to the fact that electricity consumption and generation in residential households varies significantly depending on seasonality [16], when simulating the behavior of both the thermostat-controlled appliances and the renewable energy generators, the simulator makes use of meteorological data that has been acquired using a meteorological station installed on the Department of Electrical Engineering at Nova University of Lisbon (38°39’38.2”N 9°12’17.6”W) during a one year period with a time resolution of 1-min. These measurements include the outside temperature, solar radiation and wind speed averaged during a 1-month period to produce a typical day for each of the 12 months considered. As a result, when setting up a new simulation, the user can choose the month of interest. The user has also to specify if the simulation is taking place on a week day or weekend day since it will lead to different values of occupancy and energy consumption.

2) Richardson’s Model: In the case of event-driven appliances (e.g. electrical oven) its state is dependent on the user’s interaction along the day, turning them on and off. To accommodate this characteristic, the simulator uses the stochastic model developed by Richardson et al. [15] to infer, at a 1-min resolution, the state of the devices that are dependent on the user interaction. Therefore, it is crucial that in the beginning of the simulation the user sets the number of inhabitants of the house (up to five), using the user-interface. Additionally, the Richardson’s model also provides stochastic information regarding building’s occupancy that along with the temperature is used to define the state of the Air Conditioning (AC) system. Consequently, in this study, the AC only works when the building has at least one active occupant and the temperature is out of the comfort range, defined previously by the user. In this paper an active occupant is defined as an individual that is at home and not asleep. Although Richardson’s model is used to model event-driven appliances, it also takes into consideration meteorological data that can interfere on the use of certain appliances. For instance, the use of lighting is also dependent on the level of solar radiation. As a result, this stochastic model does not just consider the odds of an event happening based on the human habits but it also takes into consideration the surrounding environment and how it might interfere on that habit.

3) Message Exchange: Using the agents’ social abilities, this simulator supports the exchange of messages between the represented entities using FIPA communication protocol (the messages exchanged between agents and its content is represented in Fig. 2 by the dashed lines). Consequently, it is possible to consider in real-time the effect that one appliance can have on another one’s behavior. For instance, a variation on the outside temperature will affect the temperature inside the building, which can lead to a change on the state of the air conditioning. That temperature variation inside the house will then influence the behavior of the water heater and the refrigerator. After a temperature change, the agents responsible for the thermostat-controlled devices (e.g. refrigerator) will interact with the respective thermal model agents to infer how much electricity they have to consume to increase or decrease the current temperature, in order to maintain its temperature within the range previously defined by the user.

4) Energy Cost: The cost of the import energy, purchased from the electrical grid when the energy produced on-site is not sufficient to satisfy the building’s demand, is calculated at the end of each simulation by using the prices for the tri-hourly tariff of a Portuguese energy provider (Energias De Portugal). The energy price within this tariff varies depending on the time of the day and the season of the year, as it is depicted in Fig. 3 and 4.

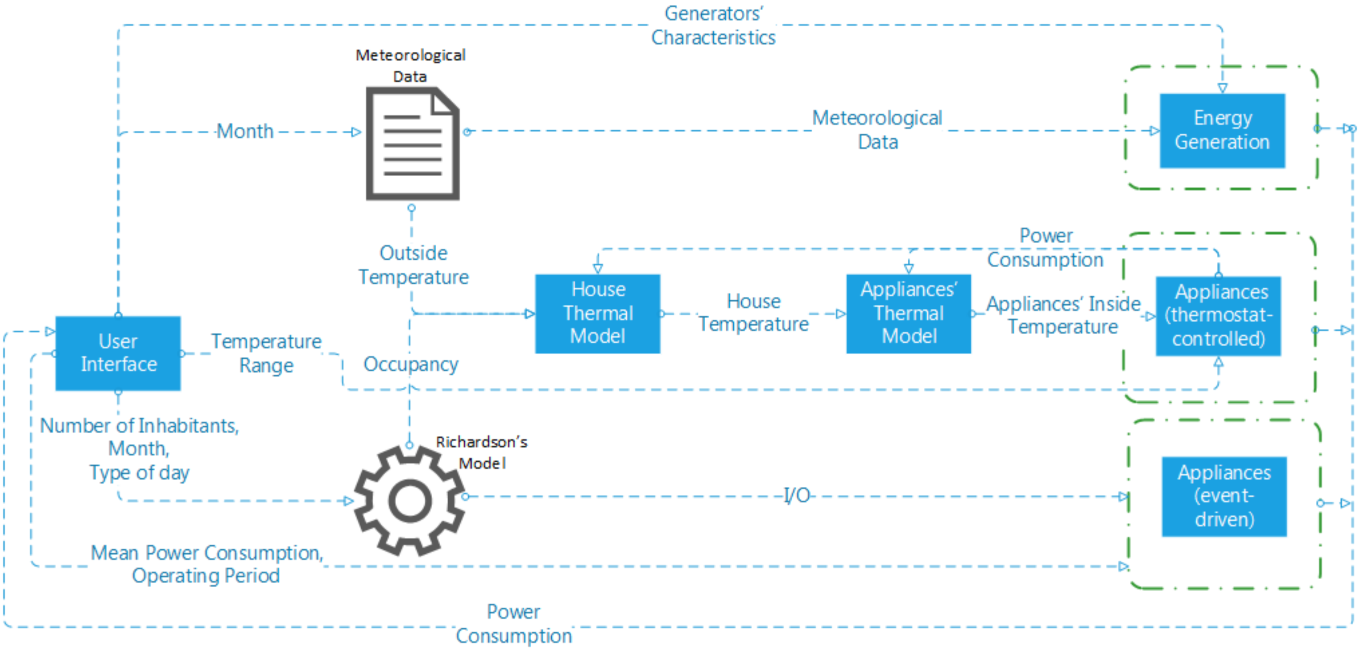

Fig. 2. Architecture of the Simulator.

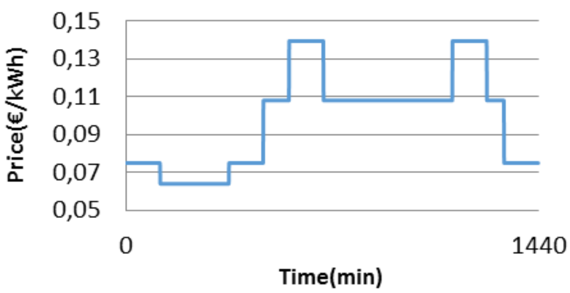

Fig. 3. Energy prices for winter months (from October to March).

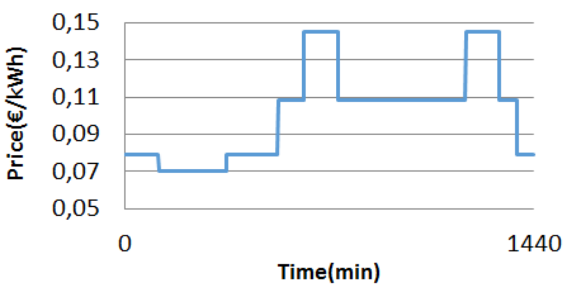

Fig. 4. Energy prices for summer months (from April to September).

Energy prices have been had to the simulator so it would be possible for the user to make several simulations in order to know when it would be cheaper to turn on the respective appliances. This information together with the estimation of the energy demand and on-site generation makes possible to introduce more control and flexibility on the demand side, once the user is now aware of the impact that each device has on the load curve and the cost associated with it. Therefore, it is possible for the user to implement demand response techniques, by rescheduling the time at which a specific device operates, in order to maximize the use of renewable energy and reduce the energy cost. Although different devices could be considered, in this paper it is assumed that the user is able to set the operation time of the following appliances: washing machine, washer dryer and dishwasher.

5) Input Data: Through the user interface it is possible to add different types of devices with different specifications. The table presented below (Table I), shows the different kinds of devices that the simulator has available for the user, as well as the data that must be provided when adding new appliances or energy generators to the simulation. It is important to mention that because this simulator follows a modular approach based on a Multi Agent System, it is possible to add other types of devices without changes on the simulator's architecture. Due to this modular architecture, the system allows the user to add as many instances of the same device with different specifications as needed according to its needs.

B. Thermal Models

It is assumed that the building has an AC that maintains the temperature inside the building within a specific range of temperature. To estimate the electricity spent by the AC, the simulator uses the thermal model described in section II-B1. Other thermostat-controlled devices, such as the refrigerator and the electric water heater are also considered in this paper. The thermal models of these thermostat-controlled devices are presented in sections II-B2 and II-B3, respectively.

1) Building: When studying the thermodynamics of a residential building certain assumptions have been made. For

TABLE I. INPUT DATA THAT SHOULD BE PROVIDED FOR EACH DEVICE

Type of Devices	**Input Data**
Photovoltaic Panel	Area of the panel
Wind Turbine	Diameter of the turbine
Refrigerator	Mean power Temperature range
Water Heater	Mean power Temperature range Water flow Temperature of the inlet water
Air Conditioning	Mean power Temperature range
Oven and Microwave	Mean power
Washing Machine Washer Dryer and Dishwasher	Mean Power Duration of the washing period Starting time
House	Number of inhabitants Month Type of day (week day or weekend day)

instance it has been considered that only the outside temperature and the air conditioning are capable of altering the inside temperature of the house. Consequently, the house's thermal mass is limited to the thermal mass of the air. Secondly, in this model the building is viewed as a single space where the circulation effects are neglected and it is assumed that the inside temperature is uniform. In (1) it is presented the equation that represents the thermal behavior of the building.

$$T_{i+1} = \varepsilon T_i + (1+\varepsilon)\left(T^0 \pm \eta \frac{q_i}{A}\right)(+: heating, -: cooling) \tag{1}$$

In (3) T_i represents the temperature inside the residential building at the instant t_i. At the instant $t_i = 0min$ the inside temperature is considered to be equal to the value of the outside temperature (for that same time). T^0 varies according to the data in the data base, which has the measured meteorological information. η represents the thermal conversion efficiency when the air conditioning is heating. On the other hand, when cooling it represents the coefficient of performance and q_i is the power delivered by the air conditioning to building. The insulation (A), as well as, the inertia factor (ϵ) are calculated through the formulas presented in (2 and 3, respectively), where S represents the surface area, x is the width of the insulation layer and k is the thermal conductivity of the material used to isolate.

$$\varepsilon = e^{\frac{-\tau A}{m_c}} \tag{2}$$

$$A = \frac{Sk}{x} \tag{3}$$

2) Refrigerator: The model used to calculate the refrigerator's inner temperature at time $T_{(i+1)}$ is based on the one proposed by [17]. This model is described by the mathematical formula shown in (4).

$$T_{i+1} = \varepsilon T_i + (1+\varepsilon)\left(T^0 - \eta \frac{q_i}{A}\right) \tag{4}$$

T_i is the refrigerator/freezer inner temperature at time t_i, m_c is the average thermal mass, and τ is the time interval between t_i and t_{i+1}. Parameter q_i denotes the electrical power required turning on the refrigerator's compressor and η is the efficiency of the cooling device. T^0 describes the ambient temperature, which varies according to the house's inner temperature and it is calculated using the formula presented in (1). The system's inertia (ϵ) depends upon the insulation (A), which equations are presented in (2) and (3), respectively. To model this device's behavior the following assumptions have been made [17]: the thermal conductivity is always constant and has the value of 3.21, the performance rate (η) is 3.0 and the thermal mass is equally distributed along the refrigerator/freezer's inner compartment and it is equal to $32kWh/^oC$.

3) Electric Water Heater: According to [18], the electric water heater can be modeled following an energy flow analysis, being the temperature of the water inside the tank obtained as a function of time, as modeled in (5).

$$Th(t) = Th(\tau)\left\{GR^{'}T_{out} + BR^{'}T_{in} + QR^{'}\right\} \left[1 - e^{\frac{-1}{RC}(t-\tau)}\right] \tag{5}$$

$Th(t)$ is the water's temperature inside the tank at time t. T_{in} is the incoming cold water temperature and T_{out} is the temperature inside the house, which varies according to the temperature measured by the thermostat presented in the air conditioning. τ is the initial time and $Th(\tau)$ is the temperature of the water in that instant. However, each time that Q or F changes τ is restarted. As a result, τ gets the value of the time at which that change happened. Insulation characteristics of the water heater are given by R (tank insulation thermal resistance). P is the heating element power and it is set in kW. The electric energy input (Q) is calculated trough (6).

$$Q = 3,4121.10^3 P \tag{6}$$

The constant C is calculated using the formula in (7), where V is the volume of the water tank, C_p is the specific heat of water and ρ the density of water. G, B and R' are defined according to the formulas shown in (8), (9) and (10), respectively. In (8) SA is the surface are of the water tank and F is the water flow rate.

$$C = \rho V C_p \tag{7}$$

$$G = \frac{SA}{R} \tag{8}$$

$$B = F\rho C_p \tag{9}$$

$$R^{'} = \frac{1}{G+B} \tag{10}$$

C. Electric Models

The simulator presented in this paper only considers as renewable energy generators the photovoltaic panel and the wind turbine. However, different types of renewable energy generators could have been added during its implementation, as mentioned in section II-A5. Section II-C1 and II-C2 present the mathematical models used to estimate the energy generated by the photovoltaic panel and the wind turbine, respectively.

1) Photovoltaic Panel: To calculate the power generated by the solar panel, a temperature dependent model presented in [19] has been chosen. The fact that the generated power depends on the ambient temperature will affect the cells' efficiency (11). Therefore, the model will be more realistic when estimating the power generated by the photovoltaic panel.

$$P_{real} = S\eta A \frac{S}{1000}\left(1 + \left(T_{cell} - 25\right)\gamma\right) \tag{11}$$

In (11) S represents the solar radiation, A is the solar panel area and γ is the temperature factor for power ($-0,005 < \gamma < -0,003$). T_{cell} is the cell's temperature and can be calculated using the formula shown in (12), where T_{amb} is the ambient temperature and $NOCT$ is the Normal Operating Cell Temperature. The ambient temperature is not constant and depends on the data available in the data base, which is updated every minute.

$$T_{cell} = T_{amb} + \frac{NOCT - 20}{800} S \tag{12}$$

2) Wind Turbine: According to [20], the amount of power that can be absorbed by a wind turbine is given by the formula in (13). C_p is the power coefficient and is calculated using the formula shown in (14). The power coefficient represents the aerodynamic efficiency of the wind turbine. Because of the Betz limit the C_p value cannot be higher than $16/27$ [21]. ρ_{air} is the air density, A is the swept area of the turbine and v is the wind velocity.

$$P = \frac{1}{2} C_p \rho_{air} A v^3 \tag{13}$$

$$C_p = 0,5176 \left[\frac{116}{\frac{1}{\lambda - 0,08\beta} - \frac{0,035}{\beta^3+1}} - 0,4\beta - 5 \right] e^{\frac{-21}{\frac{1}{\lambda-0,08\beta} - \frac{0,035}{\beta^3}}} + 0,068\lambda \tag{14}$$

For the kind of turbine considered on this study (horizontal axis wind turbine), C_p has a value between 0.2 and 0.5 [22]. β is the incident blade angle and the tip speed ratio (λ) is given by (15), where r is the turbine radius, ω is the rotational frequency of the turbine and v is the wind speed.

$$\lambda = \frac{r\Omega_r}{v} \tag{15}$$

III. Results and Analysis

Results of a simulation for a residential building with four inhabitants during the month of August on a weekend day are presented in this section. For this simulation the devices that have been used are listed in Table II together with their specifications. Note that the user could have set different parameters according to his/her needs.

TABLE II. Specifications that have been set for each device during this simulation.

Type of Devices	Specifications
Photovoltaic Panel	Installation area – $25m^2$
Wind Turbine	Wind turbine diameter – $3m^2$
Refrigerator	Mean power – $300W$ Desired temperature range – $[3; 6]°C$
Air Conditioning	Mean power – $2000W$ Comfort Temperature – $[18; 20]°C$
Washing Machine	Mean power – $2500W$ Working Period – $70min$ Starting Time – $9:30h$
Dishwasher	Mean power– $1800W$ Working Period – 50min Starting Time – $17:23h$

After setting all the specifications, the platform simulates the behavior of each device for a period of 24h. The output of the simulation presents the energy consumed/generated in the form of graphs, as shown in Fig. 5, 6, 7, 8 and 10.

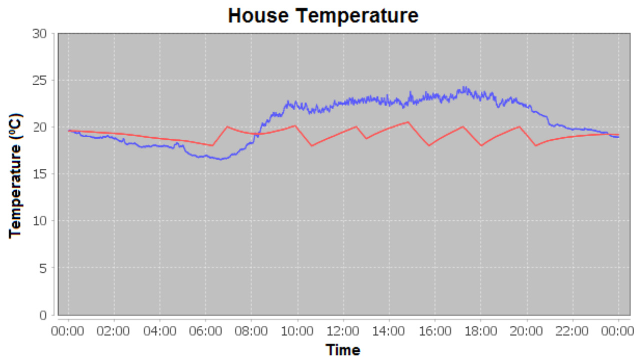

Fig. 5. Variation of the temperature inside the house (red) according to the outside temperature (blue).

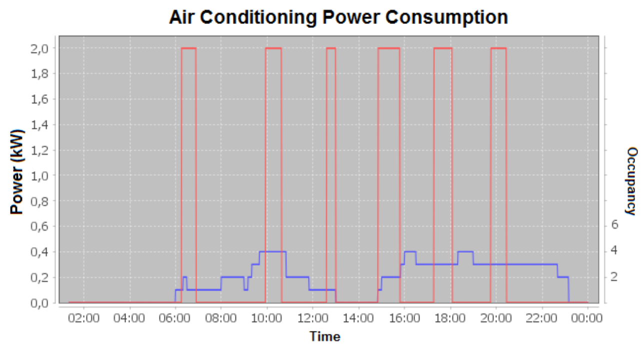

Fig. 6. Power consumption of the air conditioning (red) and occupancy (blue).

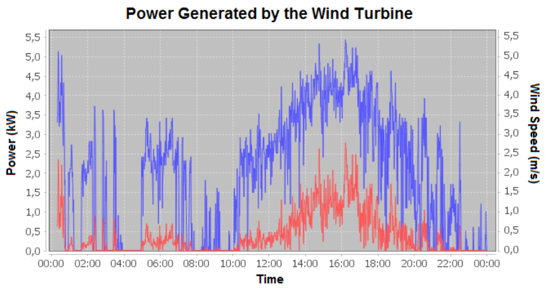

Fig. 7. Estimation of the power generated by the wind turbine (red) based on the wind speed (blue).

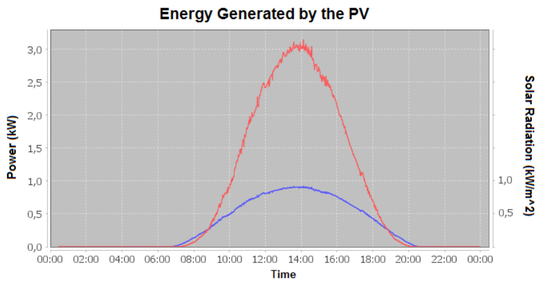

Fig. 8. Estimation of the power generated by the photovoltaic panel (blue) based on the solar radiation (red).

By analyzing the collected charts it is perceptible the impact that each device has on the building's energy demand and generation profiles (Fig. 10), as well as the interference of external influences, such as temperature, solar radiation, wind speed and occupancy (in the case of the air conditioning). Since the outside temperature is most of the time above the comfort temperature (Fig. 5) previously defined, the air conditioning has to work in order to cool down the house's temperature. A closer look to both the chart of the air conditioning (Fig. 6) and the building's inside temperature (Fig. 5) makes possible to conclude that each time the air conditioning starts, the temperature of the house decreases. Moreover, it is clear that the air conditioning only works when there is at least one active occupant (Fig.6). Furthermore, it is evident that the energy produced by the wind turbine and the solar panel is directly proportional to the wind speed and solar radiation, respectively (Fig. 7 and Fig. 8). The sharing of information between agents is important since it is possible for one device to react to another one's behavior. This is made possible through the messages exchanged between agents. Fig. 9 was taken from JADE's interface while the simulation was running and presents the messages sent by the agent representing the residential building to the other agents that are thermostat-controlled, such as the air conditioning and the refrigerator. These messages contain information regarding the ambient temperature of the house and are sent to both agents with different purposes. On one hand, it is important for the air conditioning to know the temperature of the building so it could keep its temperature within the temperature range defined by the user. On the other hand, the refrigerator must know the surrounding temperature so it can measure the impact that it might have on the temperature of the inner compartment and turn on/off the compressor in order to keep its temperature within the range previously specified.

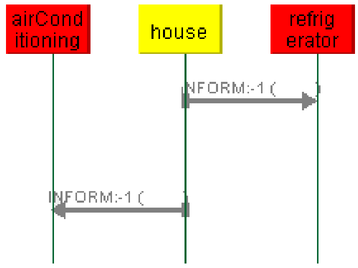

Fig. 9. Messages exchanged between the thermal devices.

A. Application to DR

Taking into consideration a scenario where the building is not able sell energy to the grid and that it only consumes energy from it when the supply of renewable energy is not enough to meet the building's demand, the simulator has calculated the energy cost of the previous simulation (section III), which was 0.79€. A second simulation was performed using the same devices and specifications, but setting a different starting time for the washing machine and the dishwasher. When comparing to the previous simulation (Fig. 10) it is possible to notice that both the washing machine and the dishwasher are now running at a time in which the renewable energy provided by the solar panel and wind turbine is sufficient to cover up its energy consumption, as shown in Fig. 11. Therefore, it would be cheaper for the user to shift both appliances. This simulation presented an energy cost of 0.36€, enabling the user to save more than 45.5% on the electricity bill by increasing the use of renewable energy. In the presented scenario, by changing its consumption habits the user is increasing the use of the energy produced on-site and saving money.

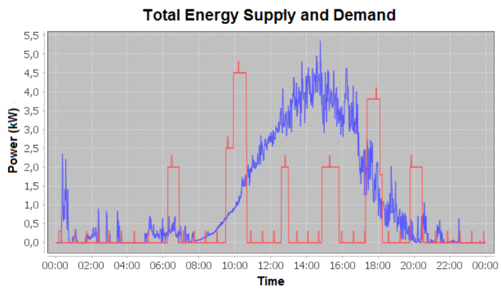

Fig. 10. Energy balance of the residential building (demand (red), supply (blue)).

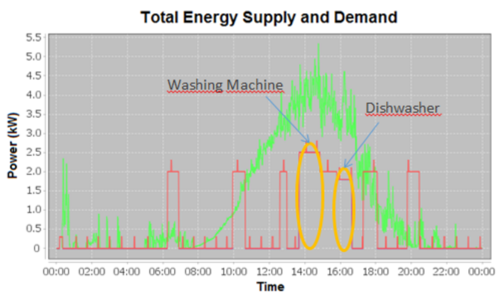

Fig. 11. Energy balance of the residential building (demand (red), supply (green)).

IV. CONCLUSIONS

In this paper it has been presented an agent-based energy simulator with the intent of providing the tenants with a tool to easily apply demand response techniques. This has been made possible through the usage of an agent-based hybrid "bottom-up" model, which uses both statistics and physics models. With this simulator it is possible to estimate the energy on-site generation and demand and consequently the respective energy cost, giving tenants valuable information to better response to changes on the electricity prices. The applicability of the developed platform is demonstrated in section III (Results and Analysis) showing a good improvement on the energy cost by increasing the use of renewable energy.

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