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Energy demand model to support the definition of sustainable energy systems

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Abstract

The dependence on fossil fuels use, and consequent environmental impacts, has result in a drive to promote sustainable energy systems, characterized by efficient energy use and the integration of endogenous and renewable energy resources. Understanding how energy is used at the consumer level is crucial to design and assess the impact of energy efficiency policy options. The goal of this thesis is to develop a residential energy demand hybrid simulation model to understand how households use energy, providing accurate results using accessible statistics data, to be used for sustainable energy planning exercises at a regional scale.

The hybrid model combines top-down and bottom-up approaches to consider buildings geometric and thermodynamic characteristics, climatic data and technologies. The model was applied in two case studies, one regarding the municipality of Odemira, and another regarding the parish of Olivais in Lisbon.

The Odemira model was used to perform sensitivity and scenario impact analyses on emissions, energy savings and shift from fossil fuels sources to renewables. The results show the potential for reductions of $50\ \%$ in CO_2 emissions, $60\ \%$ fossil fuel for water heating, $50\ \%$ of wood for space heating and $60\ \%$ of electricity for lighting.

The Olivais model was used to test the ability of the model to be applied with different spatial resolution and data availability. The results show that the ability of the model to use building by building information enables significant improvement of the accuracy, even if only geometrical information is used.

Keywords: hybrid energy demand model; sustainable energy systems; energy planning; technology options; domestic end-uses; energy vectors.

Resumo

Os impactos ambientais devido à forte dependência de fontes de energia fóssil levaram a vários países procurem utilizar a energia de forma eficiente e integrar recursos energéticos endógenos e renováveis, de modo a criar sistemas sustentáveis de energia. Compreender como a energia é utilizada ao nível dos consumidores tornou-se assim fundamental para projetar e avaliar o impacto de políticas que visam alcançar eficiência energética. O objetivo desta tese é desenvolver um modelo hibrido de procura energética no setor doméstico, com o intuito de, recorrendo a dados estatísticos de fácil acesso, ser possível auxiliar os planos energéticos a uma escala regional.

O modelo desenvolvido combina metodologias top-down e bottom-up de modo a considerar parâmetros da geometria das casas, características termodinâmicas dos edifícios, dados climáticos e tecnologias. O modelo foi aplicado em dois casos de estudo, um em relação ao município de Odemira, e outro sobre a freguesia dos Olivais, em Lisboa.

O modelo de Odemira foi usado para realizar uma análise de sensibilidade e para avaliar o impacto de diversos cenários tecnológicos do ponto de vista económico, das emissões, da eficiência energética e da utilização de renováveis. Os resultados mostram um potencial de redução de 50% das emissões de CO_2, 60% de combustíveis fósseis para aquecimento de água, 50% de madeira para aquecimento e 60% de eletricidade para a iluminação.

O caso de estudo dos Olivais foi usado para avaliar o impacto de diferentes resoluções espaciais. Os resultados mostram que dados edifício a edifício representam uma melhoria na precisão dos resultados.

Palavras-chave: modelo hibrido de procura de energia; sistemas sustentáveis de energia; planeamento energético; opções tecnológicas; end-uses domésticos; vetores energéticos.

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1. Introduction

1.1. Context, motivation and objectives

The growing awareness for climate change eased the establishment of protocols and targets to reduce greenhouse gases emissions and, as a consequence, an increased interest in renewable energy systems implementation. National energy plans translate the ambition of the Nations, as they are primarily engaged in energy supply models. Energy efficiency although regarded as a priority, as it is associated with reducing energy consumption, is more difficult to implement, as the calculation of its potential impact requires a very detailed understanding of how and when energy is used at the consumer level. This is also critical to promote a better integration of endogenous energy resources as well as renewable energies.

To promote a detailed understanding on how and when energy is used at the household consumer level constitutes the motivation for this work, which develops a detailed energy demand driven model for households. The work follows the principle that sustainable energy systems are always to be designed from demand to supply, allowing in first place to emphasize energy efficiency, and subsequently energy conversion technologies that satisfy the maximization of endogenous energy use and renewables, in order to promote the system sustainability and, as a consequence, to maximize the added value for the region.

The model proposed in this work was developed to support the design of a combined integration of energy saving measures together with renewable energy penetration at the level of the households, combining the detailed knowledge of buildings characteristics and appliances and heating and cooling technologies used with the endogenous resources availability at a regional level.

This required a new approach that complements the models available in literature in that it integrates a bottom-up approach that enables a detailed discretization of building characteristics and space heating and cooling technologies at the building level and a top-down approach that provides the characterization of other end uses, such as lighting. These model was coined as a “residential energy demand hybrid simulation model”.

This model bridges a gap in the available literature, enabling the analysis of different energy demand scenarios, making use of available data and, thus it constitutes an accessible tool to support energy technology policy options at a regional and national level.

As a consequence, three main objectives can be identified:

- The primary objective is to develop a hybrid engineering model to characterize energy demand in the residential sector, calibrated with top-down information, which can be integrated with energy planning models at a municipality or parish scale.
- The second objective is to compare how the application of the model with different spatial resolutions impacts the results obtained.
- The third objective is to assess the model contribution to regional energy planning exercises, particularly focused in the design of sustainable energy systems.

1.2. Methodology

The first step consisted in developing a literature review on models capable of characterizing energy demand at a regional or national levels. It was concluded for the need to develop a new method, a hybrid model to consider buildings geometric and thermodynamic characteristics, climatic data and technology penetration information, adequate to contribute to upgrade the sustainability level of regional energy systems.

The model was applied in two case studies that involved intensive data collection and treatment processes. One regarding the municipality of Odemira, which was used to calibrate the model with national consumption statistics [1], mostly from the Portuguese census database [2], [3] and to develop an energy planning exercise. The other regarding the parish of Olivais, with the objective of assessing the influence of different spatial resolutions on the model results made use of data sets from Census and a GIS building by building database[4].

The energy planning exercise to demonstrate the utility of the model in supporting the definition of sustainable energy systems, encompassed two methods: A sensitivity analysis to the useful energy requirements for space heating and space cooling; and a scenario impact analysis on energy consumption and emissions. The later was divided in two parts. In the first a set of technology options were analyzed regarding energy and emissions savings. In the second part, three technology possibilities were assessed in detail, regarding investment, emissions, energy savings and shift from fossil fuels sources to renewables.

Finally, the accuracy of the results obtained using accessible statics' data, census data, was analyzed with the case study of Olivais, by comparing the useful energy requirements for space heating when calculated with census data, and with GIS building by building data.

1.3. Document structure

In chapter 2, a review of the classification structure of energy models is presented, and the correspondent features are explained. The main characteristics of the two major types of energy models: top-down and bottom-up, are detailed. The energy models are discussed and a brief discussion on the main gaps existing in energy demand modelling is provided.

Chapter 3 presents the formulation of the model proposed in this work, where the mathematical details of the sub-models developed are explained, supported by available formulations made by other authors.

Chapter 4 presents the two case studies (Odemira municipality and the parish of Olivais) characterization and the data sets treatment to properly fit the model formulation.

Chapter 5 presents the main results for the case study of Odemira and discusses them along three sections. Firstly, the model calibration procedure is explained, followed by reference scenario data obtained based on national energy consumption as this was used to calibrate the model. The reference scenario data was also compared with regional consumption data. Secondly, a sensitivity analysis in section 5.2 is analyzed in terms of useful energy. Lastly, the results regarding several technological options are presented and discussed in terms of final energy savings, emissions and economic viability.

In chapter 6, a comparison between different spatial resolutions is discussed in terms of useful energy needs for space heating in Olivais. The first part of the section focus on the census' spatial disaggregation levels, while in the other part the results from the comparison between census and GIS data are discussed.

Finally, chapter 7 provides the conclusions and contributions of this work, as well possible paths towards further research.

2. Energy systems simulation models: a literature review

This chapter briefly reviews the classification scheme of energy systems simulation models, while its key features are also discussed. Secondly, the models that could better fit the purpose of this work which is focused on energy demand, are analyzed in more detail. Thirdly, the gaps of the models are identified.

2.1. Characterizing energy systems models

Energy systems models, or simply energy models are used to represent systems and assist in projecting future energy demand and supply [5]. Models are always a simplification of reality but they allow the proper understanding of the system, essential to determine the influence of certain variables on the system itself, and further support the planning of energy police measures.

The complexity of these models strongly depends on the scope to which they were planned for, and hence their classification has been addressed by various authors. Grubb [6] classified the models in six categories and later Hourcane [7] identified three ways to make a distinction between models. However, given the growing number of energy models with various aims during the late 20th century, an uniform classification was not clarified until Beeck [5]. He classified energy models, making use of a set of criteria, described below, in order to identify which kinds of models are suitable to assist energy demand projections:

- **Purpose of the model**, in two possible ways: general, which could be in the form of future forecasting, exploration or back-casting, a method to analyze the needs for changes in the present to accomplish future scenarios; and specific purposes, which regards the focus of the model such as energy demand, supply and impacts assessment.
- **Model structure**, which Beeck briefly subdivided in internal and external assumptions. The former being the assumptions embedded in the model structure, and the later those determined by the user. Hourcade et all [7] even had previously exemplified usual assumptions like energy supply technologies, efficiencies, population and economic growth or prices elasticity.
- **Analytical approach**: Top-Down vs Bottom-up (discussed ahead in this chapter).

- **Underlying methodology**, like econometric, optimization, simulation, spreadsheet, multicriteria, among others.
- **Mathematical approach**: linear programming, mixed integer programming and dynamic programming.
- **Geographical coverage.**
- **Sectorial coverage.**
- **Time horizon** of the analysis [6]: short term, being less than 5 years; between 3 and 15 years, medium term; and more than 10 years as long term.
- **Model data requirements**.

More recently, EEA [8] also classified models only in terms of thematic focus, geographical scale and analytical technique. Souza [9] also proposes a classification based on the energy carriers considered, model focus, aggregation level, underlying methodology, geographical scale, sectors considered, time horizon and time-scale of energy balance.

Amongst the different models classification suggested in the literature, the **top-down** vs **bottom-up** analytical approaches have been regularly discussed. Beeck [5] summarizes both approaches, characterizing top-down as an economic approach and bottom-up as an engineering approach. Kavgic [10] describes the first as an approach that works at an aggregated level, while the latter is assembled from disaggregated components.

Swan and Ugursal [11], focused on the modeling of energy demand in the residential sector, distinguish top-down and bottom-up as the two main modeling techniques. They defined that top-down methods do not differentiate energy consumption by individual end-uses and estimate energy demand from aggregated data, usually easy to obtain, such has GDP, employment rates, energy prices, climate conditions, housing date and appliance ownership. The downside of top-down methods, besides reliance on historical data, is the incapability to identify and analyze new technological developments and therefore their impact in energy demand, which is extremely important for planning sustainable energy systems. They distinguish top-down econometric models, mainly base on prices and income, and top-down technological models, which use characteristics like appliance ownership tendencies.

On the other side, bottom-up approaches mostly “focus on the energy sector exclusively, and use highly disaggregated data to describe energy end-uses and technological options in detail” [5]. Swan and Ugursal [11] even distinguish two bottom-up categories: statistical and engineering. The former relies on dwelling energy consumption data from samples and on techniques to regress the relationships between end-uses and energy consumption. The vast energy billing information stored by energy suppliers may be of strong usefulness in this type of models. The author identifies: regression techniques to determine the ‘weight’ of the input parameters; condition demand analysis(CDA), which performs regression based on appliances surveys to the occupants and energy consumption data from the supplier; and neural network(NN), which Swan and Ugursal say “the technique allows all end-uses to affect one another through a series of parallel ‘‘neurons’” resulting in the technique “ability to capture non-linear characteristics” [11]. The later bottom-up category, engineering methods, calculates energy consumption based on dwelling and end-uses properties, as well thermodynamic relations and technologies efficiency and power. The bottom-up approach normally requires detailed information about dwellings' properties, such as the geometry, envelop materials characteristics and equipment's data sets. This method also suggests the use of weather information and simplified households' behavioral patterns such as occupancy, equipment's usage and indoor temperature preferences. The authors make distinction between three techniques: distributions techniques, which use appliances ownership and power ratings to calculate energy consumption by end-use; archetypes, where dwellings are grouped according certain characteristics; and samples, as input data in the model. The bottom-up engineering approaches are the best to model new technologies. However, they do not incorporate economic factors, require intensive computation and do not include robust occupancy patterns, which affects energy use, as studied by Guerra Santin et al. [12] and Santin [13]. On the other hand, the bottom-up statistical approach comprises macroeconomic and socioeconomic factors, as well behavior patterns. Figure 1 summarizes the typology adopted for residential energy demand models.

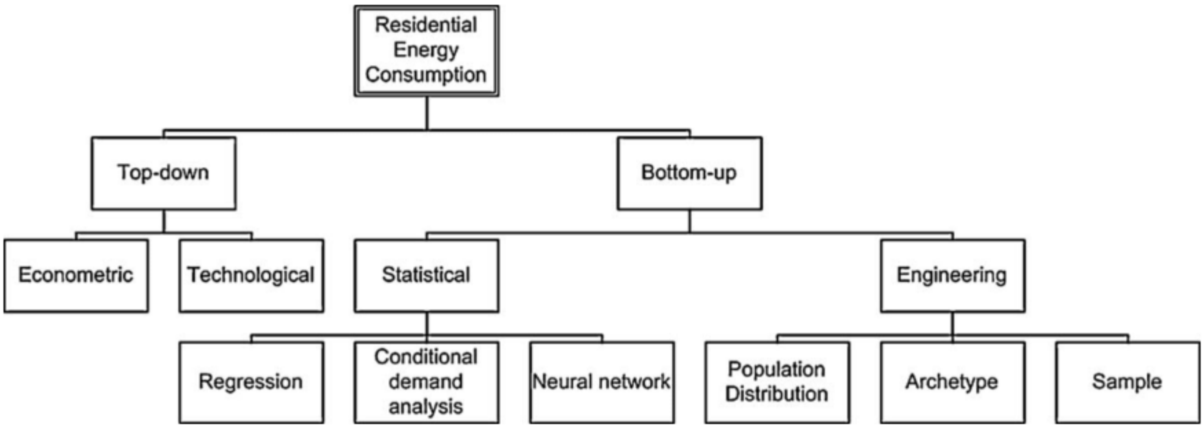

Figure 1 - Top-down and bottom-up modelling techniques for estimating the regional or national residential energy consumption [11].

In order to take advantages of both top-down and bottom-up models (statistical and engineering) approaches, several authors combined these methods to create hybrid models. Frei et al. [14] merge a bottom-up activity analysis into a computable general equilibrium (CGE) top-down model to fulfill the limitations of the top-down model which lacks empirical evidence on elasticity determining technological evolution under energy policy constrains. McFarland et al. [15] analyzed hybrid models and concluded that "it enhance the technological richness of a top-down economic model using bottom-up engineering information''. Böhringer [16] and Böhringer & Rutherford [17] also combine both models and distinguish three levels of integration between models. ''Soft-linked'' when the models are developed independently, a second level when the focus is in one of the models and the other is in a reduced representation, and a third level where the models are completely integrated within a single framework.

2.2. Review of selected energy demand models

This section reviews the most relevant models available to simulate household energy demand, based on reviews made available by several authors in the literature. Jebaraj and Iniyan [18], with the aim of helping energy planners, researchers and policy makers, gave a brief overview of the various types of energy models. They analyzed energy planning, supply-demand, forecasting optimization, neural networks (NN) and emissions models. EEA [8] has created a modeling tools inventory to support forward-looking environmental assessments and outlooks at a European scale. In its 150 models 'pool' list, the strengths and weaknesses of the models are explored. Connolly et al. [19] reviewed in details 37 tools that can be used to analyze the integration of renewable energy. The author emphasize that there is not an ideal tool but rather one that is more suitable according to the decision-makers specific objectives.

Kavgic et al. [10] assesse in a very good way the purposes, strengths and shortcomings of existing bottom-up building pyshics based residential energy models. More specifically, four models from outside of the United Kingdom and five from within. Mendes et al. [20] analyzed different tools for modelling Highly Integrated Community Energy Systems (ICES). More recently, Suganthi and Samuel [21] attempted to review various energy demand forecasting models.

The energy models highlighted in the reviews are discussed in the following paragraphs.

CREEM is the Canadian Residential Energy End-use Model [22] which was used to analyze a wide range of scenarios concerning the retrofit of residential buildings and fuel switching alternatives. The model allows a techno-economic evaluation to identify the impact on energy consumption and emissions from the scenarios. The model requires national statistics and is disaggregated in more than 8000 dwellings types. The simulation tool used for the calculations was HOT2000. The model is validated with energy billings records and is only used by the developers.

The **North Karelia Finland model** [23], is a regional building stock model designed to assist the local decision makers. This non-dynamic, bottom-up numerical model objectives are to estimate energy and greenhouse gas emissions as well an economical assessment regarding heating energy costs. The model comprises clusters of buildings in the calculations on its municipalities' representation. The aggregated clusters concern the types of buildings, like configuration with the surrounding buildings, utilization type, e.g. apartments, commercial, educational, etc. The heating technologies and respective energy sources and also the age of the buildings. Besides some major assumptions taken, the model's inability to address temporal changes, due to its steady-state physics, is one of its principal drawbacks [10].

The **Huang and Brodrick** model [24], was built to access potential improvements in United States of America buildings' energy efficiency. The model stock used with the model included single-family, multi-family and commercial buildings. With data regarding age of the buildings, type of dwelling, and total building stock per region. The model features aggregated heating and cooling loads from several building envelope components, e.g. windows and walls, rather than per dwelling. The model energy results in hourly load shapes were calculated using DOE-2.1E simulation tool. The aggregated results obtained with the model were similar to the ones used with other approaches, despite the model disadvantage of only considering gas as primary energy source.

The **Hens et al. building stock model** [25], used residential data from dwellings, namely age, type, total floor area, primary energy and presence of central heating to calculate the energy consumption for heating, hot water and ‘general’. This Belgian model, which objective was to identify possible energy reduction policies, does not consider energy consumption from lighting and appliances, neither cooling loads.

In the United Kingdom, several models have been developed to calculate the residential demand of energy. All of the fallowing bottom-up models used the Building Research Establishment Domestic Energy Model (**BREDEM**) [26] as the main calculation tool, although some of them used different versions or modified the model.

BREHOMES, is a residential energy model that uses weighted average stock to calculate energy requirements for dwellings. Requires dwellings areas, thermal properties, heating technologies, internal and external temperatures, heating patterns, number of occupants and solar gains. Lights and appliances energy are used in an aggregated manner. Johnston model uses as well weighted averages method and deals with two types of dwellings to calculate energy consumption and CO_2 emissions. UKDCM, uses a weighted stock transformation method as well to estimate the monthly space heating demand. Dwellings are classified by age, dwelling type, construction type, number of floors and floor area. DeCarb, uses a considerable disaggregated housing stock, with 8064 combinations for each age class. CDEM, comprises 47 house architypes with information regarding age and construction type. Uses the weighted average stock transformation method to calculate energy consumption and CO_2 emissions.

MARKAL (an acronym for MARKal ALlocation) “is a mathematical model of the energy system of one or several regions that provides a technology-rich basis for estimating energy dynamics over a multi-period horizon” [27]. Between the features of this linear programing tool, the energy demand per end-use is estimated based on economic and demographic projections on the desired regions, besides other user input information like new technologies. The demand for energy in each energy service is expressed in useful energy, and have its respective attributes, e.g. amounts of services to be satisfied at each time period, season, etc. The model contains a set of end-uses technologies ‘which produce an energy service to satisfy a demand.

The **Long-range Energy Alternatives Planning system (LEAP)** “is a computer-based accounting and simulation tool designed to assist policy makers in evaluating energy policies and developing sound, sustainable energy plans”[28]. It may be used as a forecasting tool to make projections over a long-term planning horizon, or simply be used with the purpose of a database. LEAP can be used to define strategies regarding emissions and energy consumption for both the energy supply and demand sides.

On the later side the model, which is demand-driven, is disaggregated in sectors of the economy, e.g. residential, industry, transports, commerce, agriculture, etc. Each of this is consequently divided in subsectors and then end-uses, which can be for example income groups, for the former, and domestic end-uses like space-heating, water-heating and so on, for the later. Finally the end-uses are divided in technologies and respective consumptions/usage. Figure 2 illustrates the LEAP residential demand model structure.

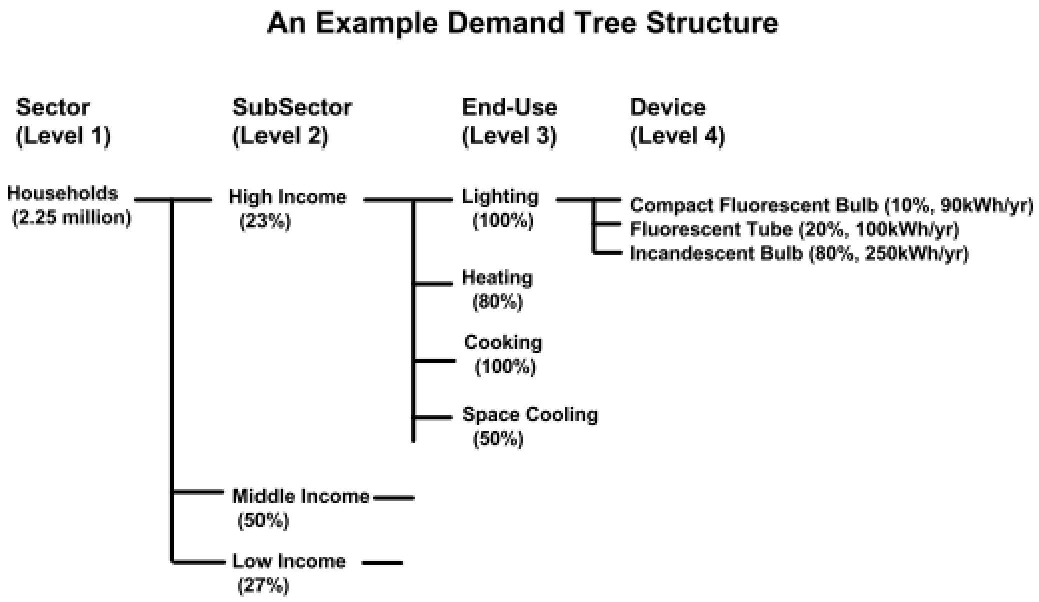

Figure 2 – Example of LEAP demand structure in the residential/households sector [28].

Despite LEAP's end-use disaggregated formulation bottom-up like, the consumptions are based on national energy balances, which is a top-down like approach. This limitates deeper technologic analysis on the demand side.

2.3. Identified gaps

The majority of the reviews revealed a greater amount of energy models focused on supply rather than on demand. Most of them modulate in both economic and energetic perspectives, and usually concentrated in policies or development of technologies in the supply side. The demand side is frequently introduced as an external input, or modeled in the form of simplified top-down approaches. Moreover, a fair amount of models work with broad geographic resolutions instead of smaller municipality scales, as intended in the present work. Finally, some models present the disadvantage of being difficult to access. These are either payed or are not available for public use.

Amongst the models and tools reviewed, those discussed in detail in the previous section were the most appropriate to be used for the purpose of this work, due to their ability to model with more detail the energy demand of a region. However, on the one hand, the models that included the level of detail aimed in this work were not available for application to the Portuguese case studies addressed in this work (a municipality and a parish), as they were either unavailable for public use or required specific data not available, e.g. CREEM. On the other hand, the models that could be applied to the Portuguese case study did not allowed for sufficient detail to characterize energy demand, e.g. MARKAL and LEAP are not able to model the physics of buildings' heating and cooling demand and are typically used to model large regions.

Therefore, the literature review showed that there is a need for a model capable of analyzing different energy demand scenarios, with a strong incorporation of technological developments in its formulation and, at the same time, with a geographical resolution adequate to municipalities and parishes and based on available data that can be applied in Portugal.

3. Residential energy demand hybrid simulation model formulation

To address the previously identified limitations, a model that discretizes energy consumption by end-use and energy vector, with high geographical detail, was developed. The model includes both bottom-up and top-down approaches for different end-uses. A bottom-up formulation was adopted to estimate the energy demand for space heating, space cooling and water heating. It considers buildings' geometric and thermodynamic characteristics, as well climatic data and technology penetration information. An appliances ownership and power rating based methodology was considered for cooking and electronic appliances end-uses consumption.

A top-down approach was used to estimate the baseline lighting end-use energy consumption. As such, this model can be classified as a **residential energy demand hybrid simulation model,** using both bottom-up and top-down approaches, applicable to small geographical scales and high detail in the energy end-uses. It is a short-term model with a one year time resolution, implemented with a spreadsheet methodology.

The outputs of the model are the final energy demand and CO_2 emissions in the residential sector. The model is intended to support energy technology policy options assessment at a regional and national level. Figure 3 outlines the inputs and outputs structure of the model proposed in the present work.

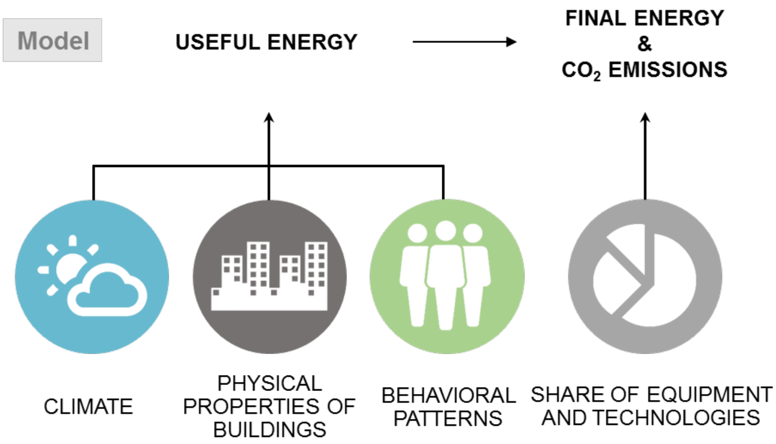

Figure 3 - Structure of the model.

The household energy demand model is formulated in seven separate divisions, each corresponding to a domestic end-use. The transformation of final energy to useful energy to than satisfy a specific energy service and therefore human needs, is made through different technologies, which constitute alternatives to different energy planning scenarios. This constitutes the main advantage in building a model that parameterizes technologies, and the different energy vectors that they may convert. Figure 4 outlines this concepts.

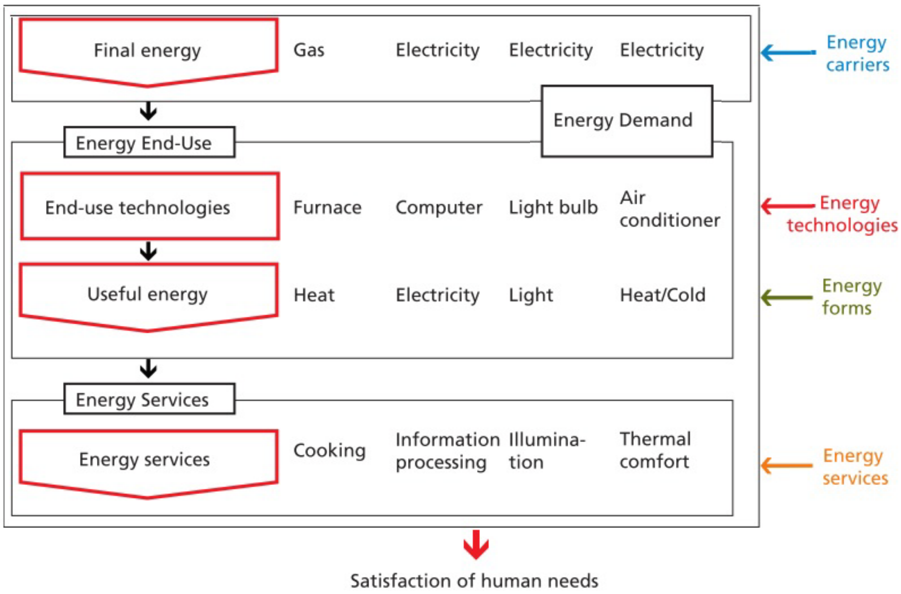

Figure 4 - Schematic diagram of the energy system with some illustrative examples, adapted from T.B.Johansson et al. [29].

The model is bottom-up, in that it first calculates the useful energy needs for space heating, space cooling and water heating, followed by final energy needs calculations. It considers buildings' geometric and thermodynamic characteristics, as well climatic data and technology penetration information. An appliances ownership and power rating based methodology was considered for cooking and electronic appliances end-uses consumption. A top-down approach was used to estimate the baseline lighting end-use energy consumption.

A major contribution of the model developed consists on the articulation of a large number of methods to characterize the different energy services relevant at a household level, such as heating, cooling, water heating, lighting, cooking and white appliances, and finally the use of electronic appliances. The fallowing formulation is intended to model energy demand expressed in kWh per year and per dwelling or per building.

3.1. Space Heating

The energy demand to satisfy the heating necessities of households has been addressed by several ways and numerous authors [12], [13], [30]–[37]. It can be concluded that the final energy demand depends essentially on four main elements: geographical location of the house, building characteristics, household behavior and heating technology. The geographical location is directly related with the ambient temperature throughout the year as well with solar irradiation. Building characteristics comprise building dimensions, orientation and constructive materials of the house, essential to calculate heat losses and gains from the outside. Behavior is also very important, it influences the desired room temperature, areas of the house which are heated or presence of people at home during the day is also determinant in the space heating energy necessities. Last but not least, the heating technology used to fulfill the space heating requirements is vital since it defines the energy vector that is converted into useful energy, i.e. the heated air, and, due to its conversion efficiency, different technologies may require dissimilar amounts of final energy for the same useful heating energy demand.

The formulation used to quantify the space heating final energy demand, Q_{SH} $[kWh]$, is represented in equation (1), and is a combination of the highly detailed model from the Portuguese energy regulation of residential buildings (REH) [38], which is well synthetized in [39], and a simpler formulation already adopted by several authors like Durmayaz et al. [40] and Stavropoulos [41].

$$Q_{SH} = \frac{\left(Q_{t\,sh} + Q_{v\,sh} - Q_{g\,sh}\right).f_{u\,sh}}{\eta_{Tsh}} \quad (1)$$

In equation (1), $Q_{t\,sh}$ $[kWh]$ are the heat losses by transmission, $Q_{v\,sh}$ $[kWh]$ are the heat losses by ventilation and infiltration, $Q_{g\,sh}$ $[kWh]$ are the heat gains, η_{Tsh} $[-]$ is the space heating technology efficiency and $f_{u\,sh}$ $[-]$ is a calibration factor which accounts for less measurable parameters such as the households' behavioral ones. The heat losses are obtained through equations (2), (3) and (4).

$$Q_{t\,sh} = 0{,}024.HDD.H_t \quad (2)$$

$$H_t = U_{wall}.A_{wall} + U_{window}.A_{window} + U_{floor}.A_{floor} + U_{ceilling}.A_{ceilling} \quad (3)$$

$$Q_{v\,sh} = 0{,}024.HDD.\frac{C_p.\rho}{3600}.ACH.V \quad (4)$$

HDD is the heating degree days, H_t $\left[\frac{W}{℃}\right]$ the global heat transfer coefficient, $U's$ $\left[\frac{W}{m^2.℃}\right]$ and $A's[m^2]$ the overall heat transfer coefficients and areas respectively. C_p $\left[\frac{kJ}{kg.K}\right]$ is the specific heat of air, ρ $\left[\frac{kg}{m^3}\right]$ is the density of air, ACH $[hour^{-1}]$ is the air changes per hour and V $[m^3]$ the building volume.

The heat gains are given by equation (5) where Q_{int} $[kWh]$ and $Q_{sol\,sh}$ $[kWh]$ represent the internal and solar irradiation heat gains respectively, calculated by equations (6) and(7), and η_{gu} $[-]$ is the gains utilization factor and is a function of the ratio between gains and losses, and a parameter $'a'$ which accounts for the building thermal mass. The later calculation is explained in detail in Appendix B and is calculated according to REH [38].

$$Q_{g\,sh} = \eta_{gu}.(Q_{int}+Q_{sol\,sh}) \tag{5}$$

$$Q_{int} = 0{,}72.q_{int}.M_{sh}.AFA \tag{6}$$

$$Q_{sol\,sh} = G_{south}.\sum_{windows,w}\left[X_i.\overbrace{F_h.F_o.F_f}^{F_s}.\overbrace{A_w.F_g.g_i}^{A_s}\right].M_{sh} \tag{7}$$

q_{int} $\left[\frac{W}{m^2}\right]$ is the average internal gains floor area, M_{sh} $[months]$ the number of months of the heating season, AFA $[m^2]$ the average floor area of the building, G_{south} $\left[\frac{kWh}{m^2.month}\right]$ the average monthly solar radiation through the heating season on a vertical south orientated surface, X_i $[-]$ is the window $'\mathrm{w}'$ orientation coefficient, F_s [-] is the windows obstruction factor that accounts for obstructions in the horizon, F_h $[-]$, and from horizontal and vertical elements adjacent to the windows, F_o $[-]$ and F_f $[-]$ respectively. A_s $[m^2]$ is the effective area, which is the product of A_w $[m^2]$, the window $'\mathrm{w}'$ area, with F_g $[-]$, the glassed fraction of the window and g_i $[-]$, which is a coefficient that accounts for properties of the glass and shading elements. The latter coefficients won't be addressed in detail since it would require an exhaustive description which is available in REH [38].

3.2. Space Cooling

Similarly to space heating, space cooling energy depends on the geographical location of the house, building characteristics, household behavior and cooling technology. Equation (8) stands for the space cooling energy demand of a building, Q_{SC} $[kWh]$.

$$Q_{SC} = \left(1-\eta_{gu}\right).Q_{g\,sc}.\frac{f_{u\,sc}}{\eta_{Tsc}} \tag{8}$$

$f_{u\,sc}$ $[-]$ and η_{Tsc} $[-]$ are respectively a calibration factor and the space cooling technology efficiency. η_{gu} $[-]$ is the gains utilization factor as already described in section 3.1. $Q_{g\,sc}$ $[kWh]$ represents the heat gains and are thus represented by the sum of solar and internal gains. However, the solar gains for the cooling season are now expressed by equation (9). This equation takes into account the solar gains during the cooling season from both windows $'w'$, left sum, and opaque elements $'o'$ like the exterior walls, right sum.

$$Q_{sol\,sc} = \sum_{windows,w} \left[G_{solar} \overbrace{F_h.F_o.F_f}^{F_S} . \overbrace{A_w.F_g.g_v}^{A_{S,w}} \right] + \sum_{\substack{opaque \\ elements,o}} \left[G_{solar}.\overbrace{F_h.F_o.F_f}^{F_S} . \overbrace{\alpha.U.A_o.R_{es}}^{A_{S,o}} \right] \quad (9)$$

The calculation of gains from windows is identical to the one for space heating and its parameters are explained in 3.1. g_v $[-]$ is a coefficient that accounts for properties of the glass and shading elements. The F_s $[-]$ for opaque elements is calculated alike for windows. G_{solar} $\left[\frac{kWh}{m^2}\right]$ is the average cooling season solar radiation for windows and opaque elements orientations. Notice that G_{solar} is the equivalent of the product $G_{south}.X_i.M_{sh}$ in equation (7) of space heating. Regarding opaque elements, $A_{s,o}$ $[m^2]$ is the effective area, which is the product of α $[-]$, the surface solar radiation absorption coefficient, U $\left[\frac{W}{m^2.℃}\right]$ the overall heat transfer coefficient, A_o $[m^2]$ the surface area and R_{es} $\left[\frac{m^2.℃}{W}\right]$ is the external surface thermal resistance of opaque element $'o'$.

Finally, in order to obtain η_{gu}, the heat exchange by transmission, ventilation and infiltration must be taken into account through equations (10) and (11).

$$Q_{t\,sc} = 0{,}72.M_{sc}.(\theta_{ref} - \theta_{ext}).H_t \quad (10)$$

$$Q_{v\,sc} = 0{,}72.M_{sc}.(\theta_{ref} - \theta_{ext}).\frac{C_p.\rho}{3600}.ACH.V \quad (11)$$

M_{sc} $[months]$ is the number of months of the cooling season, θ_{ref} [ºC] is the cooling reference temperature and θ_{ext}[ºC] is the average external temperature in the cooling season.

3.3. Water Heating

The water heating energy demand includes all the energy used to heat water for domestic use except water heating of specific appliances like washing machines and dish washers which have their own water heating system. The energy required for domestic water heating purposes in a household is given by equation (12) as Q_{WH} $[kWh]$.

$$Q_{WH} = \frac{V_w.f_{e\,wh}.C_{p\,w}.\rho_w.\Delta T.d.n}{3600.\eta_{Twh}} \quad (12)$$

$V_w \left[\frac{l}{person.day}\right]$ is the daily water volume per person, $f_{e\,wh}$ $[-]$ is a factor that accounts for hydraulic efficient systems, $C_{p\,w}$ $\left[\frac{kJ}{kg.K}\right]$ and ρ_w $\left[\frac{kg}{l}\right]$ are the specific heat and density of water respectively, ΔT $[K]$ the water temperature increase by the heating system, d $[days]$ the annual number of days of used water, n $[person]$ the number of people in the household and η_{Twh} $[-]$ the water heating technology efficiency.

3.4. Lighting

The artificial lighting necessities for a household depend mostly on the amount of natural light available and on the activities being undertaken by the occupants [42], [43]. As referred by Souza [9], the lighting requirements would ideally be measured in lumens. This also presents the advantage of being able to analyze the impact of using different light bulbs with different efficiencies, measured in watt per lumen, on the electric energy consumption. The main challenge in estimating the lighting demand is to accurately define and simulate the occupants' activities since they have different durations and lumens necessities. Therefore, a similar model to Daioglou [37], Souza [9], Shen [32] and Dopazo et al. [44] was formulated, as presented in equation (13).

$$Q_L = 0{,}001.\,d.\,AFA.\sum_{Tl}\left[\frac{S_{Tl}}{\eta_{Tl}}\right].\,L.\,T \tag{13}$$

In equation (13), Q_L $[kWh]$ is the annual energy demand for lighting for a single dwelling, d $[days]$ the annual number of days of used lighting, AFA $[m^2]$ is the average floor area of the dwelling, S_{Tl} $[-]$ and η_{Tl} $\left[\frac{Lm}{W}\right]$ are the share of lighting technology $'Tl'$ and its efficiency correspondingly, L $\left[\frac{Lm}{m^2}\right]$ is the lighting requirement and T $\left[\frac{hours}{day}\right]$ is the equivalent amount of lighting hours required per day. The latter two combined can be interpreted as the average lighting needs in lumen times hours per square meter. As mentioned in by Daioglou et al., ''for electrified households, data suggests that lighting demand (at frozen efficiency) forms a linear relationship with floor space'' [37], which therefore legitimates de use of the product $L.T$, calculated from historical consumption data, to estimate future energy consumptions for lighting in function of floor area and light bulbs technologies' shares and its efficiencies.

3.5. Cooking

Adopting an identical definition as INE [2], cooking comprises all the energy demand from the usual equipment used for meal time preparation as well large and minor appliances with exclusive or common usage in the kitchen, often called ‘white appliances’. The total energy demand for cooking in a dwelling, Q_C $[kWh]$, is consequently the sum of all the appliances consumptions, as given by equation (14).

$$Q_C = \sum Q_{C,a} \tag{14}$$

The energy demand for each type of appliance depends on the equipment power rating, usage and penetration in households. The power rating and usage can be combined in the form of the appliance specific energy consumption if this parameter is otherwise available. A more detailed formulation for an equipment consumption may as well be used if available. Therefore, like Dopazo et al. [44] and Souza [9] have used, the cooking demand for a certain appliance $'a'$ is modelled as equation (15).

$$Q_{C,a} = P_a . Sc_a \tag{15}$$

Where, for an appliance $'a'$, $Q_{C,a}$ $[kWh]$ is the annual energy demand, P_a $\left[\frac{units}{dwelling}\right]$ is the appliance penetration and Sc_a $\left[\frac{kWh}{year}\right]$ is the specific energy consumption. One shall notice the mutual use of the ‘appliance’ nomenclature for the meal preparation equipment and white appliances. Since they may not have the same energy vector source, the sum may be calculated also by type of energy vector.

3.6. Electronic Appliances

The general formulation to calculate electronic appliances energy consumption is identical to the one adopted for cooking appliances and is expressed by equations (16) and (17).

$$Q_{EA} = \sum Q_{EA,e} \tag{16}$$

$$Q_{EA,e} = P_e . Sc_e \tag{17}$$

Q_{EA} $[kWh]$ is the total energy demand for electronic appliances, $Q_{EA,e}$ $[kWh]$ is the demand for a certain appliance $'\mathrm{e}'$, P_e $\left[\frac{units}{dwelling}\right]$ and Sc_e $\left[\frac{kWh}{year}\right]$ are the appliance penetration and specific energy consumption respectively.

4. Case Studies

4.1. The Municipality of Odemira case study

Odemira is a Portuguese municipality used as initial case study to calibrate and assesse the model as a tool to support energy planning exercises. This case study is divided in two parts: One in which a sensitivity analysis was made to some of the model parameters, and a second part where sets of energy efficient measures were analyzed. The latter is furthermore divided in two subsections: one with an extensive group of measures to demonstrate the full potential of the model proposed in this work. And a second section with a scenario build from a set of three detailed measures, selected has part of an Energy Planning exercise between Instituto Superior Técnico and the Odemira Municipality. The analysis of measures is explained in section 5.3.

Located in the southwest coast of Portugal and with approximately $1721\ km^2$ of area, Odemira is the largest Portuguese municipality and has one of the lowest population densities in the country with a rough total of 26 thousand inhabitants [2] distributed by 13 parishes. With an average exterior summer temperature above $22\ ℃$ and heating degree days below $1300\ HDD$ ($1089\ HDD$ at $18\ ℃$ base Temperature), this municipality is characterized by hot summers and cool winters, receiving an REH climatic zone classification of Summer-3 and Winter-1 (from 1 to 3).

In this case study, the model is calibrated for the national data and whenever available it was customize with regional data. For example, in terms of buildings characteristics and demographic aspects a satisfying level of spatial resolution was obtained from Census and some other few surveys, but for appliances penetrations and technologies it was mostly collected from national statistics surveys.

Table 1 summarizes the type of data collected from each source and its level of spatial desegregation. Most building characteristics and population data are from the 2011 Portuguese Census [2], [3] and are available in 4 spatial desegregation levels: municipality, parishes, statistical sections (usually around 300 dwellings) and statistical subsections (usually a city block or less). Information about the family was as well collected from the Portuguese Census. Climatic data was obtained from REH [38] and [45] and it was available by NUTS III. Technologies share, appliances penetration and energy vectors consumption distribution were assumed identical to the Portuguese mainland ones, with the exception of space heating technologies which share per parish was used in the analysis of the three detailed measures.

Table 1 – Data, source and desegregation level using Census as the principal data source.

Data Source	Data	Desegregation level
[46]	U values per building age group	National
	ACH	
[3]	Number of isolated buildings	Subsections
	Number of semi-detached buildings	
	Number of townhouses buildings	
	Buildings per number of floors	
	Buildings per age group	
	Dwellings per floor area group	
	Number of residents	
	Number of households	
	Households per size	
[1]	Energy vectors consumption per end-use	NUTS I
	Appliances penetration	
	Average Heated area per household	
	Average Cooled Area per household	
[1]	End-uses technologies share	NUTS I / Parish
[47], [48]	Percentage of windows per orientation category	Climatic region
	Glassed fraction of the window	
	Appliances penetration	
[39]	Climatic data	NUTS III
[39]	External surface thermal resistance	National
	Space heating, cooling and Hot Water technologies efficiencies	
[45]	Heating degree days	NUTS III
[49]	Glazing area percentage per building age group	National
[48]	Shading elements in windows	National
[50]	Appliances average consumption	Europe
[51]	Appliances average consumption	National
[52], [53]	Appliances efficiency label	Europe

4.2. The Parish of Olivais case study

Olivais is a parish located in the municipality of Lisbon, and was used to compare how the application of the model with different spatial resolutions impacts the results. Four levels of desegregated data were analyzed: GIS building by building and three levels available in Census (by parish, statistical section and statistical subsection). This analysis was focused on useful energy requirements for space heating.

Located in the central west coast of Portugal, and with almost 34 thousand inhabitants living in approximately $11\ km^2$ of area, Olivais is characterized by high population density. With an average exterior summer temperature around $20/22$ ℃ heating and degree days below $1300\ HDD$ (18 ℃ base

Temperature), this parish has warm summers and cool winters, receiving an REH climatic zone classification of Summer-2 and Winter-1 (from 1 to 3).

In the Olivais case study, the buildings geometric and physical characteristics were gather from two distinct data sources: from Census (more specifically, BGRI) and from the Municipality GIS data base. The GIS data was formatted and processed by Monteiro et al. [4] which, unlike the BGRI data, allowed the definition of architypes with additional levels of correlation between the building parameters and therefore a greater resolution of calculus.

The calculation with Census data was made with the same sources and respective spatial desegregation as the Odemira case study and therefore Table 1 in section 4.1 is also applicable for Olivais. Regarding GIS data, Table 2 summarizes the type of data collected from each source and its level of spatial desegregation.

Table 2 – Data, source and desegregation level for Olivais.

Data Source	Data	Desegregation level
[4], [46]	U values per building age group	Building
	ACH	
[4]	Buildings geometry and configuration	
	Glazing area percentage	
	Shading factors & other	
[45]	Heating degree days	NUTS III

4.3. Data Sets and Data Treatment

In the model calculation process, two major concerns were present. The existence of data with suitable detail, i.e. resolution, to guarantee accurate results from the model and, on the other side, the proper data dimension to avoid unnecessary calculation requirements with insignificant improvements in results accuracy. The two later concerns depend essentially on two aspects, the ease in finding detailed data sets and the treatment of it. The data treatment also involved the adaptation of the ‘raw’ information into a data set appropriate for the calculations. Two different main data sets were therefore used in this project: Census and GIS database.

The Portuguese Census is the most detailed and freely accessible dataset of buildings and population characteristics at the national level, and was use as the primary source of buildings and population data for the Odemira case study. Census is a large statistical survey that is usually taken in 10 years intervals to all the population of a country with the objective of gathering information regarding demography, housing, economy, etc. In this work, whenever a reference to the word ‘Census’ is made it refers to the Portuguese 2011 Census which can be consulted in INE [2]. BGRI [3] is the geographical referenced information data base, which has a large data set, from Census, regarding multiple indicators by geographical location. The geographical location nomenclature is as fallows, according to its disaggregation: NUTSI, NUTSII, NUTSIII, municipality, parish, section and subsection.

The geographic information system (GIS), can be defined as a digital database which is referenced to a spatial coordinate system. The information available in this data base is disposed by 'layers' of information with a common referential, allowing to cross information and gather it by location [54]. This data set was used in the Olivais case study, which purpose was to compare the use of both types of data sets, Census and GIS, in order to assess the 'cost' on the results by using less detailed data.

The following subsections explain in detail both datasets, which major 'strategies' were made to avoid extensive calculations and real data collection, in the case of GIS, and how they were treated so as to adjust to the model formulation.

4.3.1. Census Data

The mathematical 'by dwelling' formulation of the model combined with the large spatial coverage of the analysis, made convenient to process the buildings data into typologies to streamline the calculations for both Census and GIS data. A typology is defined by as many indicators has variables present in the mathematical formulation. To illustrate this concept, one typology could have the number of isolated buildings built during the 90s, with 2 floors, with floor area interval between 40 and $50\,m^2$, average window orientation to west, and heat pump as heating technology. This example would be typology with 5 correlated parameters, and an even more specified typology could be used if available. Nevertheless, the increase of desegregated data, and therefore typologies with many indicators, is strictly followed by the unavailability of the data itself, and, despite the large database that Census are, the definition of typologies with it was limited by the absence of correlated parameters.

The buildings and population data from Census, more specifically from BGRI, is spatially desegregated in subsections. Each subsection is associated to a set of non-correlated building characteristics, indicators, which constrain the definition of typologies with numerous levels of correlated information. The result was the definition of a type of dwelling per subsection using weighted averages of the several properties.

Besides the inexistence of data crossing multiple dwelling properties, these characteristics were not provided for the same type of buildings use. The data regarding construction period, number of floors and configuration with surrounding buildings, refers to buildings in general, without distinguishing residential from other sorts of buildings. The data regarding dwellings' floor area is available for the category of classic dwellings with regular use, main residence of the family, which, in the case of Odemira, represents $51.4\,\%$ of the existing accommodation and $80.0\,\%$ for Olivais. The inexistence of floor area data regarding seasonal and vacant conventional dwellings implies a careful interpretation while analyzing measures affecting this later accommodation categories.

Moreover, the information regarding the buildings number of floors has only three indicators: number of buildings with 1 or 2, 3 or 4, and 5 or more floors. When analyzing locations with numerous buildings in the category of 5 or more floors, calculating a weighted average of floors number per building may become uncertain or even inappropriate.

Figure 5 clarifies the organization of categories concerning buildings and residential accommodations in Census and the data that is available and hence used for both Case studies.

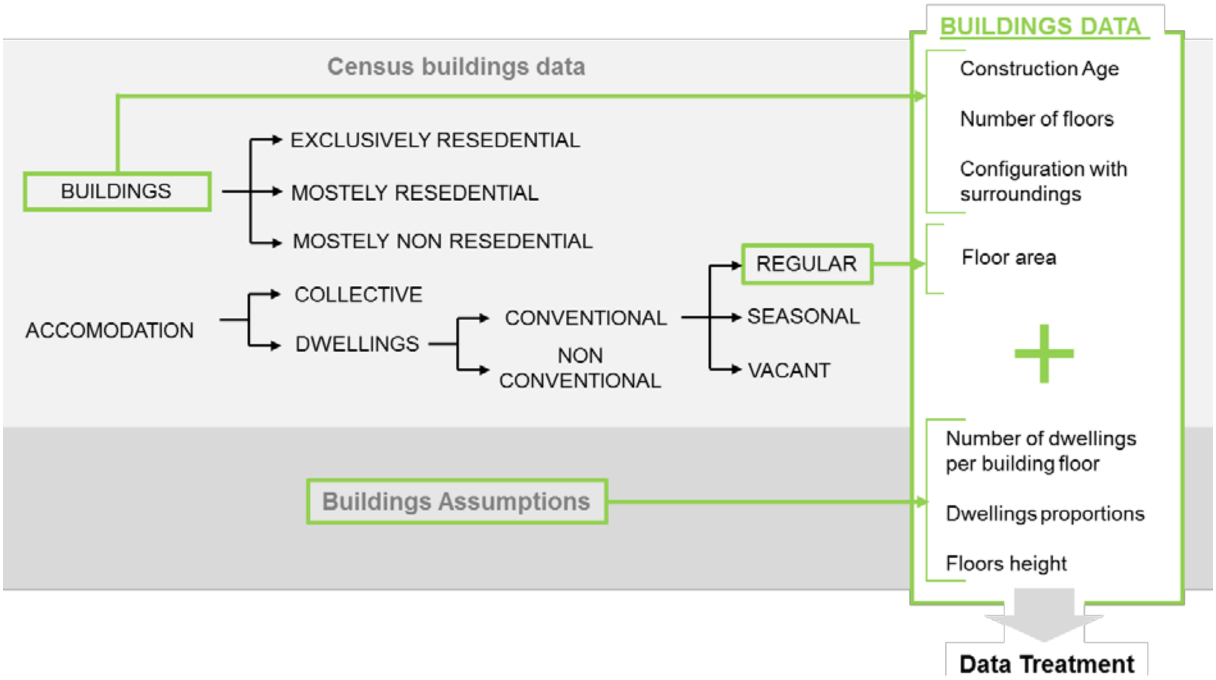

Figure 5 - Census buildings and accommodation categories, data and required assumptions used.

In Figure 5, the categories that are framed in green are the ones which have information regarding its properties and therefore used. To proceed for the data treatment and then calculations, a set of assumptions had to be previously made, which are explained later in this subsection.

In order to clarify how much of relative uncertainty may be introduced by using properties from different categories, Table 3 summarizes the frequency and relative percentage of them for Odemira and Olivais.

Table 3 - Buildings and accommodations frequency in Odemira and Olivais, adapted from BGRI [3].

Categories				**Odemira**		**Olivais**	
				[nº]	[%]	[nº]	[%]
Buildings	Exclusively residential			17622	95.5	3065	89.2
	Mostly residential			642	3.5	331	9.6
	Mostly non residential			185	1.0	39	1.1
Accommodation	Collective			108	0.5	29	0.1
	Dwellings	Non-conventional		73	0.3	14	0.1
		Conventional	Regular	10805	51.4	20869	80.0
			Seasonal	6619	31.5	2772	10.6
			Vacant	3427	16.3	2404	9.2

From Table 3 is possible to understand that the parameters used not always refer to the full amount of dwellings under analyze and include buildings out of the analysis objective. Furthermore, Odemira and Olivais have significant differences concerning the ratio of dwellings per building. Odemira's 1.1 ratio, between conventional dwellings and, exclusively plus mostly residential buildings, indicate a municipality with various single-family houses and buildings with only a few number of floors. On the other hand, the parish of Olivais has a 7.7 ratio, indicating high population density and tall buildings. This ratios were used to support the assumptions and the calculation method to determine the average number of floors per building, in each subsection, of both Case Studies locations.

Assumptions

To process the data from Census, the following set of assumptions, summarized in Table 4, were applied, depending on the Case Study.

Table 4 – Geometrical assumptions used on the Odemira and Olivais case studies.

Odemira	Olivais
• **Each dwelling has one floor.**	• Each dwelling has one floor, with the exception of a few cases
• **Each building floor has only one dwelling**	• Variable number of dwellings per floor, but mostly two
• **Each building has a rectangular shape with ratio, length/width, $\boldsymbol{r = 1}$.**	• Each building has a rectangular shape with ratio, length/width, $\boldsymbol{r = 2}$.
• **The dwelling length facade, the longest facade, is always facing the street, therefore twin houses have a common width side facade and town buildings are connected throw there width side facades.**	
• **If there are town buildings in a subsection, then there are no more than 2 town building groups, and thus only four exposed width facades.**	
• **The floor height is $\mathbf{2.7}$ meters, identical value to Stavropoulos [41].**	

Figure 6 clarifies the concepts of town, twin and isolated buildings.

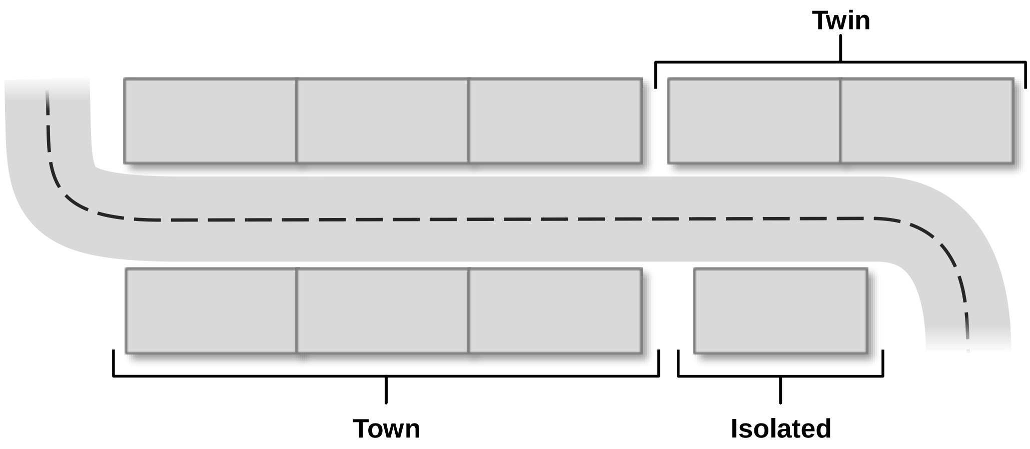

Figure 6 – Configuration of town, twin and isolated buildings.

After the definition of assumptions, the data treatment was finally possible. A subsection typology was defined by a mean number of floors and dwelling floor area. And eventually a specific distribution of buildings age and configuration, (isolated, twin and town. Figure 6), which were evenly accounted in the areas and heat transfer calculations, has explained subsequently.

Number of floors

Regarding the treatment of Census data, to apply the end-uses formulation, explained in chapter 3, the methodology was identical in both case studies, with the exception of the calculation to obtain the number of floors.

For the Odemira case study, the following formula (18) was used, given the reduced number of buildings with more than 4 floors.

$$N_{floors\ per\ building} = \frac{1{,}5.Nb_{1<f<2} + 3{,}5.Nb_{3<f<4} + 5{,}5.Nb_{f>4}}{Nb_{1<f<2} + Nb_{3<f<4} + Nb_{f>4}} \tag{18}$$

$N_{floors\ per\ building}$ $[-]$ is the buildings number of floors. $Nb_{1<f<2}$, $Nb_{3<f<4}$ and $Nb_{f>4}$ $[-]$ are the number of buildings with number of floors 'f' equal to 1 or 2, 3 or 4, and more than 4 respectively.

On the other way around, as already discussed, Olivais has a significant number of buildings with more than 4 floors, making equation (18) less accurate, and thus a different procedure was made. For each subsection, belonging to the parish of Olivais, an initial number of dwellings per floor, equal to 2, was considered and the average number of floors, of the buildings with more than 4 floors, was determined. If the value was between 4 and 20 floors per building, those would be the values for the average number of floors, and two the number of dwellings per floor. Else, if the value was higher or lower, an integer number would be added, or subtracted, to the number of dwellings per floor until an average floor number in the interval was reached. Two other situations occurred occasionally. One was that the following floors number 'jumped' the interval, and in that case, the average value between the two was assumed. The other was when the floors number was lower than 4, even with 1 dwelling per floor. In this situation it was assumed the number dwellings per floor which gave an average building number of floors of 4. This later assumption is supported by the fact that there are dwellings with more than one floor, e.g. duplex dwellings, and those less than one dwelling per floor is plausible. Equation (19) expresses the average number of floors, like it was calculated for Olivais subsections. Equation (20) indicates how it was determined the average number of floors of the buildings with more than four floors, $\overline{Nf_{f>4}}\ [-]$.

$$N_{floors\ per\ building} = \frac{1{,}5.Nb_{1<f<2} + 3{,}5.Nb_{3<f<4} + \overline{Nf_{f>4}}.Nb_{f>4}}{Nb_{1<f<2} + Nb_{3<f<4} + Nb_{f>4}} \tag{19}$$

$$\overline{Nf_{f>4}} = \left(\frac{N_{cd}.\left(Nb_{1<f<2} + Nb_{3<f<4} + Nb_{f>4}\right)}{(Nb_{er} + Nb_{mr}).N_{dwellings\ per\ floor}} - 1{,}5.Nb_{1<f<2} - 3{,}5.Nb_{3<f<4} \right) \Big/ Nb_{f>4} \tag{20}$$

$N_{cd}\ [-]$ is the number of conventional dwellings, $N_{dwellings\ per\ floor}\ [-]$ is the number of dwellings per floor, $Nb_{er}\ [-]$ is the number of buildings exclusively residential and $Nb_{mr}\ [-]$ the number of buildings mostly residential. If one recalls Figure 5 and the explanations regarding Census concepts, is easy to understand how this later approach has its limitations, and why it was not used in the Odemira case study.

Areas

The method of areas calculations is here described in a generic manner regarding the variables of floor height, dwelling ratio and number of dwellings per floor, since this formulation was used for both case studies.

The dwelling average floor area in a subsection is calculated with a weighted average of the different dwelling area classes, available in BGRI, as shown in equation (21).

$$\overline{A_{d\ floor}} = \frac{50.Nd_{A<50} + 75.Nd_{50<A<100} + 150.Nd_{100<A<200} + 200.Nd_{A>200}}{Nd_{A<50} + Nd_{50<A<100} + Nd_{100<A<200} + Nd_{A>200}} \tag{21}$$

$\overline{A_{d\ floor}}\ [m^2]$ is the average floor area per dwelling in the subsection. $Nd_{A<50}$, $Nd_{50<A<100}$, $Nd_{100<A<200}$ and $Nd_{A>200}\ [-]$ are the number of dwellings with floor area 'A' lower than $50\ m^2$, between 50 and $100\ m^2$, between 100 and $200\ m^2$, and larger than $200\ m^2$ respectively.

Due to the definition of a one level typology per subsection and to the assumptions made, the distribution of isolated, twin and town dwellings are identical to the buildings distribution of these classes, and the later were therefore used as if dwellings distribution.

The total dwelling exterior wall area, including windows, of a subsection, $A_{wall}\ [m^2]$, is calculated as equation (22).

$$A_{wall} = A_{wall\ isolated\ d} + A_{wall\ twin\ d} + A_{wall\ town\ d} \tag{22}$$

$A_{wall\ isolated\ d}$, $A_{wall\ twin\ d}$ and $A_{wall\ town\ d}$ $[m^2]$ are the dwellings wall surface of isolated, twin and town dwellings in the subsection. The later are respectively calculated has follows in equations (23), (24) and (25).

$$A_{wall\ isolated\ d} = N_{isolated\ bf}.h_{floor}.2\sqrt{r.\overline{A_{bf}}}.\left(1+\frac{1}{r}\right) \tag{23}$$

$$A_{wall\ twin\ d} = N_{twin\ bf}.h_{floor}\sqrt{r.\overline{A_{bf}}}.\left(2+\frac{1}{r}\right) \tag{24}$$

$$A_{wall\ town\ d} = N_{town\ bf}.h_{floor}.2\sqrt{r.\overline{A_{bf}}} + \begin{cases} if\ N_{town\ bf} \leq 3 & ,\quad 2.h_{floor}\sqrt{r.\overline{A_{bf}}}.\left(\frac{1}{r}\right) \\ else & ,\quad 4.h_{floor}\sqrt{r.\overline{A_{bf}}}.\left(\frac{1}{r}\right) \end{cases} \tag{25}$$

Where $N_{isolated\ bf}$, $N_{twin\ bf}$ and $N_{town\ bf}$ $[-]$ are the number of isolated, twin and town building floors, obtained through equation (26), as an example for the isolated buildings, since the remaining are determined in a similar manner. h_{floor} $[m^2]$ is the floor height, which takes the value of 2.7 in the present work. $\overline{A_{bf}}$ $[m^2]$ is the average floor area per building, given by equation (27). r $[-]$ is the building floor length over width ratio.

$$N_{isolated\ bf} = \frac{N_{isolated\ buildings}}{N_{buildings}}.\frac{N_{dwellings}}{N_{dwellings\ per\ floor}} \tag{26}$$

$$\overline{A_{bf}} = \overline{A_{d\ floor}}.N_{dwellings\ per\ floor} \tag{27}$$

$N_{dwellings}$ $[-]$ and $N_{buildings}$ $[-]$ are the total number of dwellings and buildings respectively in the subsection.

While for the dwelling wall surface calculation, it was not directly used any relation regarding the buildings number of floors, since it was used a calculation based on dwellings distribution, for the rooftop and ground floor area it was otherwise used. While assuming 5 isolated dwellings or a 5 floors isolated building with a dwelling per floor gives the same exterior wall area, the same example but for rooftop and ground floor area is instead not valid. Therefore, the rooftop and ground floor surface areas in the subsection, $A_{rooftop}$ and $A_{ground\ floor}$ $[m^2]$, are calculated as equations (28) and (29).

$$A_{rooftop} = N_{dwellings}/N_{floors\ per\ building}.\overline{A_{d\ floor}} \tag{28}$$

$$A_{ground\ floor} = N_{dwellings}/N_{floors\ per\ building}.\overline{A_{d\ floor}} \tag{29}$$

The windows surface area, $A_{windows}$ $[m^2]$, is the product of the wall area with the glazing surface percentage, expressed by equation (30).

$$A_{windows} = A_{wall}.GAP \tag{30}$$

GAP $[-]$ is the glazing area percentage.

Heat transmission and ventilation

Since it was assumed one typology per subsection and therefore the areas of all the buildings were calculated all at once instead of a building by building calculation, the global heat transfer coefficient, H_t $\left[\frac{W}{°C}\right]$, is defined by equation (31).

$$H_t = \sum_i A_i.\overline{U_\iota} \tag{31}$$

Where A_i $[m^2]$ and $\overline{U_\iota}$ $\left[\frac{W}{°C.m^2}\right]$ are the total area and the overall heat transfer coefficient of the 'i' heat transfer component: Walls, rooftop, ground floor, windows. The overall heat transfer coefficient varies with the building age and is calculated with equation (32).

$$\overline{U_\iota} = \sum_a \overline{U_a}.\frac{Nb_a}{N_{buildings}} \tag{32}$$

$\overline{U_a}$ $[\frac{W}{°C.m^2}]$ is the global heat transfer coefficient of the buildings from age group 'a', according to Census. Nb_a $[-]$ is the number of buildings in age group 'a'.

Since the GAP value used also depends on the age of the building, the walls and windows global heat transfer coefficients calculations are given by equations (33) and (34).

$$H_{t\,wall} = \underbrace{A_{wall}\sum_a (1 - GAP_a)}_{Real\ wall\ area}.\overline{U_{wall,a}}.\frac{Nb_a}{N_{buildings}} \tag{33}$$

$$H_{t\,window} = A_{wall}\sum_a GAP_a.\overline{U_{window,a}}.\frac{Nb_a}{N_{buildings}} \tag{34}$$

GAP_a $[-]$ is the glazing are percentage of buildings in age group 'a'.

The plots of Figure 7 and Figure 8 represent the GAP_a and overall heat transfer coefficients, respectively, as a function of construction age, in the Portuguese residential buildings. These values were used in both case studies, while using Census data. Both graphs were adapted from discrete values and linear interpolated for the construction periods available in Census.

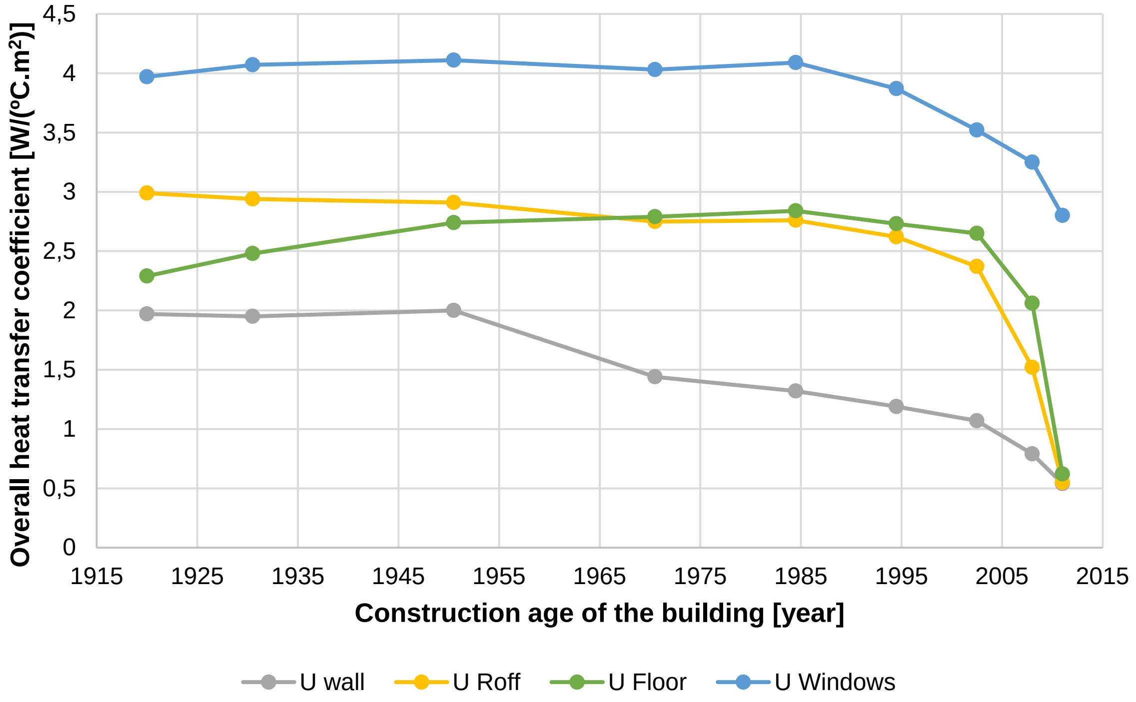

Figure 7 – Overall heat transfer coefficients with construction age of Portuguese residential buildings, adapted from BPIE [46].

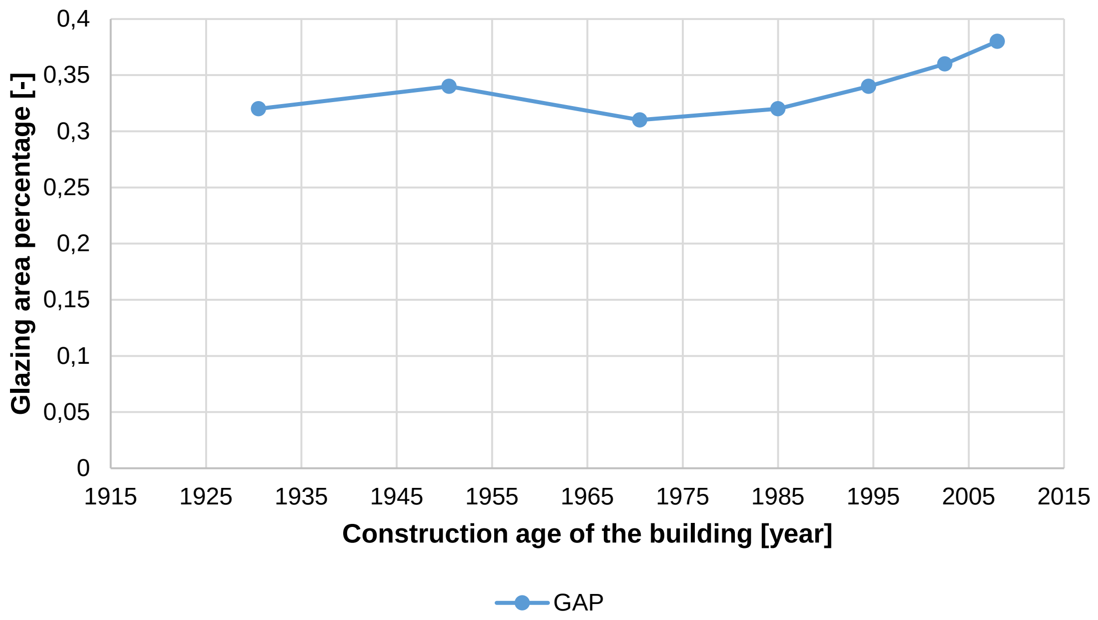

Figure 8 – Glazing are percentage with construction age of Portuguese residential buildings, adapted from Sousa et al. [49].

Similarly to the heat transmission equations in this section, the ventilation equations, (4) and (11), were also adjusted by using the total dwellings volume weighted with the share of dwellings of an age group and matching ACH_a for respective construction period. The ACH was obtained by interpolating the values in Table 5.

Table 5 – Air changes per hour with construction age, adapted from BPIE [46].

Construction age	Air changes per hour $ACH\ [h^{-1}]$
1919	1,06
2009	0,95

Coefficients

Most coefficients from the space heating and cooling formulations, subsections 3.1 and 3.2, require the orientation of certain elements, such as windows and walls, and other properties normally difficult to obtain. Therefore, it was taken the methodology as follows.

The coefficients X_i and G_{solar} for windows, equations (7) and (9), were obtained using the weighted windows orientation and orientation factor. The windows orientation distribution is represented in Table 6 for Odemira and Olivais climatic zones. The orientation factors were used according to REH [38].

Table 6 – Windows distribution per orientation and climatic zone [47].

Climatic zone	Portion of windows per orientation $[-]$							
	W	**SW**	**S**	**SE**	**E**	**NE**	**N**	**NW**
I1V2	0.12	0.18	0.11	0.12	0.18	0.17	0.12	0.00
I1V3	0.21	0.08	0.08	0.09	0.21	0.08	0.17	0.08

The G_{solar} coefficient regarding walls was calculated assuming an even orientation of walls. The coefficient F_g, also present in equations (7) and (9), was subjected to an identical approach but using Table 7 and REH [38].

Table 7 – Windows distribution per frame type and climatic zone [47].

Climatic zone	Portion of windows per frame type $[-]$	
	Wood or PVC	**Aluminum**
I1V2	0.21	0.79
I1V3	0.33	0.67

Lastly, g_i and g_v, were defined using Table 8, adapted from Quercus [48] rather than ICESD given its by climatic zone disaggregation, and assuming average distributions of the types of shading elements [38] for the later coefficient.

Table 8 – Current configuration of windows and shading elements, adapted from Quercus [48].

Portion of windows per glazing type and shading presence [−]			
Double glass & shading	**Double glass**	**Single glass & shading**	**Single glass**
0.65	0.12	0.19	0.04

4.3.2. GIS Data

The GIS data was provided by the municipality of Lisbon and later processed by Monteiro et al. [4]. The calculations were made with a plug-in for Rhino software named Grasshopper. Figure 9 illustrates the grasshopper environment used.

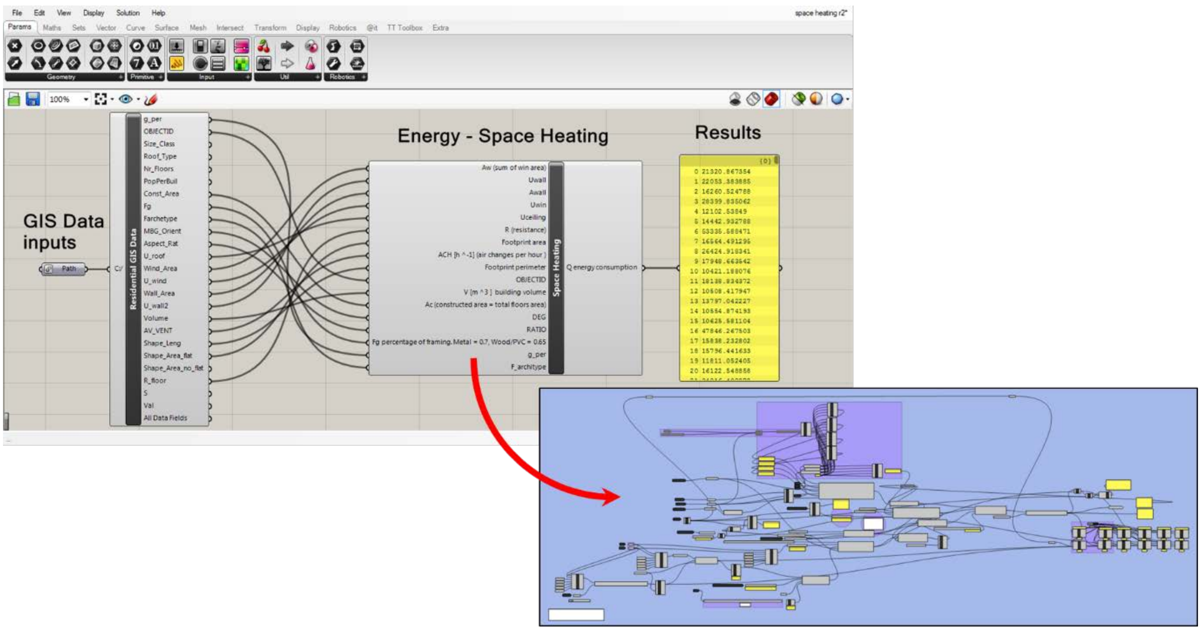

Figure 9 – Space heating model implemented in Grasshopper for Rhino.

The main difference between using raw data from BGRI and GIS data, is the building by building information present in the later, which relates mainly to the geometry of the buildings. While with Census data the information is available by statistical subsection, which bounds the calculations into assuming weighted averages of the buildings geometrical parameters for the entire spatial area, the subsection, the GIS processed data has a building by building data set, allowing a particular calculation for each building in the subsection. In the calculations point of view, with Census data all buildings in a subsection are equal in every parameter, requiring the data treatment explained in section 4.3.1. Explicitly, they have the same fraction of area from the multiple age groups, equivalent wall areas in common with each other, the same number of floors, and even have the same windows distribution and orientation. Hence a typology with one level of crossed information. On the other side, the GIS data is strongly more realistic, enabling the calculation of each building at a time with its specific geometric and physical properties.

Architypes

With GIS data was created a set of architypes by Monteiro et al. [4] with several layers of information besides the unique exclusive information of each individual building. Synthetized in Figure 10, one can see the five architypes and the layers of information associated to them.

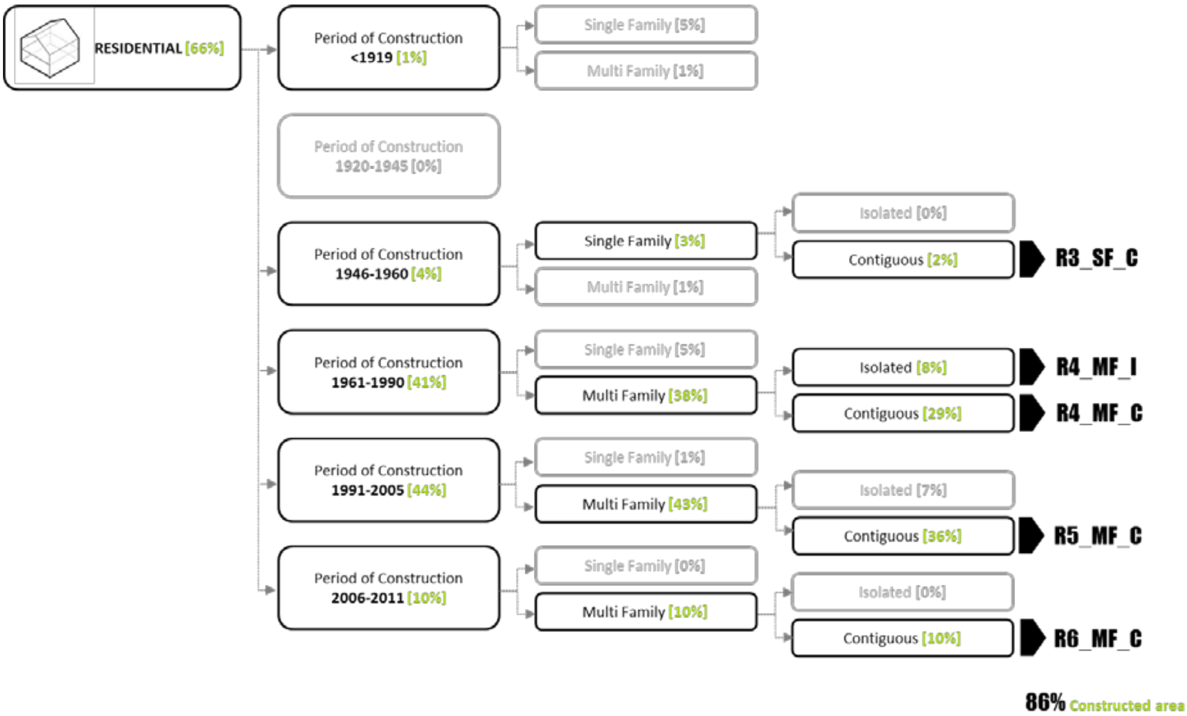

Figure 10 – Building architypes [4].

Each building architype was defined in terms of residential housing type, age of construction, single or multifamily and isolated or contiguous building. Despite the 24 possible residential buildings architypes, only the five with highest frequency, which represent 86 % of the residential constructed area in Olivais, were selected since collecting building properties for the architypes requires an exhaustive time consuming effort. The buildings without any correspondence with the selected architypes were not accounted in the energy demand calculations.

Buildings belonging to the same architype have the following common parameters

- Overall heat transfer coefficients.
- Floor to floor height.
- Floor to ceiling height.
- Shading coefficients.

Apart from the architypes features, every building has its particular geometric properties, from dimensions to orientations.

Calculations

Since most parameters used in the energy demand calculations were already present in the GIS dataset for each building, the methodology of data treatment and calculus was a straight forward application of the end-uses formulation in chapter 3.

5. Application to Odemira

The Odemira model results are described in the following three sections. Firstly, the calibration procedure and variables are explained, as well the baseline data obtained regarding final energy consumption is presented. This is followed by a sensitivity analysis in section 5.2. concerning useful energy for Odemira. Finally, the results regarding several technological options are presented and discussed in terms of final energy savings, emissions and economic viability.

5.1. Model calibration

A baseline scenario calibration was adopted to the Odemira case study in order to match the model output values with actual consumption figures, by energy vectors and end-use services. While applied to the Odemira case study in this thesis, the calibration procedure can be applied to any region. The resulting calibration parameters were validated with other studies to guarantee they are in line with commonly used values. Figure 11 schematizes the adopted validation methodology.

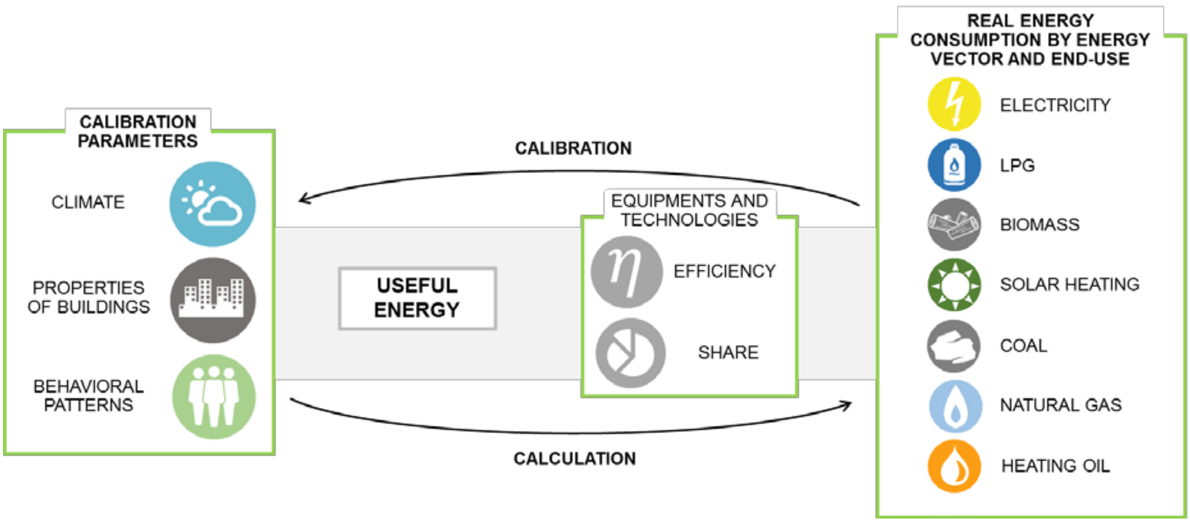

Figure 11 – Schematic of the validation methodology.

Looking at Figure 11, one can see that a convergent-like process was applied. Using the model parameters, the useful energy was calculated, followed by the calculation of the final energy demand using the share of technologies, which satisfy the useful energy demand, and its respective efficiencies.

The share of technologies, i.e. penetration of technologies, plays a fundamental role on the model since it bridges the demand for useful energy to the energy vectors or carriers and is intrinsically related with the adopted calibration methodology. Nevertheless, the proper clarification of the concept used in this work has to be done to avoid misinterpretations.

Besides national consumption per end-use and energy vector, ICESD [1] provides the number of technologies and dwellings which used them. With the exception of appliances and electronic equipment, this information was not directly used as the share of technologies by the following reasons:

- Different technologies may be used to satisfy in different ways the useful energy demand in a dwelling. For example, one dwelling having a space heating boiler will most likely have a larger portion of its space heated than a dwelling with a fireplace. Similarly, the later may better satisfy the heating demand than a dwelling with one isolated electric radiator.
- As energy prices may influence the households in their equipment's usage, the fact that one household uses two different equipment does not mean that it uses both of them in the same way and with the same intensity, as one may be cheaper than the other and be preferred by the household owners. As the statistics only indicate if a household uses a certain equipment and not how much it uses that equipment, using this data would require significant assumptions.

Therefore, the shares of technologies used were calculated as the shares that, through its efficiencies, result in the national proportion of final energy consumption by end-use and energy vector.

The final energy values were then compared to the real consumption data and subsequently the chosen parameters, i.e. calibration parameters, were iteratively corrected until the calculated final energy demand was equal to the real data consumption.

The specific energy demand data for which the model was calibrated were the following: energy consumption per dwelling, for space heating and cooling, water heating, cooking and electronic appliances; lumen hour per floor area per day, for the lighting service. In each end-use, the correspondent share for the final energy carriers was as well taken into calibration. Finally, to calculate the consumption for the whole municipality, the national share of dwellings that use or not the end-use was furthermore applied. The model was validated with data of energy consumption for the available energy vectors, at municipal level, as provided by INE [2].

5.1.1. Calibration parameters

For space heating, the key parameters used were an heating degree days base temperature of $15.5\ ℃$ which is in line with other studies for Lisbon [41], or Turkey [55], and the windows obstruction coefficient.

For cooling, the reference temperature was used to calibrate this end-use, as well the windows obstruction coefficient. It resulted the values of $27.0\ ℃$ of cooling reference temperature which is acceptable when compared with the $25\ ℃$ referenced in REH [38].

Water heating was calculated with the daily volume of heated water per person. For the case studies, it was used a value of 36.5 liters, close to the 40.0 liters used by REH.

For lighting, a top-down approach was taken using equation (13) to first calculate the artificial lighting hours required, $T\left[\frac{hours}{year}\right]$, assuming $L=80\left[\frac{Lm}{m^2}\right]$ for lighting requirement [32], adopting lighting technologies efficiencies from Souza [9] and using ICESD [1] data for mainland electric energy consumption just as well for lighting technologies penetration(available per technology per power intervals). Since in ICESD there was not a penetration per power interval for LEDs technology, was assumed a LED power equal to $1\ W$ based on Quercus [48] as well a technology efficiency identical to the CFL bulbs, $60\left[\frac{lm}{W}\right]$ [9]. Subsequently, a $T=3.7$ hours was obtained which is a reasonable value when compared with 4 hours assumed by Shen [32] and Dopazo et al. [44].

As explained in subsection 3.5 , the Cooking model includes energy used to cook and appliances usually found in the kitchen, the commonly called ‘white appliances’. The electric energy consumed by this appliances was calculated based on their penetration [1] and specific consumption [50], [51]. The energy used for preparing food was subsequently calculated in order to match the energy consumption by energy vector in ICESD [1].

For electronic appliances, a similar approach was taken by means of the appliances with available penetration data [1] and specific consumption [50], [51], and an “other appliances” category was calculated to satisfy the deficit in electronic appliances electric energy consumption, once more, to match the electronic appliances energy consumption in ICESD.

5.1.2. Reference scenario

In this section, the baseline outputs regarding energy consumption are presented for each end-use and energy vector. The energy model developed to Odemira was calibrated based on national data for consumption per energy vectors and per end-uses, as well regarding technologies share, as discussed in section 5.1. Through this method, the total useful energy requirements and consequent final energy demand were calculated.

Since there was data available for the technologies penetration for space heating and per energy vector for each parish in Odemira, the space heating technologies share was modified for the analysis of the detailed measures, in section 5.3.2.

Figure 12 represents, in the form of a Sankey diagram, how the estimated consumption per final energy vector for Odemira is distributed along the different domestic end-uses. The yearly consumption values are also shown, expressed in MWh.

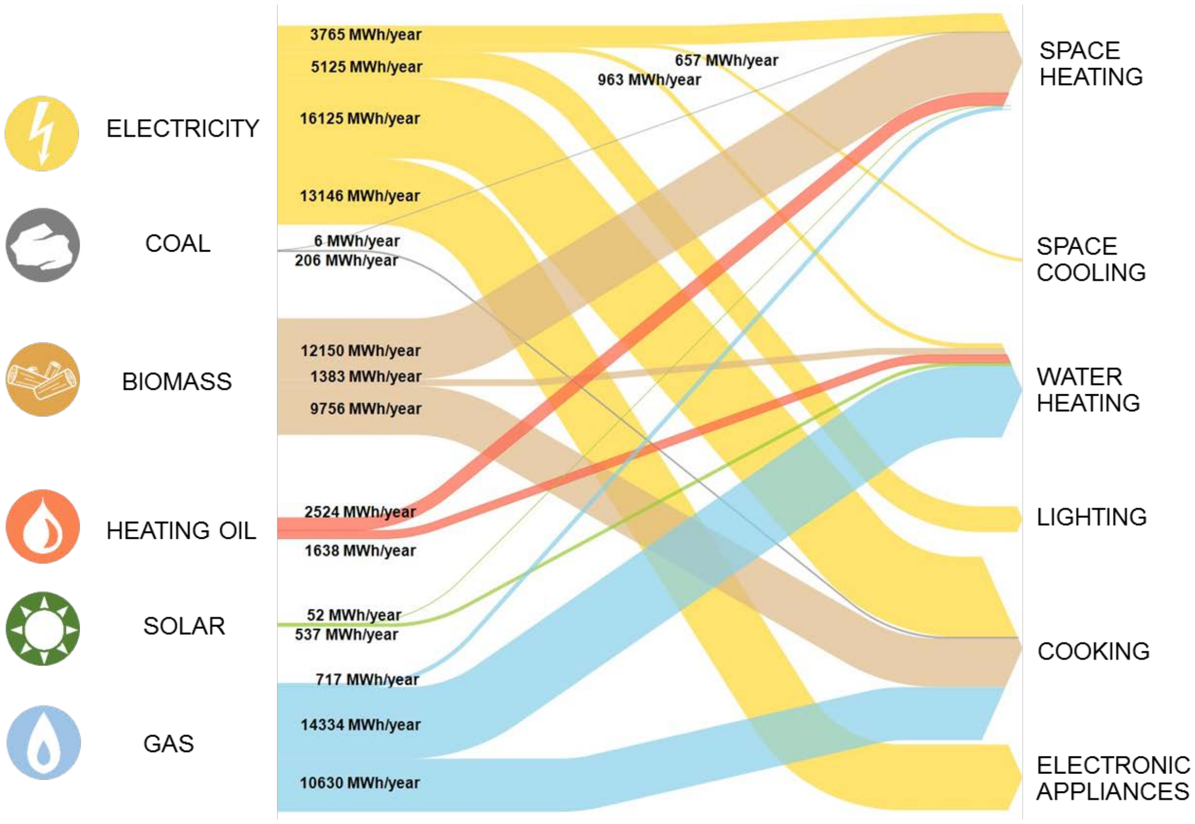

Figure 12 – Final energy consumption for Odemira, estimated with the proposed model and using national data for technologies and calibration.

In Figure 12, one can see how the consumption of the several energy vectors, on the left, are distributed to satisfy the domestic end-uses, on the right. Table 9 quantifies the share of the total energy consumption per end-use and energy vector.

Table 9 – Share of total final energy per end-use and final energy vector.

Energy vector	Space Heating	Space Cooling	Water Heating	Lighting	Cooking	Electronic Appliances	Energy vector fraction
Electricity	4.0%	0.7%	1.0%	5.5% (5.7%)	17.2%	14.0%	42.4% (42.5%)
Coal	0.0%	-	-	-	0.2%	-	0.2%
Biomass	13.0%	-	1.5%	-	10.4%	-	24.9% (24.8%)
Heating Oil	2.7%	-	1.7%	-	-	-	4.4%
Solar	0.1%	-	0.6%	-	-	-	0.6%
Gas	0.8%	-	15.3%	-	11.3%	-	27.4%
End-use fraction	20.5%	0.7%	20.1%	5.5% (5.7%)	39.2% (39.1%)	14.0%	100.0%

In Table 9, the red values represent the national percentage, and are only shown on the cells which values differ at least one decimal. One can see how identical the share of energy vectors and end-uses is between the model output for Odemira and the National average.

Regarding the actual figures of domestic final energy consumption, Table 10 summarizes the demand for electricity and gas obtained, the real consumption estimated by DGEG [56] and the respective difference between them.

Table 10 – Annual domestic demand of electricity and gas estimated by the model vs real data and respective error.

Energy vector	Model	DGEG 2011	Regional/National difference
Electricity [GWh]	39.8	33.4	19.0 %
Gas [GWh]	25.7	11.9	115.6 %

The difference of the electricity consumption was around 19 %, which is an acceptable value. On the contrary, the estimate for gas exceeds the actual consumption by more than two times. The principal reason for this differences is the calibration nature used in this work. The equipment penetration and share, the households' behavior and even the demand for the energy services may very substantial across Portugal. Using Odemira's space heating technologies shares, the respective end-use consumptions obtained were as in Figure 13.

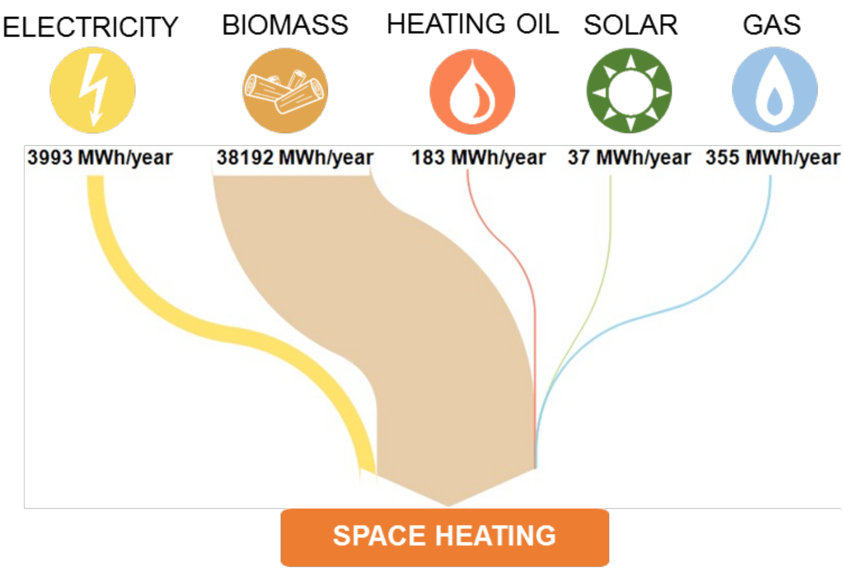

Figure 13 – Space heating final energy consumption for Odemira, estimated with the proposed model and using technology shares per parish and energy carrier.

Comparing the energy resources consumption in Figure 12 and Figure 13, is possible to verify the substantially larger consumption of biomass in the later, which increases around 214 % regarding the calculation with national data. This mainly due to the major use of fireplaces to heat the dwelling when compared with the national average.

5.2. Useful energy sensitivity analysis

The results of the sensitivity analysis of the model parameters are here exposed, using Odemira census' data as model inputs. This analysis is essential to understand the parameters influence on energy consumption and subsequently their environmental and economic impact. In a certain way, this analysis may be used as a guide line for assessing which parameters should be taken into consideration while making energy efficiency plans.

For instance, a sensitivity analysis can be used to assess the priority that could be given to improve a certain type of equipment in households that may be related to the buildings physical properties like glazing area percentage, floor heat transfer coefficient or even outside walls color. Or can be made to more subjective parameters that depend on households' behavior, like the reference temperature from which occupants turn on the heating. The later type of analysis is essential in order to understand the possible impacts of, for example, an awareness campaign to the population regarding this matter.

To avoid an exhaustive sensitivity analysis, this section is focus in just three different model parameters.

- The HDD and Cooling reference temperature sensitivity analysis so as to understand the influence on energy requirements to satisfy the needs for different dwellings space temperatures.
- The overall heat transfer coefficients, to understand the buildings construction age which have the best environmental return regarding energy consumption for space heating and cooling, when submitted to a retrofit measure.
- And last but not least, the windows shading influence on residential energy demand.

5.2.1. HDD and Cooling reference temperatures

As an example, it was analyzed the relevance of heating degree-days base temperature and cooling reference temperature sensitivity analysis. In Figure 14 the final energy consumption change in Odemira is plotted as a function of heating degree days' base temperature variation, in red, and cooling reference temperature, in blue.

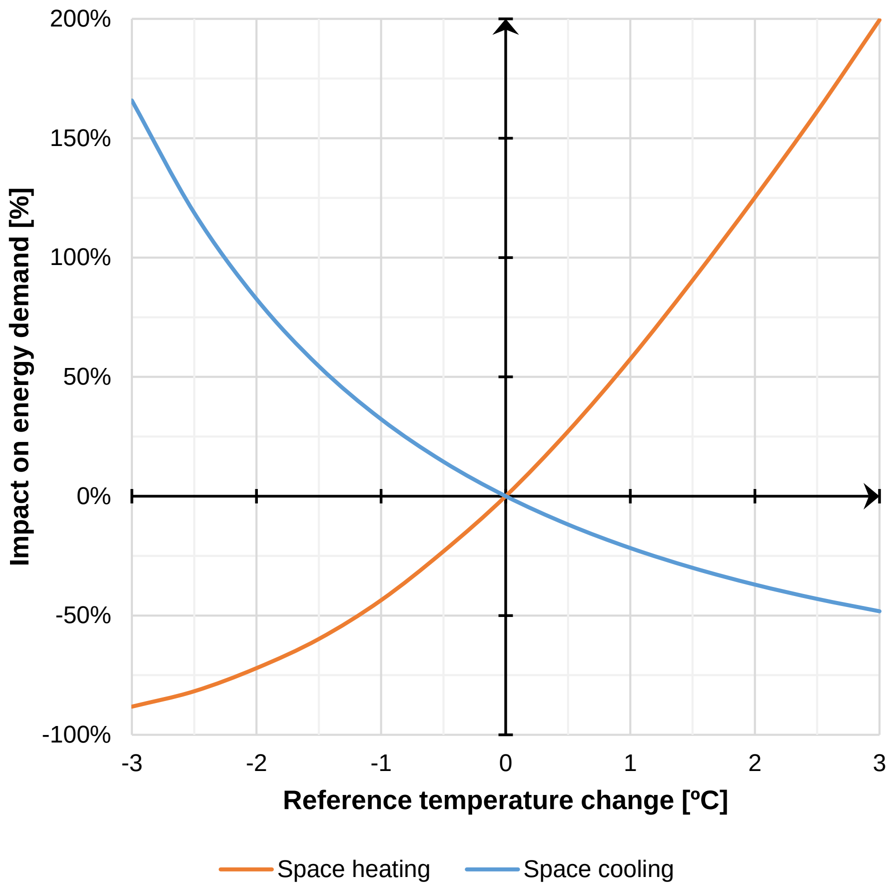

Figure 14 – Energy consumption sensitivity to HDD and Cooling reference temperatures.

This shows that a $3\ ^\circ\mathrm{C}$ increase in heating temperature, therefore from $15.5\ ^\circ\mathrm{C}$ to $18.5\ ^\circ\mathrm{C}$, results in a $200\ \%$ increase in energy consumption, while an identical drop in reference temperature decreases the energy consumption by $88\ \%$.

For the space cooling reference temperature, a $3\ ^\circ\mathrm{C}$ increase, from $27\ ^\circ\mathrm{C}$ to $30\ ^\circ\mathrm{C}$, represents a $48\ \%$ saving in final energy consumption, whereas the identical decrease represents a $166\ \%$ enlargement of energy consumption for that end-use.

From this analysis, the strong influence of a slight increase or decrease of the reference temperature for heating and cooling is clearly evident, wherein one can notice the exponential growth on demand for energy by a modest ‘one more’ degreed of comfort intended by the households. The awareness for this behavior of energy requirements with temperature may be crucial towards the definition of sustainable energy systems, aiming to be defined as CO_2 emissions free and keeping themselves bearable for the families’ economies.

5.2.2. Overall heat transfer coefficients and ventilation

To explore de influence of overall heat transfer coefficients and ventilation on energy demand, in particular space heating and cooling, a simulation regarding the retrofit of buildings per age of construction was made. Their results are represented in Figure 15.

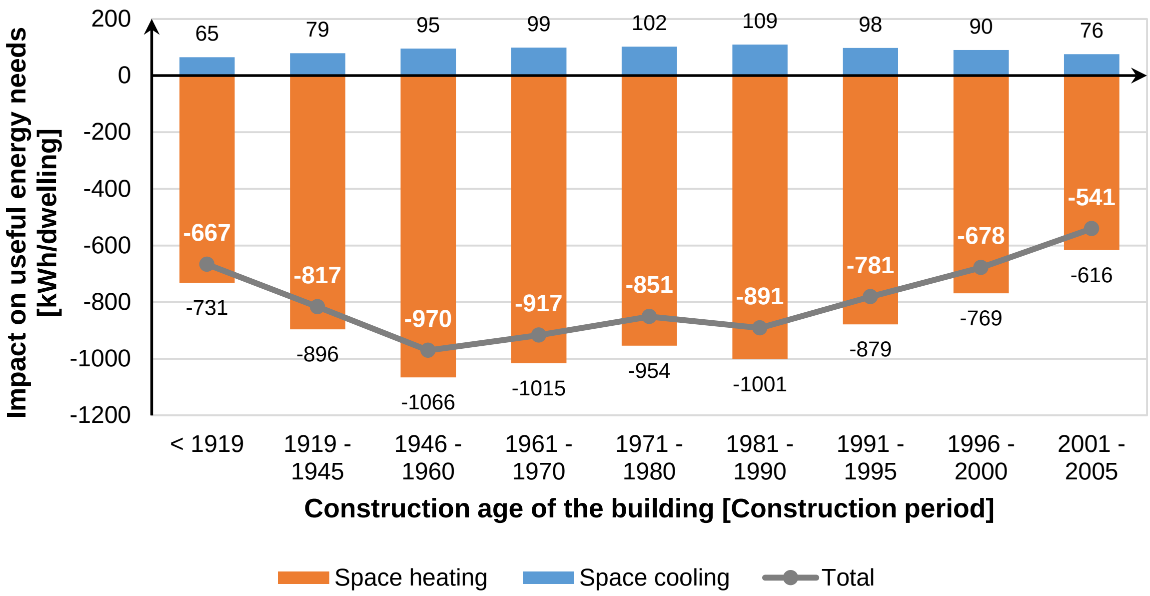

Figure 15 – Impact on useful energy needs for space heating and cooling from retrofitting buildings by construction age.

In Figure 15, each bar refers to the retrofit of a dwelling from a correspondent construction age, on the bottom of the graph. The orange bars correspond to space heating, the blue to space cooling and the grey line to the sum of them. The bars length match the average impact on useful energy requirements, whose values, for heating and cooling, can be read on the bottom and top respectively. The values in white, immediately above the grey line, are the sum of the two end-uses impact regarding useful energy needs. All the values are in $kWh\ per\ dwelling$ and concern the average values when retrofitting all the houses from that construction period in Odemira. In the calculations point of view, the retrofit corresponds to the improvement of overall heat transfer coefficients and air changes per hour, of an age group, to the ones from recent buildings, meaning buildings between 2006 and 2011.

One can see in Figure 15 that the buildings' retrofit has an absolute larger influence on space heating than on space cooling, more specifically, around 8 to 11 times more. In addition to that, the end-uses have opposed results. Space cooling energy requirements increase with the retrofit, whereas space heating energy necessities decrease. This is due to the fact that the sensibility analysis in only made to the overall heat transfer coefficients and ventilation rates. Finally, the best net impact on dwellings useful energy demand for thermal space comfort occurs for the dwellings built between 1946 and 1960, which average savings were estimated to be around $970\ kWh$ per year. Nevertheless, the major impact by buildings age group belongs to the ones between 1981-1990, $-7.8\ \%$, given their common presence in Odemira. The total impact is $43.7\ \%$

In an actual policy making exercise, this sensitivity analysis would give technical support for the decision makers to define the specific actuation points.

5.2.3. Windows' glazing and shading

In a dwelling, the windows have influence on heat transmission which is a function of its thermal resistance. Moreover, windows are the principal component allowing heat transfer by radiation in a dwelling. More precisely, radiation gains from the Sun. The radiation gains in winter are crucial for diminishing the energy requirements for space heating, but in summer time, i.e. the cooling season, the solar radiation is a setback.

To assess the useful energy needs' sensitivity to some of the windows properties that affect the radiation gains, the analysis was focused on the effect of single vs double glazing windows, and also on the impact of using shading elements or not during the cooling season. In this analysis the windows overall heat transfer coefficients were kept constant.

The current distribution used in the model was already shown in Table 8, subsection 4.3.1.

The effect of these configurations is measured through the parameter g_i and g_v, from equations (7) and (9) in subsections 3.1 e 3.2 respectively. The used values are summarized in Table 11.

Table 11 – Glass and shading windows configuration coefficients for space heating and cooling seasons, adapted from REH [38].

Heating season				
Windows configuration	Double glass		Single glass	
$\boldsymbol{g_i}$ $[-]$	0.630		0.765	
Cooling season				
Windows configuration	Double glass & shading	Double glass	Single glass & shading	Single glass
$\boldsymbol{g_v}$ $[-]$	0.252	0.583	0.275	0.751

Finally, the useful energy demand sensitivity to windows configuration results are shown in Figure 16.

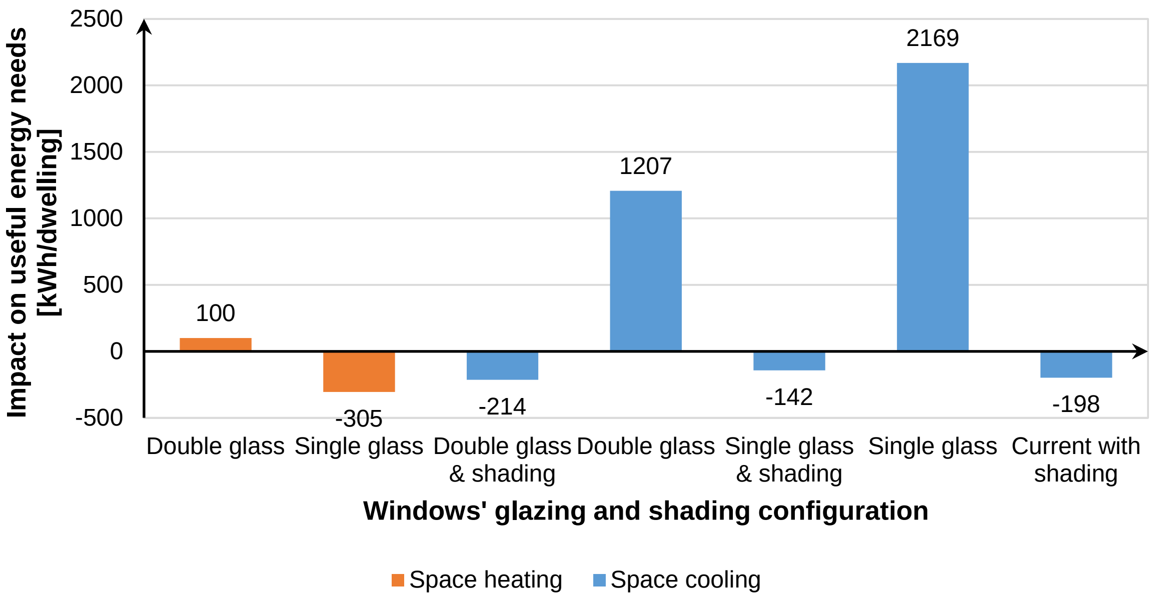

Figure 16 - Impact on useful energy needs for space heating and cooling from different windows' glazing and shading configurations.

In Figure 16, the orange bars represent the impact per dwelling on space heating useful energy needs, from changing all the windows to double or single glazed ones. Similarly, the blue bars represent the impact on space cooling from using double or single glazed windows, with or without shading elements, and a last situation where the current glazing situation with shading elements in all of the windows is represented.

In winter, from the radiation gains point of view, the double glass windows are unfavourable and changing all the windows in Odemira increases the annual average useful heating requirements by $100\,kWh$ per dwelling (heat transfer coefficients were kept constant, therefore the increased requirements). On the other way around, the change to single glass windows reduces the heating necessities by $305\,kWh$ since more solar radiation is transferred through the windows to heat the dwelling air. For cooling, the effects are the opposite. An exclusive single glass windows' scenario has more solar gains than one with double glass windows. Consequentially, the energy need to cool the house, in a no shading situation, increases $2169\,kWh$ while for double glass windows only increases $1207\,kWh$. The results also show how sensible the energy requirements for cooling are to shading elements. The transition from no shading to an all shading situation saves 2312 kWh on single glass windows and $1421\,kWh$ on double glass ones. Which, in comparison with current scenario mean $142\,kWh$ and $214\,kWh$ useful energy reductions, respectively. Last but not least, keeping the present distribution of glass types and using shading in all the windows results on a $198\,kWh$ useful energy reduction for space cooling.

This analysis shows the importance of using shading elements and having double glassed windows in summer, to block excessive solar radiation. In winter, the double glassed windows obstruct a larger amount of solar radiation. The acquaintance of this facts by the households could by itself have a progressive impact on energy consumption in a municipality.

5.3. Analysis of Energy Efficiency Measures

In this section the analysis of energy efficiency measures are presented and discussed along two subsections. In the first subsection, a set of extensive group of measures that simulate sustainable energy strategies scenarios is analyzed in order to demonstrate the full potential of the model proposed in this work. This measures affect all end-uses services and are related to technologies, equipment and dwellings properties. Regarding baseline scenario technologies, the national-based share was used for all end-uses. The measures and respective results are exposed regarding their impact on energy consumption and CO_2 emissions.

In the second, subsection 5.3.2, three technological options for Odemira are compared and discussed in elaborated manner, in terms of energy, emissions and economic viability. This detailed measures are the implementation of photovoltaic panels to produce electricity, solar panels for domestic water heating and the retrofit of open fire places to similar ones with a heat recovery system.

The measures were selected after referring Odemira municipals and identifying possible energy options. The three represent, in a certain way, a trio of different types of measures which application leads to the definition of a sustainable energy system which, for the Odemira case study, symbolize a possible path towards a sustainable municipality. The trio of measures acts in three distinct ways. The photovoltaic panels is a technology that allows the change of a primary energy source, e.g. fuel fossils, used to produce electricity, into a rather more environmentally friendly energy vector, the solar radiation. It does not reduce the final energy need (it promotes the shift from fossil to endogenous renewable primary energy) nor changes the final energy vector, the electricity. The implementation of solar panels for water heating is the change of a technology that is used to satisfy the human needs of a specific energy service, the heated water, changing the final energy vector for solar energy. Finally, the retrofit of fireplaces is the efficiency improvement of a current technology which, without changing the final energy source, reduces drastically the needs of that energy vector to similarly satisfy the same useful space heating requirements. In this set of measures, the distribution of space heating technologies per parish were directly used as the baseline, in order to ensure a more realistic impact.

5.3.1. Sustainable Energy Strategies Scenarios

In this section different scenarios regarding equipment and technologies choices to satisfy users' end-uses energy services are analyzed. The analysis in this subsection is focused on energy and CO_2

emissions, discarding any economic breakdown. Nevertheless the latter is as well an imperative factor to have in consideration in full energy efficiency plans.

Hot water, space heating and cooling technologies

In Table 12 are summarized thirteen possible scenarios, tested with the proposed model, regarding changes and improvements on end-uses technologies. In between them, eight concern space heating, SH, one space cooling, SC, and four water heating technologies, WH.

Table 12 – Space heating, SH, space cooling, SC and water heating, WH, technologies scenarios in Odemira.

	Scenario description
SH1	Conversion from fireplaces and heating stoves to heat pumps
SH2	Adaptation of heating recovery systems to open fireplaces
SH3	Conversion from fireplaces and heating stoves to natural gas boilers
SH4	Conversion of all boilers to natural gas fueled ones
SH5	Using electric radiators instead of fireplaces or heating stoves.
SH6	Substituting all technologies by heat pumps
SH7	Substituting all technologies by solar heating system
SH8	Substituting all technologies by heating stoves and fireplaces with heat recovery systems
SC1	Substituting all technologies by heat pumps
WH1	Substituting all technologies by solar water heating system
WH2	Substituting all technologies by electric water heaters, except solar water heating systems
WH3	Conversion of all boilers and water heaters to natural gas fueled ones, except solar water heating systems
WH4	Conversion of all boilers and water heaters to natural gas fueled ones, except solar water heating systems and biomass fueled ones

Figure 17, shows the change in CO_2 equivalent emissions and final energy consumption, which comprises all used energy vectors, for the thirteen possible scenarios, described in Table 12.

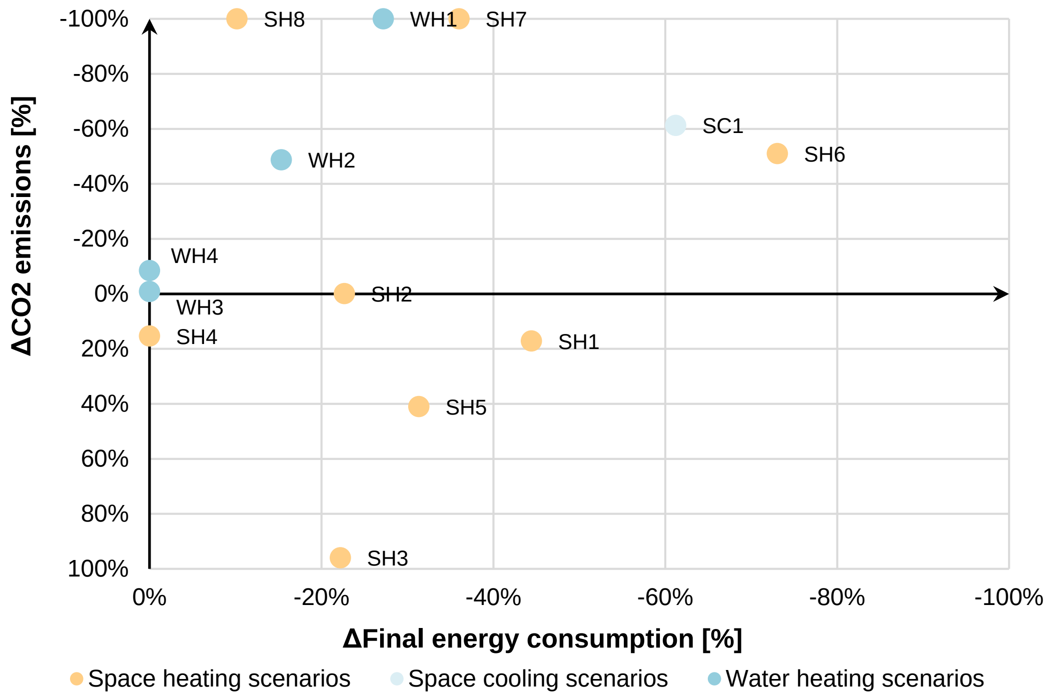

Figure 17 – Impact on final energy annual demand and CO2 emissions from Space heating, SH, space cooling, SC and water heating, WH, technologies scenarios in Odemira.

In Figure 17, both axes are inverted on purpose so that the pathway to better technological options matches the upward and rightward directions. On the x-axis is the final energy consumption change, i.e. savings, in percentage of the current consumption, calculated with the model. On the y-axis is the scenario impact on the reduction of CO_2 equivalent emissions. Both impacts are relative to the end-uses in which the scenarios were applied.

The analysis of Figure 17, shows that the scenarios provide very distinct performances in terms of energy consumption and CO_2 emissions, as one can identify solutions with a high range of contributions for energy efficiency (from 0 % to 80 %) to which correspond reductions or even increased CO_2 emissions. The scenarios which increase the share of biomass fueled heating technologies are the least CO_2 emitters. Scenarios that adopt the increase of heat pump technology penetration are the ones with the major final energy consumption reduction. Other scenarios may became relevant under other perspectives: for instance, if a certain energy vectors like natural gas has a much lower price, technologies that use this vector may be a far more interesting alternative then more environmental friendly options. Similarly, if a certain energy vector has a stronger endogenous presence, this may be seen as a preferable option by the municipality decision makers. Finally, the primary energy conversion process should also be taken into account: for instance using natural gas instead of electricity may be better depending on the efficiency of the electricity conversion process.

Lightbulbs

Regarding the lighting service, it was consider a hypothetical scenario where all incandescent and halogen bulbs are replaced by LED bulbs. The later technology has substantially higher efficiency than the filament light bulbs which lighting process is accompanied by large energy losses. This dissemblance between light bulbs efficiencies justifies the current contrast between the share of energy consumption and the lighting needs, useful energy, that each technology satisfies, as one can observe in Figure 18 and Figure 19.

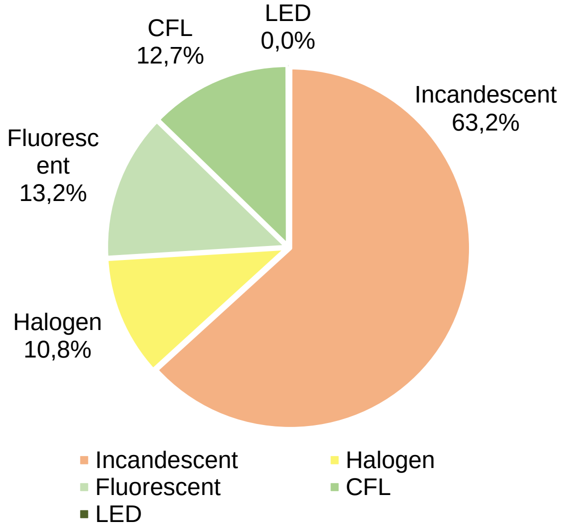

Figure 18 – Share of electric energy consumption by lighting technology.

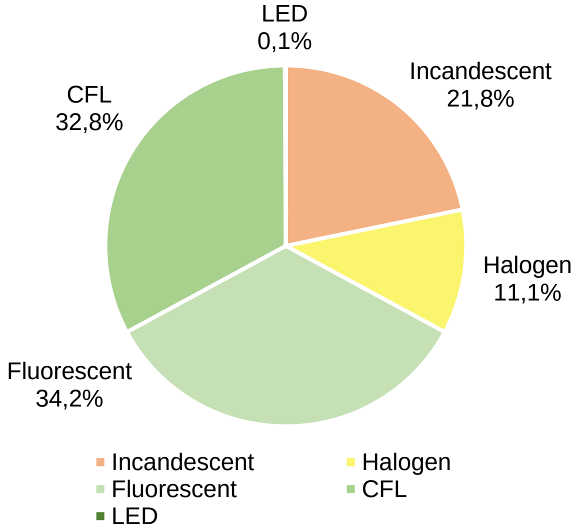

Figure 19 - Share of lighting service by lighting technology.

By looking at the previous figures, the influence that light bulbs efficiency has on energy consumption is evident. Incandescent bulbs consume the largest part of the electric share, $63.2\ \%$, although being only responsible for $21.8\ \%$ of the lighting needs. On the other hand, more efficient technologies as compact fluorescent lamps, CFL, satisfy about $32.8\ \%$ of the lighting service while consuming only $12.7\ \%$ of the total lighting energy.

Figure 20 represents the share of energy consumption from the proposed scenario.

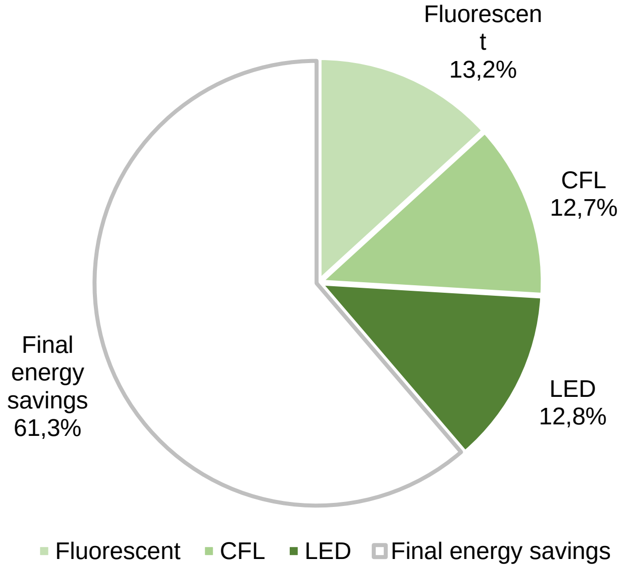

Figure 20 – Scenario for lighting in Odemira.

As one can observe in Figure 20, the substitution of the incandescent and halogen bulbs by LEDs represents 61.3 % of final energy savings, and a similar reduction of CO_2 emissions. Revealing LEDs enormous energy and emissions saving potential. The high efficiency and consequent low power consumption, associated with LEDs other advantageous such as reliability, rugged construction and durability [57], make this technology scenario an excellent option towards a sustainable energy system in Odemira.

White appliances

In the white appliances scenario all refrigerators, freezers, washing machines drying machines and dishwashers, with EU efficiency label lower than 'A' are replaced by equivalent appliances of efficiency 'A+++'.

In Figure 21, the equipment encompassed by the scenario are presented by their penetration in dwellings, grey line, and current share of efficiency classes for each of them, stacked columns.

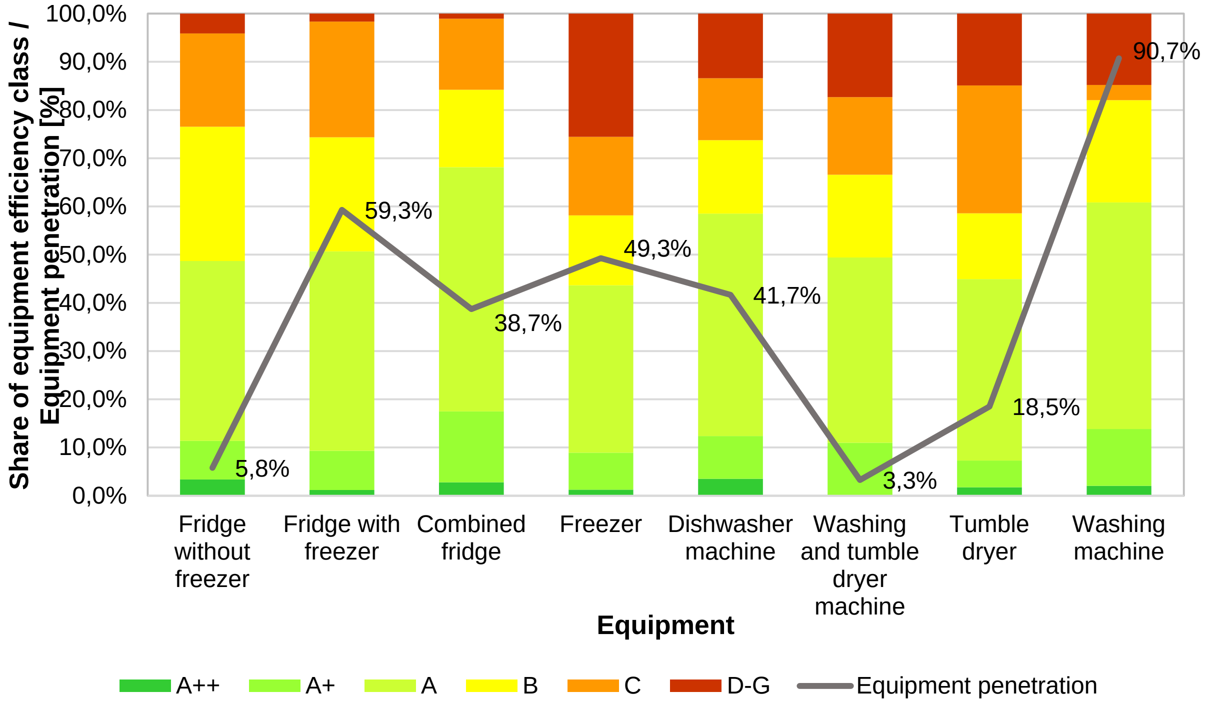

Figure 21 – Current penetration of white appliances and respective share of efficiency class, adapted from ICESD [1].

In Figure 21, is possible to identify that the most affected white appliances by the scenario are the freezers and the tumble dryers, which scenario implies the change of around $56.4\ \%$ and $55.1\ \%$ of those equipment respectively. However, such fact does not imply that the larger set of equipment to be replaced belongs to those groups, since the tumble dryer has a relatively low penetration whereas other equipment, for instance washing machines, have a rather high penetration in residential homes.

The scenario under analyzed is exposed in terms of share of equipment efficiency class in Figure 22.

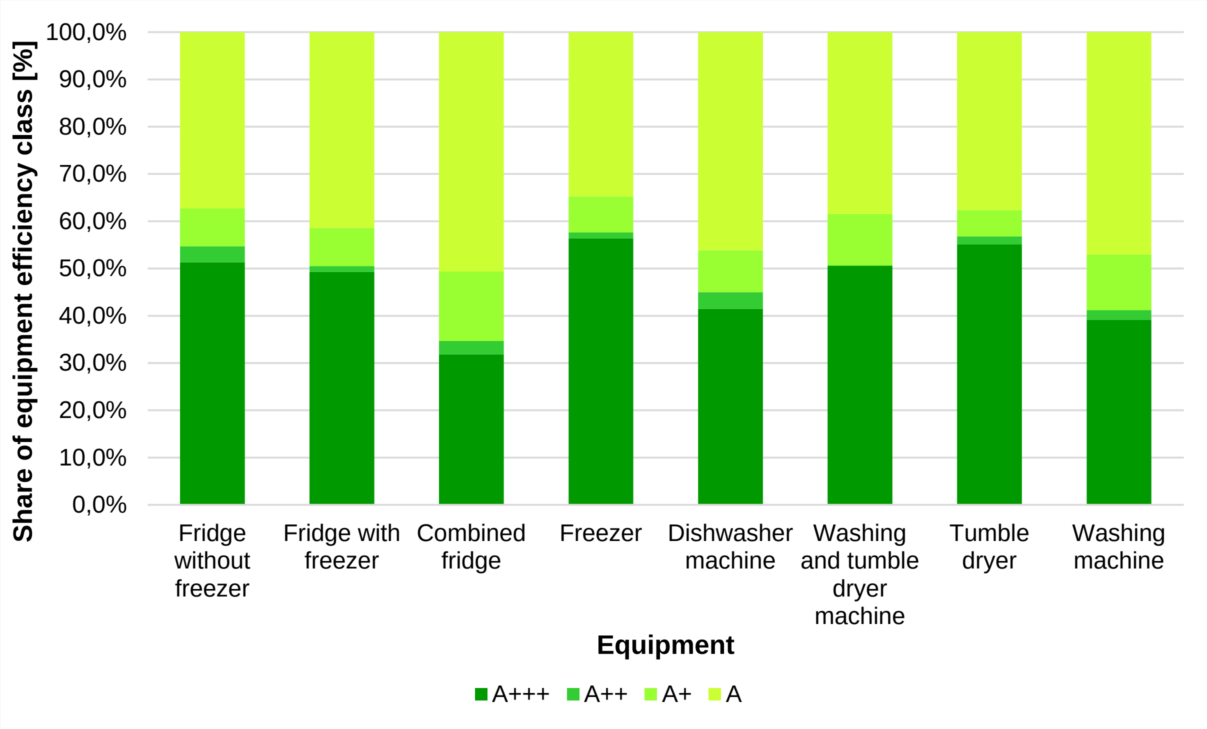

Figure 22 - Share of equipment efficiency class according to the white appliances scenario.

The scenario in Figure 22, linked with the equipment penetration, which was kept constant, results on the following number of replaced equipment, summarized in Table 13.

Table 13 – Number of equipment replaced by equipment type.

Equipment	**Fridge without freezer**	**Fridge with freezer**	**Combined fridge**	**Freezer**	**Dishwasher machine**	**Washing and tumble dryer machine**	**Tumble dryer**	**Washing machine**
Number of equipments [-]	321	3158	1333	3001	1868	178	1101	3840

The washing machine are the type of white appliances that cover the greater number of equipment to be replaced in Odemira, about 3840 out of 14800. Although not having the largest fraction of inefficient equipment.

The impact on electric energy consumption depends not only on the share of equipment efficiency class and penetration but as well on the specific consumption of each [52], [53]. Figure 23 presents the annual average consumption of electric energy per equipment efficiency class, colored bars. It also shows the current and in-scenario average consumption per equipment type, lines, which were weighted with the annual consumptions and respective shares already presented in Figure 21 and Figure 22.

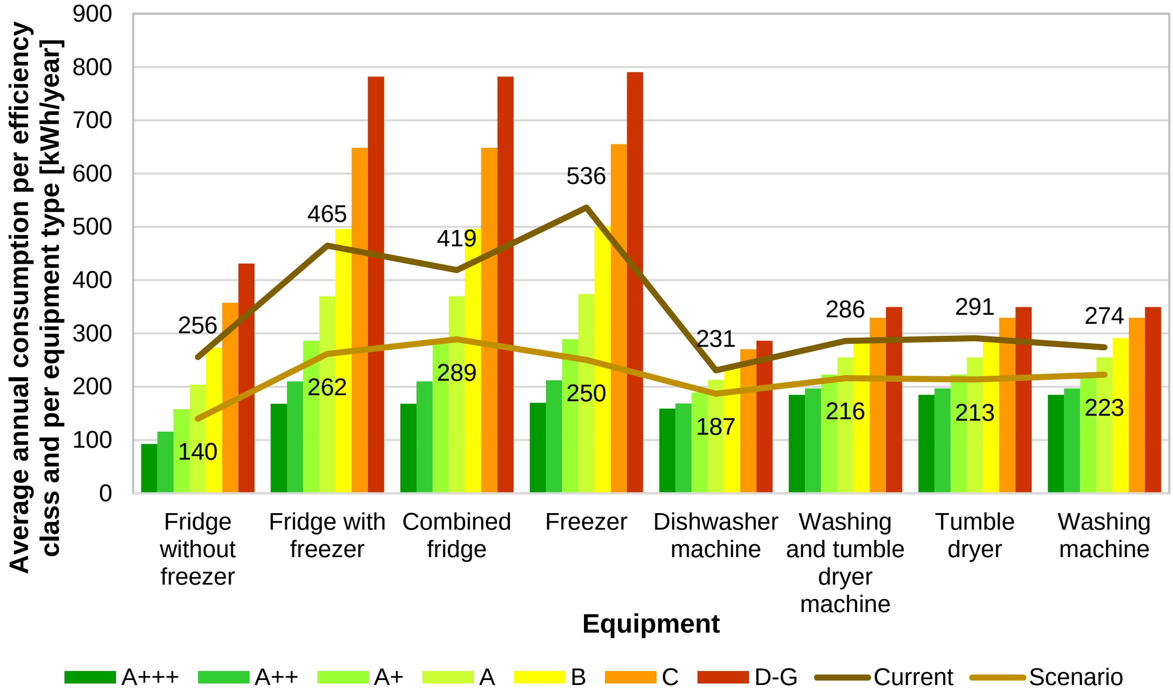

Figure 23 – Average annual consumption per efficiency class and per equipment type with the current situation and with the scenario.

Looking at Figure 23, one can notice which equipment type the scenario has more impact on average energy consumption. The replacement of freezers has an annual average electricity reduction, across the municipality, of $286\ kWh$ per unit. This reduction is substantial important not only in terms of environment but also on the households' electric bill. On the other way, for the dishwasher machine, since the difference between efficiency classes is not as severe, the average reduction floats around $44\ kWh$ per unit.

In global terms, the replacement of less efficient appliances affects $44.5\ \%$ of the total white appliances lot, 33193 for Odemira, resulting in $26.8\ \%$ cooking electricity savings ($10.9\ \%$ total electricity savings), $11.8\ \%$ final energy savings for this end-use and $12\ \%$ less CO_2 emissions, which makes the renovation of the white appliances lot a relevant measure.

5.3.2. In-depth Measures Analysis

In this subsection is analyzed three specific measures for Odemira, chosen after having inquired the municipals. Unlike subsection 5.3.1, a brief economic assessment as well the discussion of other parameters regarding energy consumption and emissions is included in this analysis, which are discussed in parallel along this subsection.

Implementing **photovoltaic panels** in dwellings is often suggested has a measure towards the definition of sustainable energy system in locations with solar potential for such application, which is supported by the 2013 market growth in Portugal, where $80\ \%$ of the $36\ MW$ installed capacity in the PV market was for residential applications EPIA [58]. This technology features both important advantages and disadvantages. In between the advantages, such technologic option has eco-friendly benefits like the renewable energy characteristic of the primary energy, the solar radiation and the CO_2 emission free energy production process. Moreover, less transmission energy losses occur with this technology since it is a local energy production process, commonly called embedded generation [59], instead of the typical electric grid supply. Nevertheless, has already mentioned, this solution has some drawbacks. The CO_2 emissions during the production of the photovoltaic panels, the relatively high implementation cost given the usual power output, and additionally, late economic return to the families. Although due to the latest developments in this technology, it has become more accessible to the households.

In Portugal, the legislation [60] defines that the new photovoltaic panels should be implemented and settled for the ''self-consumption'' mode. The electricity produced by the panel is directly used for local consumption by the households and the production surplus or deficit is injected into the grid or satisfied by the later respectively. The ''self-consumption'' mode requires the correct dimensioning of the panels according to the dwelling consumption patterns since the economic benefit of this technology is greater when its use is optimized for predominant local consumption rather for frequent into the grid electricity injection.

This measure was simulated assuming the implementation of a single 250 W panel per dwelling, in $85\ \%$ of regular dwellings (approximately the number of single-family houses). Table 14 shows the principal properties of the panel considered in this analysis.

Table 14 – Properties of the Photovoltaic panel.

Photovoltaic panel	
Expected life time $[years]$	20
Annual production $[kWh]$	392
Price [€]	720
LCA energy $[kWh]$	1277
LCA emissions $[kg\ CO_2]$	246

In Table 14, the expected life-time, annual production and price are based on a PV simulation made in EDP [61]. The LCA (Technology production process **L**ife **C**ycle **A**ssessment) values were adapted from Stoppato [62]. Since is a low power PV option, in the calculations was considered that the produced energy is fully used for self-consumption.

The use of **solar panels for water heating** in the residential sector is significantly growing. The notorious ecologic benefit, by using a renewable source, and the monthly bill saving make this technology option an appropriate choice for the families.

With the integration of this technology in residential dwellings, a fair amount of the hot water used to satisfy the households' needs is satisfied with the technology, sometimes even completely fulfilled by the solar panels without the support of another heating water technology.

Similarly to the PV options, this measured was applied only to single-family houses. And exclusively to the ones without this technology yet. To create a realistic scenario, it was assumed that the solar panels implemented would satisfy 70 % of the hot water required by the households, while the remaining would be satisfied by the already existent technology. Table 15 summarizes the SP specifications.

Table 15 – Properties of the Solar panel.

Solar panel	
Expected life time $[years]$	15
Service satisfaction [%]	70
Price [€]	2500
LCA energy $[kWh]$	3194
LCA emissions $[kg\ CO_2]$	721

In Table 15, the first three properties were defined based on several commercial options [63]. LCA values were based on Ardente [64].

In Portugal, the use of fireplaces to heat the surrounding air in dwellings is still noteworthy, and, despite its not dominant share, the low energy efficiency of the common fireplaces is a serious drawback of this type of technology regarding the definition of sustainable systems. The ease in obtaining inexpensive wood pallets, sometimes even freely accessible, may be a determinant reason for the fireplaces usage. Economic reason which often has more influence in households' decisions rather than environmental concerns.

The **retrofit of fireplaces** consists in adapting the current open fireplaces to ones with flue gases **heat recovery systems**. This technology improvement allows a better control of the heat generation process, the combustion, and greater benefit from hot flue gases to heat the house, which, without the retrofit, would otherwise be inefficiently expelled through the chimney without avail of the heat. This technology modification allows the households to keep the same final energy source to satisfy their space heating needs, but with fewer resources consumption.

This technological option was applied to the regular dwellings with fireplace as their main space heating technology. To simulate the impact of this measure, a change in the efficiency of the fireplaces heating technology was applied to its technology share in the model. It was assumed an improvement from 19 % to 50 % in the retrofitted fireplaces. Table 16 shows the properties assumed in this work for the heat recovery system.

Table 16 – Properties of the Heat recovery system.

Heat recovery system	
Expected life time $[years]$	25
Efficiency [%]	50
Price [€]	1500
LCA energy $[kWh]$	2500
LCA emissions $[kg\ CO_2]$	100

In order to clarify the results present along the current section, the following points must be taken into consideration:

- In the results tables, negative 'Net saving' values have a negative connotation, which means they are not savings/reductions.
- The 'hh' abbreviation in the units stands for household.
- An unit '$per\ hh$', always refers to the households which measures were applied. On the other way, the ones who do not, refer to the whole Municipality of Odemira.
- Values related to baseline consumptions or emissions refer either to those of the end-use covered by the measure or refer to the energy vector affected by it. Water or space heating in the solar panels and heat recovery systems measures, respectively, or electricity in the photovoltaic panels' case.
- 'w/o' stands for 'without'.

Table 17 shows the number of dwellings, inhabitants and expected duration of the measures.

Table 17 – In-depth measures application range and expected life-time.

Indicators	Photovoltaic panels	Solar panels	Heat recovery systems
Dwellings	**9184**	8408	4476
Inhabitants	**22156**	20283	10798
Technology life-time $[years]$	20	15	25

From the measures under analysis, the photovoltaic panels are eligible for the greater amount of dwellings, since, according to a low end estimative of 85%, based on buildings with 1 or 2 dwellings, the majority of dwellings in Odemira are single-family houses. Regarding Solar panels, only the ones without were considered, while for the heat recovery systems only dwellings with an open fireplace were accounted.

Regarding the life-time of each measure, which is the life-time of the technology, the heat recovery systems are the ones with the highest expected longevity while solar panels the ones with the least. Nevertheless, this values may vary substantially.

Economic

In an economical perspective, it was consider the investment required for this technological options and whether it brings a positive outcome or not.

The prices used for energy vectors may be seen Appendix C. However, this values are merely representative and a careful interpretation of the values present in this analysis must be taken. Prices, from both technologies and energy carriers, vary substantially with time, location and specific dwelling consumption. Table 18 summarizes the economic parameters concerning the measures.

Table 18 – In-depth measures economic analysis.

	Indicators	Photovoltaic panels	Solar panels	Heat recovery systems
Economic	Investment $[M€]$	**6.6**	21.0	6.7
	Investment $\left[\frac{€}{hh}\right]$	**720**	2500	1500
	Net savings $\left[\frac{k€}{lifetime\ year}\right]$	461.4	149.2	**675.5**
	Net savings $\left[\frac{€}{lifetime\ year.hh}\right]$	50.24	17.74	**150.92**
	Payback time $[years]$	8.3	13.6	**7.1**
	Net savings w/o investment $\left[\frac{€}{lifetime\ year.hh}\right]$	86.24	184.41	**210.9**

As shown in Table 18, the implementation of solar panels for water heating demands the largest investment of all three measures. The complex piping system, water reservoir and solar collector panel itself are in-between the reasons for such individual high price when compared with the other options. The heat recovery systems option is around twice the individual price of the photovoltaics panels. However, given its smaller application range, the total investment in the municipality is similar in both situations. In a situation where the municipality council decides to support the investment, this options may be seen as equivalent when considering only an economic perspective. As a side note, is important to refer that the investment of public money to support this options does not necessarily translates in a direct investment by the municipality council. It may be in the form of local taxes benefits or any other approach decided be the decision makers. The investment value can also be seen has an added value for the region economy.

All three measures have an in-lifetime payback time, which provides investment safety to the municipality and households. The payback time, although not differing substantially between photovoltaics and heat recovery systems measures, is more advantageous in the latter option with 7.1 expected years. The photovoltaic panels are expected to start having economical return after 8.3 years while the solar panels option may pay itself only after 13.6 years of use. From a brief combination of this values with the expected life-time, in Table 17, is possible to conclude that the heat recovery system is the safest investment since, besides the shortest payback time, has the longest life-time margin to reach the investment return point.

In terms of net savings along the technologies life-time, the results depend if the investment is fully made by each householder or is it instead supported by the municipality council. Seeing the municipality as a whole, the net annual savings of $675.5\ k€$ along the lifetime, which is in addition the longest, makes the heat recovery systems the best option under an economic perspective. This savings advantage is enhanced when the net savings per dwelling are analysed. The heat recovery systems option, with 150.92€ per year, has at least three times more economic net benefit than the second best measure, the photovoltaic panels. Regarding the investment supported hypothesis, is interesting to notice how the solar panel option becomes substantially more pleasant, mainly due to the high investment requirement.

CO_2 emissions

The impact of the measures on CO_2 emissions were substantially divergent amongst them. In Table 19, one can see the CO_2 emissions indicators regarding each option.

Table 19 – In-depth measures CO_2 emissions analysis.

	Indicators	Photovoltaic panels	Solar panels	Heat recovery systems
CO_2 Emissions	Net savings $\left[\frac{t\ CO_2}{lifetime\ year}\right]$ (%)	328 (5.7%)	**1750 (47.5%)**	-18 (-2.9%)
	Net savings $\left[\frac{kg\ CO_2}{lifetime\ year.hh}\right]$	36	**208**	-4
	Emissions payback time $[years]$	5.1	**2.8**	n/a
	Net savings w/o LCA $\left[\frac{t\ CO_2}{lifetime\ year}\right]$ (%)	441 (7.6%)	**2154 (68.8%)**	0
	Net savings w/o LCA $\left[\frac{kg\ CO_2}{lifetime\ year.hh}\right]$	48	**256**	0

Observing Table 19, one can notice that the results for the heat recovery systems measure are negative. However, since the fire places with and without heat recovery systems are fuelled by wood and biomass, and therefore CO_2 emission factor null, the apparent negative performance in terms of emissions comes from the emissions during the production process, the life cycle assessment.

Regarding the net savings, the implementation of solar panels has the strongest positive impact, avoiding the emission of 1750 metric tonnes of CO_2 per year for the whole municipality. The shift from fossil fuels carriers to an emission free source, the solar energy, represents a 47.5% reduction of the current annual emitted emissions in Odemira for domestic water heating purposes. The households in which this measure applies, may reduce their 'pollutant trail' by 208 kilograms a year during the expected technology lifetime. The photovoltaic measure has a relatively low value regarding emissions savings,

$5.7\,\%$, regarding the use of electricity in the domestic sector. The reason for this value relies on the already fair share of renewables in the national electric grid, $72.36\,\%$ (in 2014) [65]. The net savings values become even higher if one despise the LCA emissions, since these may not be produced locally.

In Table 19, is also evident the low emissions payback time for the photovoltaic and solar panels. 5.1 and 2.8 years to effectively start avoiding CO_2 emissions. Looking at the 20 and 15 years of expected lifetime of these technologies, one can ascertain the sustainability of these two measures in terms of CO_2 emissions.

Final energy consumption

The results regarding energy consumption from the three measures under analyse are synthesized in Table 20.

Table 20 – In-depth measures final energy consumption analysis.

	Indicators	Photovoltaic panels	Solar panels	Heat recovery systems
Energy	Net savings $\left[\frac{GWh}{lifetime\ year}\right]$ (%)	-0.6 (-1.2%)	1.2 (7.5%)	**20.9 (48.8%)**
	Net savings $\left[\frac{kWh}{lifetime\ year.hh}\right]$	-64	144	**4665**
	Energy payback time $[years]$	n/a	9.0	**0.5**
	Energy return factor	n/a	1.7	**47.7**
	Net savings w/o LCA $\left[\frac{GWh}{lifetime\ year}\right]$ (%)	0	3.0 (18.7%)	**21.3 (49.9%)**
	Net savings w/o LCA $\left[\frac{kWh}{lifetime\ year.hh}\right]$	0	357	**4765**
	Increase in Renewables $\left[\frac{GWh}{year}\right]$ (%)	1.0 (2.9%)	**6.5 (248.1%)**	-21.3 (-51.9%)
	Fossil Fuels imports reduction $\left[\frac{GWh}{year}\right]$ (%)	1.0 (7.6%)	**9.5 (58.5%)**	0

As shown in Table 20, the heat recovery systems' measure has the largest positive impact on energy consumption. This measure represents 20.9 Gigawatts-hour of net savings per year. An overall final energy reduction of $48.8\,\%$, used for space heating in Odemira. In fact, each dwelling covered by the measure saves 4665 kilowatt-hour per year from wood and biomass combustion. This savings are mainly due to the substantial improvement in the efficiency of the flue gases heat exploitation process.

The solar panels measure, despite representing more than 17 times less net energy savings in comparison with the heat recovery systems, have an annual reduction of 1.2 Gigawatts-hour. $7.5\,\%$ of the currently energy demand for water heating. Given the brother range of the solar panels measure, the net savings per household which measure applies, $144\ kWh$, is almost 32 times inferior to the ones for the heat recovery systems.

The results for the photovoltaics measure, regarding the previous indicator, are negative. This is due to the fact that the measure itself does not imply a direct reduction of electricity consumption, and, since the implementation of it upholds energy expenditures belonging to the life cycle assessment, the resultant net savings end up being negative.

Regarding the energy payback time, the heat recovery systems only need half heating season to 'pay' their energy life cycle spending. This represents an energy return factor of 47.7, which means that during its expected lifetime, a heat recovery system saves almost fifty times the amount of energy that was used for its implementation. The solar panels have a more modest payback time of 9.0 years and a return factor of 1.7.

Concerning the increase of renewables and decrease of fossil fuels imports, the heat recovery systems have an apparent undesirable value in the former. The value is owing to the large decrease in the use of wood and biomass, yet without increasing the use of any other energy carrier, which makes the measure rather favourable for the environment in Odemira. The solar panels have the best impact on this matter, increasing the use of renewables on the water heating end use by $248.1\ \%$, $6.5\ GWh$ per year, and reducing the fossil fuels imports by $58.5\ \%$, $9.5\ GWh$ per year. Finally, the photovoltaic panels also have a positive balance between the increases of renewables use, $1\ GWh$ per year, and an identical reduction of fossil fuels usage for electricity production in Odemira.

6. Application to Olivais

In this chapter, the annual space heating useful energy requirements for the parish of Olivais, calculated with four different spatial resolutions are compared. In section 6.1, the resolutions available in Census are analyzed, followed on section 6.2 by a comparison between the most detailed Census resolution and the GIS building by building data usage.

6.1. Comparison between Census spatial levels

Using BGRI data set for Olivais, the calculations were made by parish data, by section and by subsection. The adopted methodology was the one described on 4.3.1. The results obtained are plotted in Table 21 as average useful energy requirements of space heating per square meter for Olivais.

Table 21 – Space heating useful energy demand with three different Census spatial resolutions.

Spatial Resolution	Space heating useful energy $[\frac{kWh}{m^2}]$
Parish	18.4
Section	20.6
Subsection	21.9

The results obtained are consistent in terms of order of magnitude but they have worth mentioning discrepancies. Considering the subsection resolution as the ‘best’, the calculation results with section spatial resolution differs: $-1.3\ \mathrm{kWh/\ m^2}$. Regarding the aggregated parish data, a difference of $-3.5\ \mathrm{kWh/m^2}$ was obtained. This deviations of $-5.9\ \%$ and $-15.9\ \%$ directly indicate the importance of having desegregated data to avoid significant differences on the model outputs with reality.

To further explore the data aggregation impact on the model results, an error analysis was made changing the degree-days set point temperature and keeping all other variables constant. Figure 24 shows the obtained results.

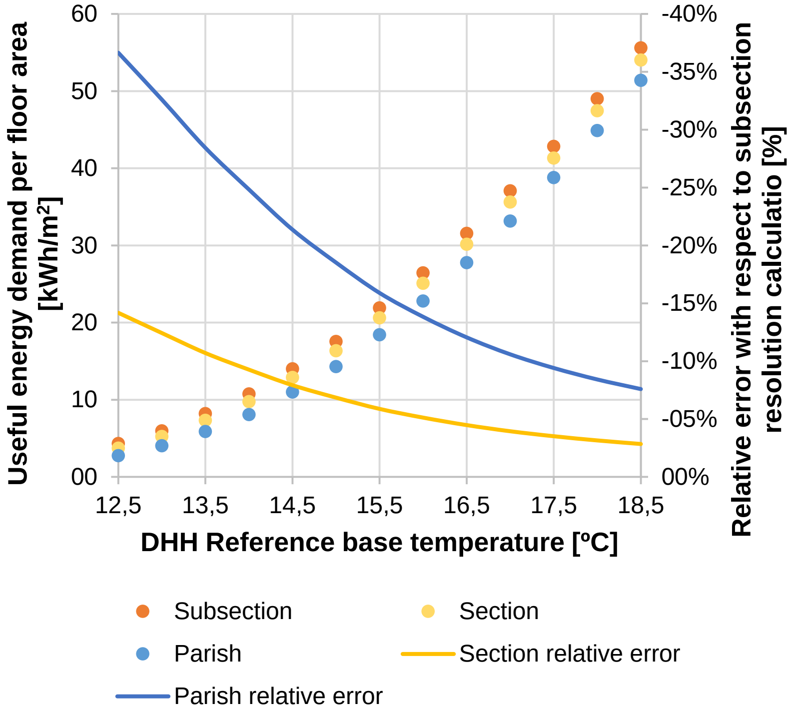

Figure 24 – Space heating useful energy demand per floor area as a function of HDD base temperature for Olivais, calculated with three different Census spatial resolutions, and respective relative error.

In Figure 24, the useful energy demand per floor area is represented in dots, for the three spatial resolutions under analysis: by subsection, by section and using aggregated data for the whole parish. The relative errors of the 'by section' and 'parish as a whole' calculations comparatively with the results by subsection are line plotted and their values can be read on the graph right axes.

One can perceive that, regardless of the spatial resolution used in the calculations, the increase in HDD reference base temperature implies a very similar absolute increase in useful energy requirements. This behaviour of the results translates in a decreased relative error while dealing with higher absolute values of energy consumption.

For instance, for a $12.5\ ℃\ HDD$ base temperature, the useful energy necessities obtained through subsections, sections and parish as a whole are 4.3, 3.7 and $2.7\ kWh/m^2$ respectively. Where the latter two have $-14.2\ \%$ and $-36.6\ \%$ of relative difference when compared with the best spatial resolution case. On the major consumption case in Figure 24, $18.5\ ℃\ HDD$ base temperature, the calculations with these three levels of spatial resolution resulted in a consumption of 55.6, 54.0 and $51.4\ kWh/m^2$. These represent a relative difference of $-2.8\ \%$ and $-7.6\ \%$ with the calculations per subsection. In absolute values, this means that for the section and parish calculation, the useful energy needs increase 15 and 19 times, from 12.5 to $18.5\ ℃$, but the absolute error increases only around three times, therefore its decrease in relative terms as already discussed. This shows that an apparent gross relative error, may be justified with the values low order of magnitude. And not properly because of the worse or better used spatial resolutions.

Despite this plausible reason for relative errors, the permanent presence of an absolute error cannot be disregarded. So this leads to the question of why a behaviour like this once different spatial resolutions are being applied. To which the answer may be in both model formulation, chapter 3, and data treatment, section 4.3.1.

At first sight, since the data is treated with weighted averages, it would be expected for the results to be similar despite spatial resolution, and consequently, a residual absolute error would be predictable. However, due to the gains utilization factor, in equation (5), the model becomes non linear. It can be deduced that this gain more relevance when carrying out calculations in regions with distinct thermal properties. The effect of aggregating and 'averaging' multiple locations, that are residentially heterogeneous, may lead to crucial losses of accuracy and thus a better spatial resolution of calculus should be considered.

The importance of making the calculations per subsection is thus strengthened to make sure the thermal mass effects are properly considered in the calculations, otherwise, with low spatial resolution, a gross value is used in consequence of the large amount of buildings in the weighted average methodology.

6.2. GIS versus Census Data

In the previous subsection, the spatial resolutions under analyze were from the same data source: Census. All the parameters were provided by identical sources, even the ones not available in Census. On the contrary, GIS data set, besides its building by building geometrical information (higher spatial resolution) had in addition other properties such as heat transfer coefficients and shading factors. Despite having more information beyond geometrical data, which is advantageous, it distorts the comparison between using census building information and GIS data, since different overall heat transfer coefficients are being used for buildings with the same construction age. Hence a first analysis is made using the GIS native heat transfer coefficients and ventilation rates, ACH, and a second comparison where, in function of the GIS building age, the later parameters are set according to the same sources as the ones used for Census data. In the GIS buildings data there were 1816 buildings, representing 148 subsections out of 278, and 54 sections out of 81. Therefore the census values analyzed are relative to the sections covered by the GIS data.

Table 22 the space heating useful energy consumption per unit of area for the whole parish, using all the parameters available in GIS.

Table 22 - Space heating useful energy demand with GIS building resolution and Census subsection resolution for Olivais.

Spatial Resolution	Space heating useful energy $[\frac{kWh}{m^2}]$
Subsection (Census)	20.6
Building (GIS)	6.4

The useful energy consumption per unit of area was substantially different from the calculation with Census per subsection data. The $14.2\ kWh/m^2$ useful energy demand gap between the spatial resolutions represents a $-68.9\ \%$ difference among GIS and Census best case. Despite this major difference, most subsections have a smaller deviation between the two, as one can see in Figure 25, where the histogram of Census and GIS subsections consumption difference is represented.

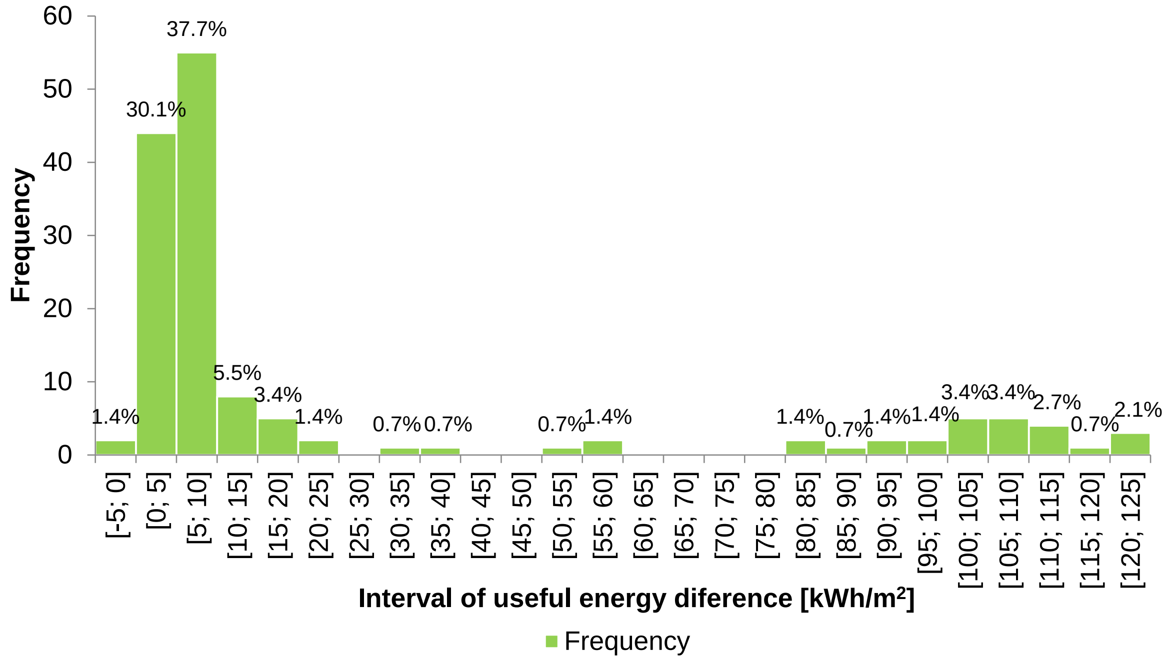

Figure 25 – Histogram of statistical subsections by useful energy difference between Census subsections and GIS spatial resolutions.

The Figure shows that $31.5\ \%$ of the Subsections under comparison have a $5\ kWh/m^2$ inferior absolute error and $69.2\ \%$ under $10\ kWh/m^2$. Yet, $17.1\ \%$ have an $80\ kWh/m^2$ more discrepancy which is a substantial difference.

In spite of the fact that the global results for useful energy consumption were substantially different, the relative energy demand per unit area across Olivais' sections were mostly identical while using both spatial resolutions, as one can observe in Figure 26.

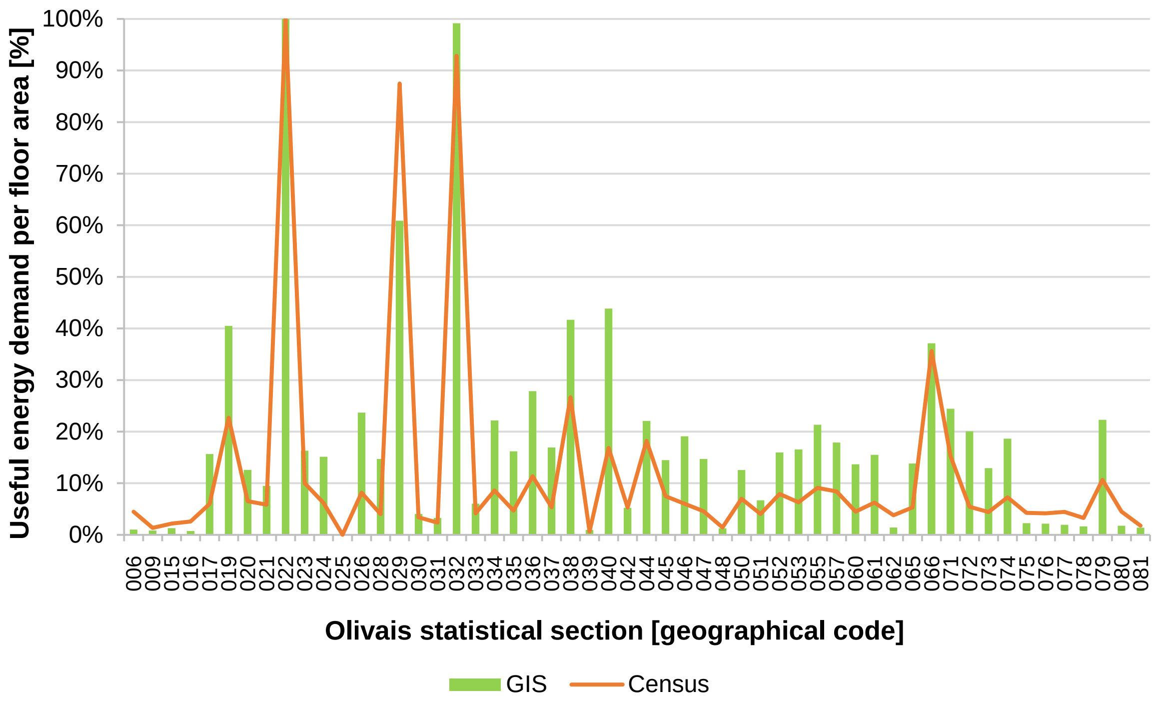

Figure 26 – Space heating useful energy demand per unit floor area relative to the minimum and maximum values of the sections calculated with GIS and Census best spatial resolutions.

In Figure 26, the green bars represent the space heating relative useful energy consumption, calculated with the GIS data set. For these, $100\ \%$ and $0\ \%$ correspond to the sections under analyze with the highest and lowest demand in between the GIS calculated ones. The orange line represent identically the useful energy demand, but calculated with Census data with the highest spatial resolution (by subsection). Once more, the maximum and minimum values correspond to $100\ \%$ and $0\ \%$.

In Figure 26 both results from GIS and Census show an identical consumption 'profile' across the parish. Sections 022 and 025 as the ones with highest and lowest useful energy requirements per square meter.

Table 23 presents the useful energy results obtained with the GIS buildings characteristics, Census correspondence between construction age of the buildings and respective overall heat transfer coefficients and air changes per hour.

Table 23 - Space heating useful energy demand with GIS building resolution, with and without GIS U-values and ACH, and Census subsection resolution for Olivais.

Spatial Resolution	Space heating useful energy $[\frac{kWh}{m^2}]$
Subsection (Census)	20.6
Building (GIS)	6.4
Building (GIS) using only the geometry	11.1

As shows Table 23, the results from the GIS calculation using only the geometry are closer to the subsection calculation. The $11.1\ kWh/m^2$ useful energy demand calculated with GIS data without its local overall heat transfer coefficients represents $9.5\ kWh/m^2$ difference, $-46.1\ \%$, when compared with Census best case, which a smaller gap than the complete GIS data calculation.

As well as in the previous case, the current has significant amount of subsections with a smaller deviation between the two spatial resolutions, as one can see in Figure 27.

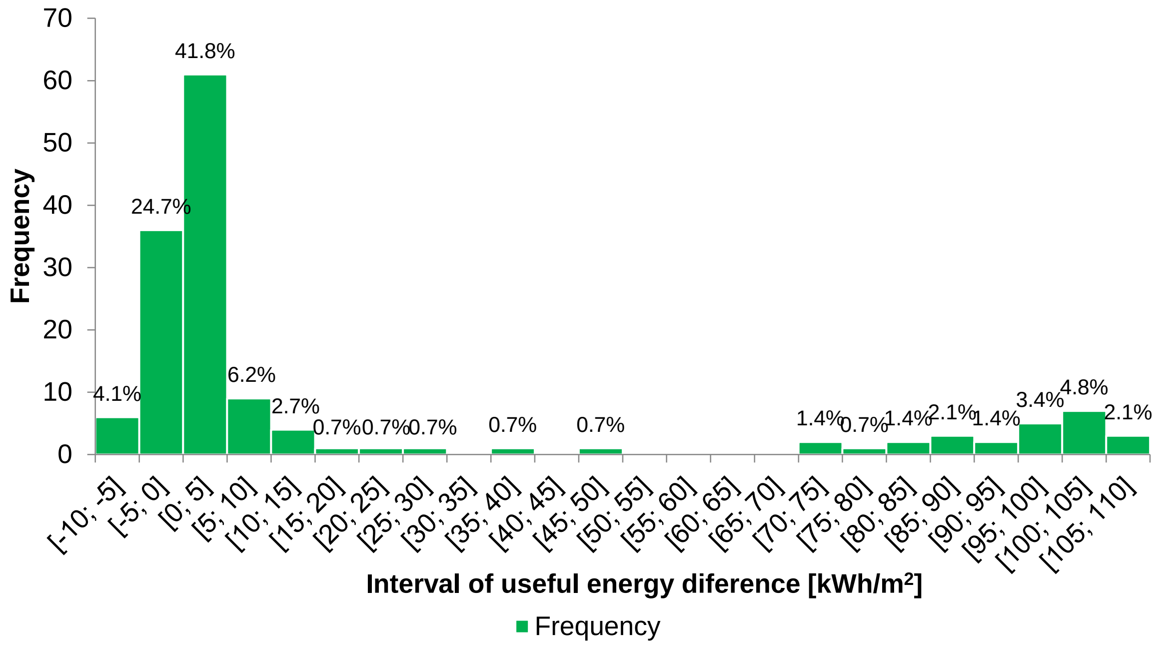

Figure 27 – Histogram of statistical subsections by useful energy difference between Census subsections and GIS, without its local overall heat transfer coefficients, spatial resolutions.

$66.5\ \%$ of the subsections under comparison have $5\ kWh/m^2$ inferior absolute error, and $15.2\ \%$ have a $80\ kWh/m^2$ larger difference.

In Figure 28 the useful energy demand per unit of area and per section is shown.

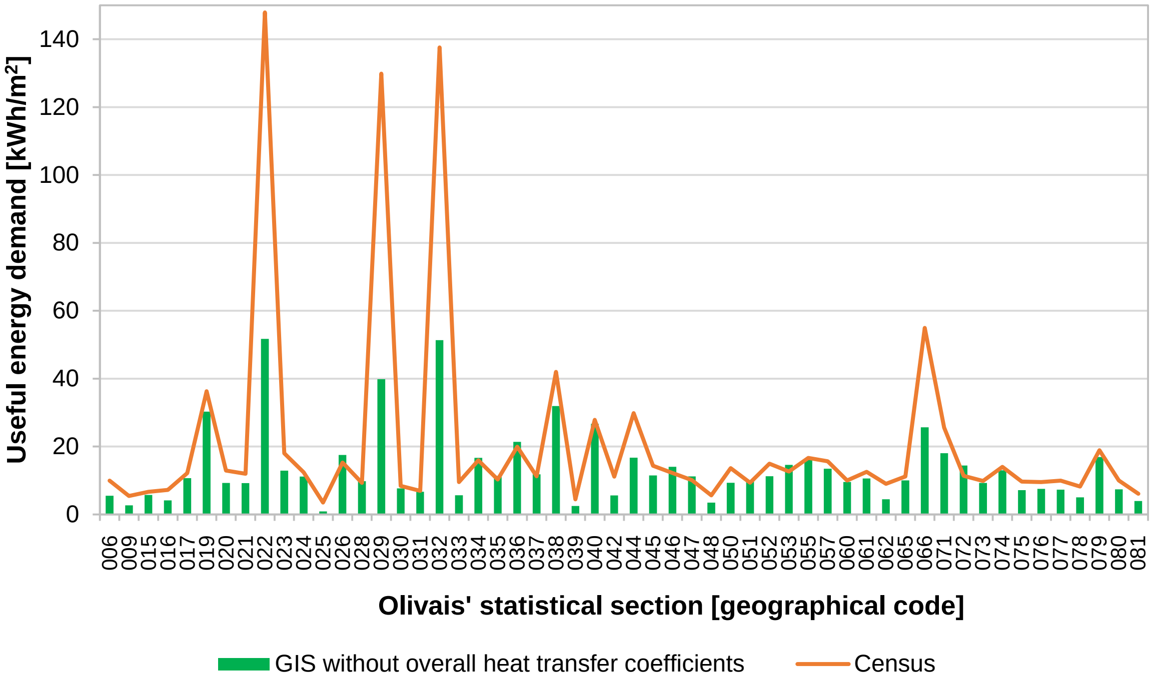

Figure 28 – Space heating useful energy demand per unit floor area for Olivais' statistical sections, calculated with GIS and Census best spatial resolutions.

In Figure 28, one can without effort verify the 'profile' similarity between the results obtained with Census by subsection resolution and GIS data set without its overall heat transfer coefficients. Despite the similarities, sections 022, 029, 032 and 066 have significant discrepancies amongst the two calculation methods. So a question arises - why the contrast on those four sections, using two different methodologies? - The answer lies on the methodology used in Census regarding number of floors. These four sections have low number of floors as a result of many single-houses, and due to the methodology used, the minimum number of floors used in the calculations is one and a half floors. This turns out to become a less than ideal approximation if most buildings in a statistical subsection have only one floor. It can be concluded that one shall wisely analyze if the data treatment is appropriate for the data sets or not, and critically reflect which consequences on the results should expect.

Excluding these sections from the analysis, the annual average useful energy demand for space heating in Olivais, calculated with Census data, is $12.8\ kWh/m^2$. This value is more satisfactory when compared with the $9.5\ kWh/m^2$ obtained with GIS. However, is still a considerable difference. The buildings 'sample' in the GIS does not concern all the buildings in these sections and subsections analyzed, thus the results from this analyze may be affected by this. Nevertheless, the difference in the results suggests that the use of building by building information enables it to significantly reduce modeling errors, even if only geometrical information is used.

7. Conclusion

In this work a demand driven hybrid simulation model was developed to support the design of a combined integration of energy saving measures together with renewable energy penetration at the level of the households. The model adopts a bottom-up approach for space heating, cooling and water heating by considering building geometric and thermodynamic characteristics, climatic data and technology penetration information, adequate to be integrated in energy planning models at a regional level; and a top-down or equipment ownership approach for the other end-uses. The parameters used and the end-uses model formulation, allowed for a detailed analysis of the residential energy services and its influence on alternative energy vectors use as a function of technological shifts, building rehabilitation and equipment's modernization. The model was applied to two case studies: Odemira Municipality and Olivais parish in Lisbon.

The application to the Odemira case study allowed the model to be calibrated with top-down information, mostly available in statistical data and national surveys. While the calibrated parameters were used in the model, a sensitivity analysis was performed to identify how some parameters impact the results obtained. The analysis showed that parameters such as the heating and cooling reference temperatures are critical in the calibration process.

Finally, the case study was used to demonstrate how a demand driven technology based analysis can support energy planning activities. This is, identify technology options and measures which of them may contribute to simultaneously improve energy efficiency, to reduce CO_2 emissions and to maximize the use of renewable and endogenous energy and therefore to increase local added value to the regional economy. For example, the results showed that the retrofit of open fireplaces represents about $7\ M€$ of added value for the economy, and could lead to a $50\ \%$ yearly reduction of wood use for space heating. Solar panels implementation represents a $50\ \%$ reduction of CO_2 emissions and 60 % fossil fuel detachment regarding the current water heating situation.

The application to the Olivais model was used to test the ability of the model to be applied with different spatial resolution and data availability. The results showed that the ability of the model to use building by building information enables it to significantly reduce modeling errors, even if only geometrical information is used.

Therefore, the hybrid model developed can provide a good support for energy planning analysis towards defining a sustainable region due to its modeling detail and the substantial number of parameters considered. Nonetheless, a good description of the region under analysis was found to be crucial, with the use of average values in some parameters having a high impact on the modeling results.

7.1. Future work

To improve the developed model, the formulation can be modified to include more detail. For instance, the effect of thermal bridges and linear overall heat transfer coefficients could be consider, as it is formulated in REH, but a comparison of these results with the ones obtained with the actual formulation should be performed to assess de advantages or disadvantages of increasing the mathematical detail of the formulation. Another area where additional detail could be provided concerns the equipment specific consumptions. For example, instead of a specific annual consumption for the washing machine, a model with water per washing cycle and amount of clothes could be implemented instead, as other authors have suggested. Another path for development can be the use of a transient thermal balance for the space heating and cooling calculations, as an alternative to the heating degree days approach. This method, associated with a robust weather data source could return more accurate results, despite the increase of calculation requirements which imposes a cost-benefit analysis regarding the comparison with the HDD formulation. The formulation may also be adapted to integrate end-uses between themselves. For example, the internal gains could be linked to the equipment power ratings and households' heat losses. The space for improvements is evident, but one shall maintain the concerns about the benefits of having a very detailed model with extensive data requirements rather a simple formulation one, which simultaneous robustness and simplicity characterize the major advantage of the later, when compared with the already available complex tools.

Furthermore, the model could be improved to perform daily or hourly calculations, which could represent a first step to integrate it with a supply model. Regarding the lighting service, it is also plausible to adapt a completely different formulation, with actual lumen requirements based on activities of the households, occupancy patterns and windows location.

Another path for development has to do with the data sets. It would be interesting to use the model in case studies with more specific data sets, for example, local equipment share in all end-uses. It would be fundamental in those case studies to compare and calibrate the results with data of all energy vectors consumption in the region under analysis, and per end-use if available. For example, energy certificates (which use the REH formulation) could be used in the model formulation, instead of using census building stock, or be used to compare the results between these certificates and the results from the model. The comparison with other commercial tools, assessing the errors in baseline scenarios and with the application of measures, would provide a benchmark for the developed model.

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Appendices

Appendix A. Heating degree days

Table 24 – HDD Odemira, adapted from [45].

Reference Temperature [℃]	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5
Jan	42	51	62	73	85	98	112	127	142	157	173	188	204
Feb	52	60	71	81	93	106	119	132	146	160	174	188	202
Mar	27	33	41	50	60	72	84	97	111	125	139	154	168
Apr	8	12	16	21	28	36	44	54	64	76	87	99	112
May	2	4	6	9	13	17	22	28	35	43	51	61	71
Jun	0	0	0	1	1	2	5	8	12	16	22	29	36
Jul	0	0	0	0	0	0	1	3	4	8	12	17	23
Aug	0	0	0	0	0	0	1	1	2	4	7	11	16
Sep	0	0	0	0	0	0	1	2	2	4	6	9	14
Oct	1	2	2	3	4	6	8	11	14	18	24	30	38
Nov	16	21	26	33	40	49	58	68	80	92	105	118	132
Dec	49	57	67	77	89	101	114	128	142	157	172	187	203
Winter (considered)	194	234	283	335	395	462	531	606	685	767	850	934	1021

Table 25 – HDD Olivais, adapted from [45].

Reference Temperature [℃]	**12.5**	**13**	**13.5**	**14**	**14.5**	**15**	**15.5**	**16**	**16.5**	**17**	**17.5**	**18**	**18.5**
Jan	86	98	111	125	140	154	170	185	200	216	231	246	262
Feb	67	78	90	102	116	129	143	157	171	185	199	213	227
Mar	31	39	49	58	69	80	92	104	117	130	143	157	171
Apr	5	7	11	15	20	26	34	41	50	60	70	81	93
May	1	1	2	4	6	8	11	14	19	23	30	36	44
Jun	0	0	0	0	1	2	3	5	8	10	15	19	25
Jul	0	0	0	0	0	0	0	0	0	1	3	4	8
Aug	0	0	0	0	0	0	0	0	1	1	3	4	7
Sep	0	0	0	0	0	1	2	3	6	9	14	18	24
Oct	0	0	0	0	1	2	3	4	7	10	13	17	22
Nov	8	11	16	21	28	35	45	55	66	78	91	104	119
Dec	70	81	93	106	120	135	150	165	181	196	211	227	242
Winter (considered)	267	314	370	427	493	559	**634**	707	785	865	945	1028	1114

Appendix B. Gains utilization factors

The gains utilization factors, for both space heating and cooling needs are calculated according to equations (35) and (36).

$$\eta = \begin{cases} if\ \gamma \neq 1\ and\ \gamma > 0 & \dfrac{1-\gamma^{a}}{1-\gamma^{a+1}} \\ if\ \gamma = 1 & \dfrac{a}{a+1} \\ if\ \gamma < 0 & \dfrac{1}{\gamma} \end{cases} \tag{35}$$

$$\gamma = \frac{Q_g}{Q_t + Q_v} \tag{36}$$

"a" can take the values of 1.8, 2.6 and 4.2 according to buildings' weak, average and strong thermal inertia [38].

Appendix C. Energy vectors CO_2 emission factors and price

Table 26 – Energy vectors CO_2 emission factors and price, adapted from [66]–[68].

	Electricity	Coal	Biomass	Heating Oil	Solar	Gas
Emission factors $\left[\frac{g\ CO_2}{kWh}\right]$	122.5	367.2	0	266.8	0	227.2
Price $\left[\frac{€}{kWh}\right]$	0.222	0.100	0.443	0.133	0	0.162