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Mestre em Engenharia do Ambiente

Residential Sector Energy Consumption at the Spotlight: From Data to Knowledge

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From Data to Knowledge

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Abstract

Energy consumption is at the core of economic development, but its severe impacts on resources depletion and climate change have justified a call for its general reduction across all economic activities. Lowering households' energy demand is a key factor to achieve carbon dioxide emission reductions as it has an important energy-saving potential. Households in the European Union (EU28) countries have a significant weight (25%) in the total final energy consumption. However, a wide range of variation is observed within the residential sector from 7.6 to 37.4 GJ *per capita*/annum, with the lowest consumption indicator observed in Southern EU countries.

Energy consumption in the residential sector is a complex issue, explained by a combination of different factors. To pinpoint how to reduce energy consumption effectively while deliver energy services, we need to look not just at technology, but also to the factors that drive how and in what extent people consume energy, including the way they interact with technology (*i.e.*, energy efficiency). The main objective of this research is to understand the differences in energy consumption arising from different socio-demographic, technologic, behavioral and economic characteristics of residential households.

This research brings to the spotlight the needs and benefits of looking deeper into residential sector energy consumption in a southern European country. Portugal and the municipality of Évora, in particular, were selected as case studies. Residential sector consumption is a moving target, which increase the complexity of adequate policies and instruments that have to address the bottleneck between increase demand for *e.g.* climatization due to current lack of thermal comfort and to comply with objectives of increased energy efficiency which ultimately intend to reduce energy consumption. This calls for different levels of knowledge to feed multiscale policies. This dissertation expands the understanding of energy consumption patterns at households, consumers' role in energy consumption profiles, indoor thermal comfort, and the levels of satisfaction from energy services demand. In a country potentially highly impacted by climate change, with low levels of income and significant lower energy consumption *per capita* compared to the EU28 average, looking into these issues gains even more importance. The work combines detailed analysis at different spatial (national, city and consumers level) and time scales (hour to annual) taking advantage of diverse methods and datasets including smart meters' data, door to door surveys and energy simulation and optimization modelling.

The results identify (i) ten distinct residential sector consumer groups (*e.g.*, under fuel poverty); (ii) daily and annual consumption patterns (W, U and flat); (iii) major energy consumption determinants such as the physical characteristics of dwellings, particularly the year of

construction and floor area; climatization equipment ownership and use, and occupants' profiles (mainly number and monthly income). It is (iv) recognized that inhabitants try to actively control space heating, but without achieving indoor thermal comfort levels. The results also show (v) that technology can overweight the impact of practices and lifestyle changes for some end-uses as space heating and lighting. Nevertheless, important focus should be given to the evolution in the future of uncertain parameters related with consumer behavior, especially those on climatization, related to thermal comfort and equipment's use. Furthermore, the research work presents a (vi) bottom-up methodology to project detailed energy end-uses demand, and (vii) an integrated framework for city energy planning.

This work sets the ground for the definition of tailor-made policy recommendations for targeted consumer groups (*e.g.*, vulnerable consumers) and climatization behavior/practices to reduce peak demand, social support policies, energy efficiency instruments and measures, renewable energy sources integration, and energy systems planning.

Keywords: Residential Sector, Determinants of Energy Consumption; Consumer Behavior, Energy Services Demand, Smart Meters, Integrated Energy Planning.

Resumo

O consumo de energia está na base do desenvolvimento económico, mas os impactos no consumo de recursos e a contribuição para as alterações climáticas o que justifica a sua redução em todas as atividades económicas. O consumo de energia no sector residencial é um vector-chave para a redução das emissões de dióxido de carbono, uma vez que tem um elevado potencial de poupança de energia. Este sector tem um peso significativo (25%) no consumo de energia final nos países da União Europeia 28. No entanto, existe uma ampla variação entre países no consumo de energia *per capita* (7.6 a 37.4 GJ) por ano, observando-se valores mais baixos na generalidade dos países do Sul da Europa.

O consumo de energia no setor residencial é uma questão complexa, que pode ser explicada por uma combinação de características físicas, tecnológicas, demográficas, climáticas, características das habitações e comportamento dos ocupantes. De forma a identificar como reduzir eficazmente o consumo de energia mantendo ou aumentando os níveis de satisfação de serviços de energia, é necessário ter em conta não só a tecnologia (*i.e.*, eficiência energética), mas também os fatores que determinam como, e em que medida as pessoas consomem energia, incluindo a forma como interagem com a tecnologia. O objetivo principal deste trabalho de investigação é a compreensão das diferenças no consumo de energia decorrentes de características distintas como sócio-demográficas, tecnológicas, comportamentais e económicas dos consumidores residenciais.

A investigação realizada nesta dissertação identifica as necessidades e os benefícios de uma análise aprofundada do conhecimento do consumo de energia no setor residencial num país do Sul da Europa. Portugal e o município de Évora, em particular, foram selecionados como casos de estudo. O consumo no setor residencial é um alvo em movimento, o que aumenta a complexidade no desenho de políticas e instrumentos adequados que têm de lidar com a dicotomia entre o aumento da procura de serviços de energia (*e.g.* para climatização devido à falta de conforto térmico atual) e o cumprimento dos objetivos de maior eficiência energética que, em última análise, pretendem reduzir o consumo de energia, o que exige diferentes níveis de conhecimento para alimentar políticas e instrumentos de atuação a diferentes escalas.

Esta dissertação avança o conhecimento na compreensão dos padrões de consumo de energia em habitações, o papel dos consumidores nos perfis de consumo eléctrico, o conforto térmico e os níveis de satisfação da procura de serviços energéticos. Num país que potencialmente será muito afetado pelas alterações climáticas, com baixos níveis de rendimento e consumo de energia *per capita*, significativamente inferior à média da UE28, a análise destas questões ganha ainda mais relevância. O trabalho combina análise detalhada em diferentes escalas espaciais

(nacional, municipal e consumidores) e temporais (hora a anual), aproveitando diversos métodos e conjuntos de dados, incluindo registos de contadores inteligentes, inquéritos porta a porta, modelos de simulação térmica de edifícios e de otimização de sistemas energéticos.

Os resultados obtidos (i) identificam 10 grupos de consumidores distintos (por exemplo, associados a pobreza energética); (ii) analisam padrões diários e anuais de consumo (W, U e Plano); (iii) caracterizam os principais determinantes do consumo eléctrico, tais como características físicas das habitações (ano de construção e área), taxa de posse e padrões de uso de equipamentos de climatização, e perfis dos ocupantes (*e.g.*, número e rendimento mensal). Os resultados focam ainda (iv) a identificação de comportamentos de consumo ativo para aquecimento de espaço, reconhecendo, no entanto, uma significativa falta de conforto térmico nas habitações da região; e mostram que (v) a tecnologia pode anular práticas e mudanças de estilo de vida para alguns usos finais como aquecimento de espaços e iluminação. No entanto, deve ser dada atenção à incerteza associada a parâmetros relacionados com o comportamento do consumidor, especialmente os relativos à climatização com impacto no conforto térmico e no uso de equipamentos. Para além disso, este trabalho de investigação apresenta (vi) uma metodologia *bottom-up* para projeções de procura detalhada de serviços de energia por uso final e (vii) uma estrutura integrada para o planeamento energético urbano.

Este trabalho contribui para a definição de políticas e medidas para grupos de consumidores de energia específicos (*e.g.*, consumidores vulneráveis); análise de comportamentos de climatização que possam ser geridos em picos de procura, políticas de apoio social, medidas e instrumentos de eficiência energética, integração de fontes de energia renováveis e planeamento de sistemas energéticos.

Palavras Chave: Sector Residencial, Determinantes do Consumo de Energia, Comportamento dos Consumidores; Procura de Serviços de Energia, Contadores Inteligentes, Planeamento Energético Integrado

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Abbreviation and Units

- AC – Air Conditioner
- CDM - Cloth Drying Machines
- CENELEC – European Committee for Electro Technical Standardization
- CFL - Compact Fluorescent Lamps
- COPERT - Computer Programme to Calculate Emissions from Road Transport
- CWM - Cloth Washing Machines
- DGEG – Direcção Geral de Energia e Geologia [General Directorate for Energy and Geology]
- DHW – Domestic Hot Water
- DSO – Distribution System Operators;
- DWM - Dishwasher Machines
- EC – European Commission
- ESCO – Energy Service Company
- ESD – Energy Services Demand
- ETSAP - Energy Technology Systems Analysis Programme
- EU28 - European Union [Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, United Kingdom, Austria, Finland, Sweden, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, Bulgaria, Romania and Croatia].
- FSK - Frequency-shift keying
- GDP – Gross Domestic product
- GHG – Greenhouse Gases
- GIS – Geographic Information System
- HL - Halogen lamps
- HVAC – Heating, Ventilating, and Air Conditioning
- ICEP – Integrated City Energy Planning
- IEA – International Energy Agency
- IL - Incandescent lamps
- INE – Instituto Nacional de Estatística [Statistics Portugal]
- InSMART – Integrative Smart City Planning
- LED - Light-emitting Diode
- LNG – Liquefied Natural Gas
- MCDM – Multi Criteria Decision Making
- NEEAP - National Energy Efficiency Action Plans
- OE – Other Electrics
- OECD - Organization for Economic Co-operation and Development
- NGO – Non-Governmental Organization
- PLC – Power Line Communication
- PROMETHEE - Preference Ranking Organization Method for the Enrichment of Evaluations
- PV – Photovoltaics
- PVC – Poly(vinyl chloride),
- REF – Reference Scenario
- RES – Renewable Energy Sources
- SILC – Statistics on Income and Living Conditions
- TFL - Tubular Fluorescent Lamps
- TIMES – The Integrated MARKAL-EFOM System
- VAT – Value Added Tax
- WEO - World Energy Outlook
- °C – degree Celsius
- GJ – gigajoule (10^9 joule)
- GWh – gigawatt-hour (10^9 watt-hour)
- HDD - heating degree-days
- kHz – kilohertz
- kVA – kilovolt-amps
- kWh – kilowatt-hour
- kWp - kilowatt peak
- MW – megawatt
- PJ – petajoule (10^{15} joule)
- pkm - passenger-kilometer
- tkm – tone-kilometer

Chapter 1 | General Introduction

1.1 Relevance of the study

1.1.1 Global greenhouse gases emissions and energy consumption trends

The 2015 Paris climate change agreement has set a long-term goal of keeping the increase in global average temperature to well below 2°C above pre-industrial levels, aiming to limit the increase to 1.5°C, meaning that the increasing trends of the last decades of global greenhouse gases emissions (GHG) must be reverted. After 2010, a declining growth in global CO₂ emissions has occurred, starting from 5.7% (2010) down to 0.7% (2012). Afterwards, the global emissions have stalled, aligned with the slowing trend in annual emission growth, especially over the last three years, starting from 2.0% in 2013 to 1.1% in 2014 and further down to -0.1% in 2015 (near 36 Gt CO₂ from fossil fuel and industry) (Figure 1.1) (Olivier *et al.*; (2016); GCP (2016)). Several authors consider controversial whether the plateaued emission level will continue and results from structural changes (*e.g.* Jackson *et al.* (2016); Green and Stern (2016)). Olivier *et al.* (2016) and IEA (2016a) highlight that this trend is decoupled from the gross domestic product (GDP) trend, as global GDP kept up with an annual growth of 3.0% in 2015 compared to 2014.

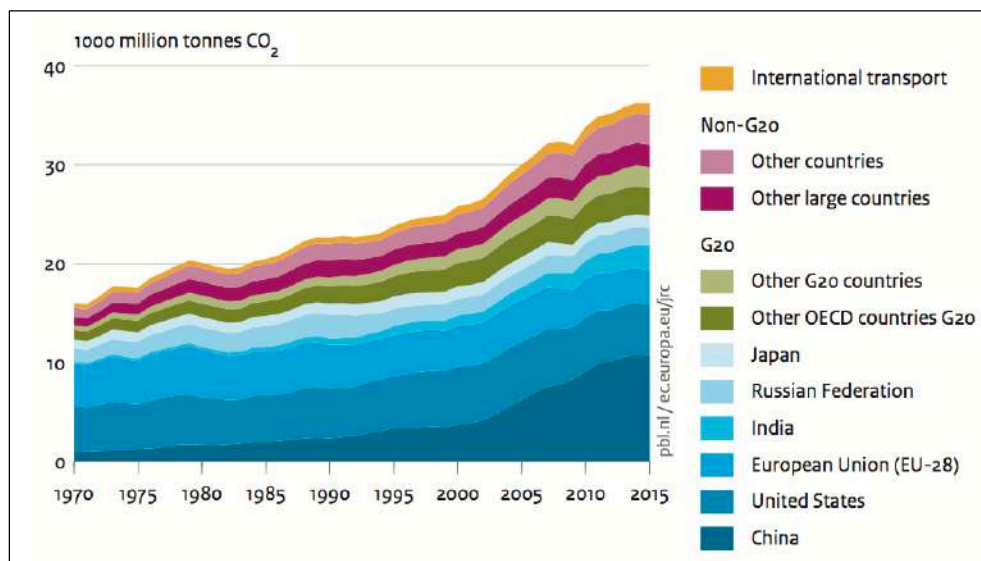


Figure 1.1 – Global CO₂ emissions per regional from fossil-fuel use and cement production (Adapted from EC-JRC/PBL, 2016)

Global primary energy consumption increased by 1.0% in 2015 compared to the previous year, below the 10-year average of 1.9%, despite the widespread fossil fuel prices decrease (Olivier *et al.*, 2016). The sustainability debate is linked to the climate debate, within which reducing CO₂ emissions is the highest priority (Ellegard and Palm, 2011). Current trends in energy supply and consumption of developed countries are patently unsustainable and must be altered, since regional improvements would be outstripped by the increased energy demand worldwide (OECD, 2012). Though, according to the World Energy Outlook 2016 (WEO) (IEA, 2016a),

primary energy demand is expected to increase by 43% between now and 2040 under the 'Current Policies Scenario', by 31% under the 'New Policies Scenario' and by a mere 9% under the '450 Scenario'. The CO₂ emissions associated with these scenarios could rise by 36%, 13%, and fall by 43% respectively (IEA, 2016a).

Energy is at the heart of the global warming challenge, being critical for economic and social development (Zhao *et al.*, 2012). By looking at the energy consumption profile trend from the Organization for Economic Co-operation and Development (OECD) countries, there are two broad (and complementary) means of reducing the energy related emissions of GHG. The first one is to develop renewable zero-emission energy sources, but this might continue to instigate energy consumption, while the second is to reduce final energy consumption among end-users. The latter leads to a need for demand-side actions in order to reduce energy consumption with implications on energy supply security and affordability, climate change. It will also foster the growing share of renewable energy as primary energy sources for electricity generation. This last issue is particularly important, since it may cause future load planning problems.

1.1.2. Residential sector

In OECD countries, efforts have been focused on reducing coal and oil consumption, increasing energy efficiency, and mitigating the impacts of oil price fluctuation on the economy (Kowsari and Zerriffi, 2011; Brounen *et al.*, 2012). Within these factors, the residential energy sector is crucial to achieve CO₂ emission reductions as it has an important energy-saving potential, and its environmental controls are difficult to displace to other countries (Pablo-Romero *et al.*, 2017). Energy consumption in residential buildings represents a significant share of energy consumption in OECD countries which; however, is very distinct among the EU28 countries (12% in Luxembourg to 37% in Croatia) (PORDATA, 2016).

These differences arise from different economic structures but also from different stages of energy efficiency and delivery of energy services. The increase demand for energy services in households (as total and per square meter), may be explained, partially, by new end-uses, increased degree of basic comfort and amenities, and widespread utilization of new types of loads/equipment and by patterns of use that offset the gains of increasing efficiency in households' equipment (*e.g.*, Jevons Paradox (Alcott, 2005)).

In the last decade, the research in energy demand in households has assumed a higher importance, with energy scholars devoting substantial effort to understand it. Engineering, economics, psychology, sociology, and anthropology have been the main contributors to the field of household energy use with its own biases, frameworks, and techniques (Keirstead, 2006; Volland, 2017).

Energy consumption in residential sector is a very complex topic depending on several factors from socio-economic (*e.g.* type of dwelling, dimension or income of the family), to behavioral (*e.g.* values, culture), technological (*e.g.* equipment efficiency), climate, as well as, local factors such as architectural traditions, building materials and technical characteristics of the dwelling (Howden-Chapman (2009); Kowsari and Zerriffi (2011), Sutterlin *et al.* (2011), Brounen *et al.* (2012); McLoughlin *et al.* (2012); Wyatt (2013); Jones *et al.* (2015)). The dynamic aspects of these factors are also of high importance when making future energy projections and planning, since under or overestimating energy demand may cause energy scarcity or redundancy in resources (Ünler, 2008).

We already know that energy efficiency (EE) is the low-hanging fruit of energy and climate policy, also on households. However, the estimates are based on the assumption that energy efficiency reduces energy demand in a linear and direct manner. Rather, as generally assumed in energy and climate forecasting and scenario planning, the economy is nonlinear, especially when responding to changes in the relative price of goods and services (Jenkins *et al.*, 2011) as well as to cultural habits. Earlier research had found that technological improvements have gained more focus than behavioral related measures. In this sense, efficiency is not a way of changing lifestyle but changing technical equipment. This takes the responsibility away from the householders for the side effects, since the increasing demand in more items also includes an increased demand of energy (Gyberg and Palm, 2009).

Energy efficiency policies and measures are crucial, as depicted in the WEO2016, where EE could reduce around 15% of the EU energy consumption by 2040 (IEA, 2016a). Nonetheless, efficiency alone is not sufficient to meet the targets of energy and emissions reduction, it is also needed to look beyond efficiency improvements towards the reduction of absolute energy demand. This is especially true in countries where the balance between complying with targets of energy consumption reduction and the demand for increased thermal comfort levels and other basic energy services still needs to be achieved.

Conventional climate mitigation strategies (which generally ignore rebound effect, human behavior and other drivers behind energy consumption and energy savings) are dangerously over reliant on increased energy efficiency and technological improvements (Howden-Chapman, 2009; Jenkins *et al.*, 2011). Researchers have been exploring various dimensions of household energy use in order to design and implement strategies, not only to provide secure access to energy services, but also to facilitate the transition to modern fuels, eradicate energy poverty, address environmental concerns, and mitigate GHG emissions. Despite more than four decades of effort, our understanding of household energy use patterns and the variables associated with household energy use remains limited (Kowsari and Zerriffi, 2011; Wiesmann *et al.*, 2011). This is probably due to the distinct patterns of consumption across regions and

countries as a consequence of socio-economic profiles and consumption habits and the lack of comprehensive and detailed data to support the identification of determinants of energy consumption and consumers with different behaviors.

Energy policy strategies should encompass effective reduction of energy consumption wherever possible, while guaranteeing the maintenance or improvement of crucial energy services as heating and cooling. Since energy use is related, not only with technologies, but also with behavioral and socio-economic characteristics and changes, policies and measures must wide its scope and goals to cover effective determinants. Households' energy use has unique characteristics that make it harder but challenging to assess and analyze when compared to other sectors, with complex interactions between energy, environmental, social and economic issues.

1.1.3 Energy consumption in Europe

Energy consumption is at the heart of economic development with severe impacts on the consumption of resources and climate change. Figure 1.2 shows the evolution of the total final energy and electricity consumption *per capita* of the EU countries from 1990 to 2015, while Figure 1.3 presents for the same period the residential sector final energy consumption *per capita*. We can see from both figures that the development among EU countries was very different. Numerous countries increased their total final energy consumption *per capita* consumption, with several EU southern countries being among them (*e.g.* Portugal, Spain, Malta, Greece) mainly due to increased energy services demand; others like Italy and the Netherlands remained quite stable and still, while others like Germany, Austria, Czech Republic and Estonia strongly reduced their *per capita* energy consumption due to different reasons, among others, increased energy efficiency, fuel switches, and structural economic changes. The trends in electricity consumption are significantly different, within an overall growth at EU28 level of around 20% in the period. Countries like Portugal and Malta increased by 90% the electricity consumption *per capita*, Greece and Ireland around 60%, and the bulk of EU countries around 20%. This electrification trend might be driven by increasing energy services, fuel shifts due to electrical equipment and ease of use.

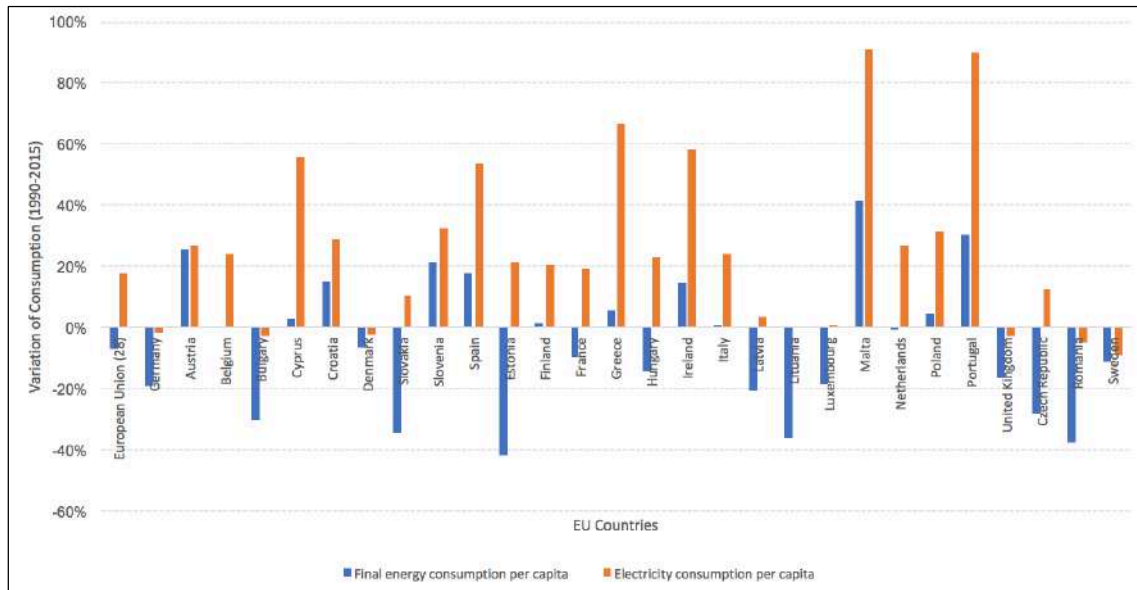


Figure 1.2 – Variation of total final energy and electricity consumption per capita from 1990 to 2015 for EU countries (PORDATA, 2016)

In European Union (EU), residential buildings are responsible for around 25% of final energy consumption in 2015 (PORDATA, 2016), and serious efforts have been devoted to improve energy efficiency (EE) in buildings and appliances (Energy Performance of Buildings Directive, Eco-design and Labelling Directives, the Energy Efficiency Directive). According to the analysis of Serrano *et al.* (2017), European inhabitants live in bigger houses but spend less in energy *per capita* and even less when their income is higher. This decreasing trend could be because they have access to more efficient housing and appliances, improving energy efficiency.

Looking at the consumption change from 1990 to 2015 at the residential sector level, the analysis is similar to the total final energy, with EU southern countries depicting a sharp increase in the 90's followed by a significant reduction from 2004/2005 onwards, but most significantly after 2010; but with differences on the relative increase/decrease of consumption of the countries (Figure 1.3). These differences show that EU energy policies in the residential sector are not equally bringing the expected results on energy consumption reduction since there are other determinants of energy consumption besides technology that should be evaluated, such as consumer behavior in each country.

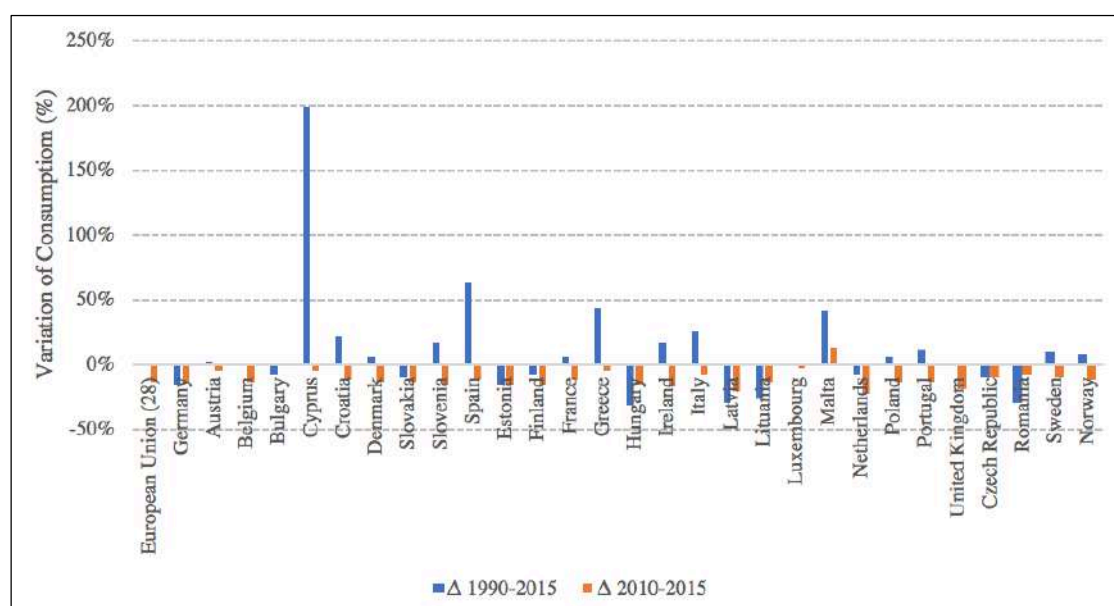


Figure 1.3 –Variation of final energy consumption per capita from 1990 to 2015 and 2010-2015 at residential buildings of EU countries (PORDATA, 2016)

In 2014, energy intensity¹ in the EU28 was 34% below 1990 levels (Figure 1.4). Since 2005, energy efficiency results have accelerated. Between 1990 and 2014, all EU28 showed an absolute or relative decoupling of GDP growth from gross inland energy consumption development. Portugal is the EU28 country where the improvements from 1990 basis were lower (-11%). At the higher end with significant reductions, are Eastern European countries as Lithuania (-68%); Romania (-62%), Bulgaria, and Estonia (-56%). For a matter of comparison, other Southern European countries as Spain Italy and Greece, reduced 18%, 15%, and 12% respectively. This reduction of energy intensity was influenced by improvements in energy efficiency — both for final users and for power generation — as well as by the increase of renewable energy in the power mix and by structural changes within the economy. The latter included an increase in the contribution of services to GDP and a shift within the industrial sectors from energy intensive industries to less energy intensive industries that have a higher value added (EEA, 2016).

¹ Energy intensity is expressed as the ratio between gross inland energy consumption and GDP.

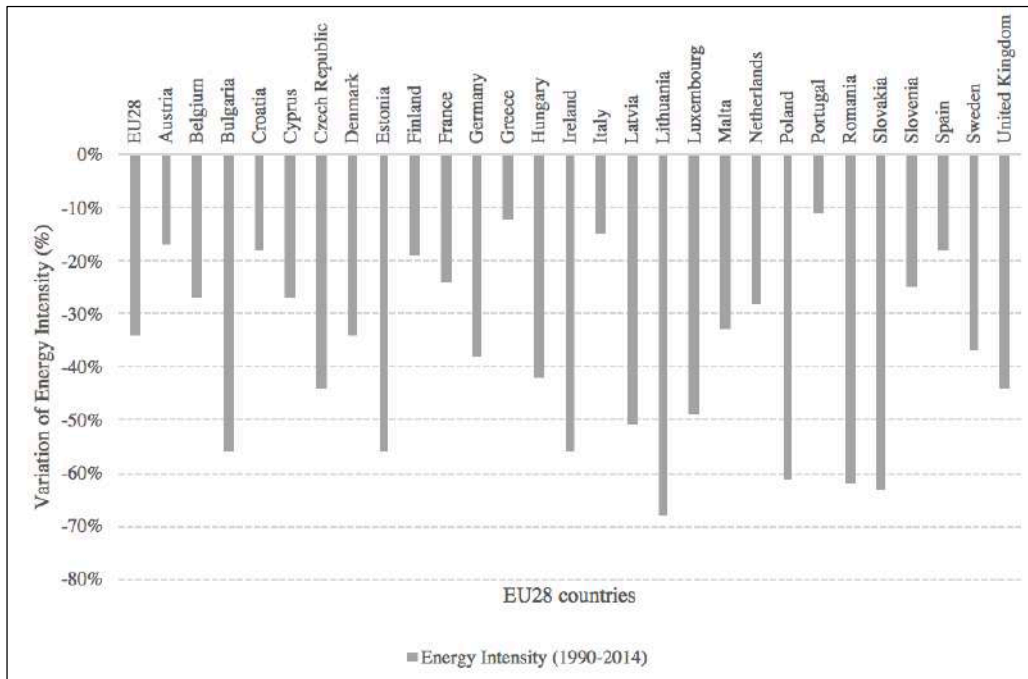


Figure 1.4 - Variation of energy intensity from 1990 to 2014 for EU28 countries

1.1.4 Energy policies with impact on residential sector energy consumption

As highlighted in previous sections, current energy policies are not being sufficient to achieve an effective energy consumption reduction with increased energy efficiency while increasing thermal comfort and living conditions of citizens. It is also true that tailor-made policies² cannot be ignored since the knowledge on the way different demographic groups consume electricity is valuable to design and evaluate the effect of energy policy on different population groups. Since effectiveness of energy-efficiency policies is crucial, it is of key importance to understand energy-related practices and drivers as well as their social differences among countries.

More than forty years after the 1970's oil crisis, renewed attention to energy consumption, energy efficiency and energy savings in households is motivated by concerns about pollution, global warming, fossil fuel depletion; and it is essential to give a boost and revitalize programs for the promotion of energy efficiency and effective energy reduction at all levels of European society.

Recently, the European Commission (EC, 2016) proposed to update the existing Energy Efficiency Directive that set 20% energy savings target by 2020 (when compared to the projected use of energy in 2020); by aligning energy efficiency targets with the EU 2030 climate and energy framework (30% target for energy efficiency).

² Under this work, we refer to tailor-made policies, policies addressed to specific segments of consumers and not to individual households.

Southern European countries energy efficiency policies are aligned with the relevant EU regulations and directives. Box 1.1 presents a brief identification of the example for Portugal of the national legislative framework addressing or affecting the residential sector energy consumption and energy efficiency. The level of acting of each policy is identified, as well as a short description.

The majority of policies are developed at a strategic level, lacking in general proper effectiveness of instruments to deliver the expected results or are very focused in equipment replacement, as in the National Energy Efficiency Action Plans (NEEAP) with windows and insulation replacement, efficient lighting and heating equipment. In several energy related themes, Portugal is still behind compared to other EU countries. As an example, BPIE (2017) includes Portugal as slow starters for smart building revolution.

The scope of the current work focuses on the assessment of residential sector energy consumption and energy services demand for a Southern European country.

Box 1.1 – Identification and description of selected policies affecting the residential sector energy consumption

Title	Description	Target
Portugal Green Growth Commitment 2030	<p>The Commitment for Green Growth seeks to lay the foundations for a commitment to policies, goals and targets that foster a development model that will reconcile essential economic growth with lower consumption of natural resources, social justice and quality of life for the population.</p> <p>Goal 7 - Improve energy efficiency: From 129 toe/€M of GDP in 2013 to 122 toe/€M of GDP in 2020 and 101 toe/€M of GDP in 2030.</p>	Multi-Sectoral Policy
Energy efficiency target declared by Portugal under the EU Directive (2012/27/EU)	Portugal set a target of 25% reduction in primary energy consumption by 2020 compared to projections.	Multi-Sectoral Policy
Decree-Law n° 319/2009, 3 November - Implementation of the EU Energy Services Directive	It establishes the need to create conditions for promotion and development of a market for energy services and to develop measures to improve energy efficiency to consumers. It also promotes mechanisms, incentives and institutional frameworks - financial and legal - to overcome existing constraints and market failures preventing better efficiency in energy end-use through the spread of low-consumption equipment, and rationalization of energy consumption to be adopted by consumers.	Buildings, Multi-Sectoral Policy,
Decree-Law n° 68-A/2015, 30 April - Transposition of Directive 2012/27/EU on energy efficiency	Establishes a framework on energy efficiency and cogeneration, transposing to national law Directive 2012/27/EU of the European Parliament and the Council of 25 October 2012, on energy efficiency.	Buildings, Multi-Sectoral Policy,
Decree-Law n° 50/2010, 20 May - Energy Efficiency Fund	The Energy Efficiency Fund aims to fund the programmes and measures under the National Energy Efficiency Action Plan and has three main objectives: - To encourage efficiency by citizens and businesses, - To support energy efficiency projects in areas where until now such projects had not yet been developed, - To promote behavioral change in this area.	Buildings
Cabinet Resolution 20/2013 of 10 April	Adopted and published the 2013-16 NEEAP (Energy Efficiency Strategy – PNAEE 2016) and the 2013-20 National Renewable Energy Action Plan (Renewable Energy Strategy – PNAER 2020). This Cabinet Resolution also repealed the previous National Energy Strategy for 2020.	Buildings, Multi-Sectoral Policy,
Decree-Law n. ° 118/2013 transposes the Directive on the Energy Performance of Buildings (EPBD, 2002/91/EC, recast as 2010/31/EU)	Ensures regulatory application with regard to energy efficiency conditions and the use of renewable energy systems in accordance with the requirements and provisions of the Energy Performance Regulations for Residential Buildings (REH) in order to ensure the energy performance of buildings; identify measures to correct or improve energy performance for buildings and main types of technical building systems, thus also subject to minimum standards of energy efficiency, HVAC systems, preparation of hot water, lighting, use of renewable energy power management.	Buildings
Ordinance n. ° 278-C/2014 - Implementation of the Social Tariff	Establishes the procedures and the other conditions required for the assignment, application and maintaining social tariff	Buildings

1.2 Problem definition

The discussion about the “energy paradox” *i.e.*, the apparently irreconcilable contradiction between the profitability of energy-conserving technologies and the slow diffusion of these technologies, suggests that the market responds slowly (Brounen *et al.*, 2012). Besides, the increasing technological progress to achieve the needs of comfort and safety - individual and collective results with an increase of the energy services demand worldwide (Carmona, 2006). As a result, energy reduction has been limited. Highly energy efficient houses consume more energy than expected and refurbishments of buildings rarely reduce their carbon footprints. Also, despite all the different tax incentives and subsidies towards energy savings (Vassileva *et al.*, 2012) and energy use awareness and labeling campaigns, increasing new uses and energy services demand offsets in part those initiatives.

Obtaining knowledge about physical, technological, demographic, climatic and behavioral characteristics of a dwelling and its occupants is important in order to address the complexity of these intertwining factors that determine the energy consumption patterns in the residential sector. Moreover, this improved knowledge will help (i) a better energy planning through more accurate, reliable methodologies encompassing several energy determinants; (ii) to feed targeted oriented policies, *e.g.* to specific groups of consumers, such those under fuel poverty or neighborhoods and (iii) to be integrated in a boarder framework of policy analysis (*i.e.* country or city level) evaluating the role of energy policies and instruments for the residential sector.

This dissertation use several intertwined concepts that are defined in Box 1.2. Energy efficiency relates to energy consumption and energy conservation as illustrated in Figure 1.5. The horizontal axis indicates the change in energy consumption, increasing from left to right. The vertical axis shows the change in benefits derived from the energy consumption, increasing from bottom to top. The left-hand side of the graph corresponds to energy conservation (SEI, 2009). The green dotted line that moves from the bottom left quadrant to the top right quadrant separates the graph into two areas associated with increasing or decreasing energy efficiency. This scheme shows that EE may coincide with increasing energy consumption (top-right quadrant to the left of the green dotted line), as long as the benefits of energy consumption are increasing at a faster rate than the energy consumption itself. A decline in energy use with increasing benefits (top-left quadrant) always corresponds to increasing energy efficiency (SEI, 2009). Energy conservation is presented in the bottom-left quadrant to the right of the green dotted line.

Box 1.2 - Overview of key concepts

Energy services refer to a measure of the service provided to final consumers by their own use of energy in any of its forms; it encompasses the short and long term components of service demand (*e.g.* consumer behavior and area of households) but only the direct component of service demand (*e.g.* lighting, cooking); therefore, not considering the range of indirect (embodied) energy services (*e.g.* food, furniture).

Energy consumption refers to all energy consumed by the final consumer for all energy uses within the residential sector (*e.g.* electricity, natural gas).

Energy efficiency is the use of less energy to provide the same level of performance, comfort, and convenience (energy service). According to Directive 2006/32/CE it is the ratio between an output of performance, service, goods or energy, and an input of energy (*e.g.* substitution of CFL lamps by LEDs).

Energy savings or energy consumption reduction is the amount of saved energy determined by measuring and/or estimating consumption before and after implementation of one or more energy efficiency measures, whilst ensuring normalization for external conditions that affect energy consumption (Directive 2006/32/CE) (*e.g.* improving the efficiency class of an equipment through substitution but maintaining the level of use). In this research, energy savings and energy consumption reduction are used interchangeably, reflecting the combined result from both technological and non-technological drivers.

Energy conservation is the act of reducing or going without a service to save energy. It is not usually related to improving EE, but has the advantage that there is not the need to an initial investment. It generally relates to changes in energy consumption habits, behavioral changes, translating in many situations in the need to perform some sacrifices in terms of comfort and/or use of goods and services of poor quality (Bertoldi and Rezessy, 2008).

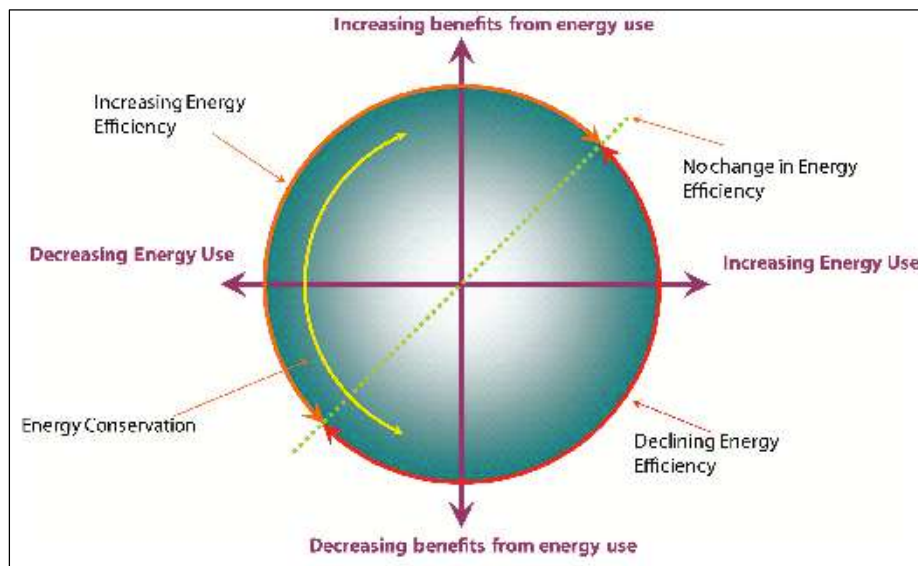


Figure 1.5 – Energy Efficiency, energy consumption and energy conservation (Adapted from SEI (2009))

Therefore, and as above-mentioned there are numerous examples of energy efficiency measures that have not always resulted in lower energy consumption (*e.g.* due to rebound effect), which may partially offset the improvements in efficiency through greater use of equipment or improved comfort (increased energy services demand). Thus, reducing energy consumption also

does not mean the need to reduce energy services demand. All these variations are a result of the interactions between the different energy consumption determinants.

1.2.1 Determinants of energy consumption

Determinants of energy consumption can be defined as the numerous factors that may affect energy consumption in the residential sector. This section explores the existing backbone of research with the aim to better define the problem to which the research carried by this dissertation contributes to solve and highlight.

Households do consume energy to provide end-uses services delivered by energy. The consumption of energy to deliver energy services is embedded within an extremely complex system involving elements of technical (*e.g.*, equipment efficiency), economic (*e.g.*, energy prices), social (*e.g.*, gender), cultural (*e.g.*, cooking practices), and psychosocial origin. According to Kowsary and Zerriffi (2011), all these determinants are interrelated and the study of energy consumption in the residential sector should take these interdependencies into account, as well as the physical environment (*e.g.*, climate) (Masera *et al.*, 1997). In the residential sector, population and households are key; but to be able to significantly reduce energy consumption in households while fulfilling the demand for energy services, we have to know not only about the households' physical characteristics, but also how the various family members use the available equipment.

Understanding the determinants that govern energy consumption has been the subject of abundant international literature for more than 30 years (Cayla *et al.*, 2011). Van Raaij and Verhallen (1983) in their research in the 1980s, recognized several factors that drive household electricity consumption behavior, such as energy-related attitudes, personality, socio-demographic factors, building characteristics, energy prices, feedback and general information about energy use.

Already in the 1970s, but mainly from the late 1980s, literature has demonstrated and some authors estimated the effect of factors that could not be explained by technology (*e.g.* Wei *et al.*, 2007; Gram-Hanssen, 2011). Early in 1978, Socolow showed that identical homes in Princeton, equal in terms of building characteristics, design, size, and equipment, with the same technological set-up, had different energy consumption levels (Socolow, 1978). Several other authors presented similar findings for other locations: Gram-Hanssen (2011)) for Denmark concluded that for heat consumption in technically completely identical houses, the consumption can vary by a factor of three. Santin *et al.* (2009) for the Netherlands showed that occupant characteristics and behavior significantly affect energy use (4.2%), but building characteristics still determine a large part of the energy use in a dwelling (42%); thus, indicating

that user practices are important though only to a limited degree are determined by objective occupant characteristics (Larsen *et al.*, 2010).

A study of Abrahamse (2007) unveiled that household energy consumption is related to socio-demographic variables which are completely different from the drivers of energy savings. For instance, households with higher incomes or larger in size often use more energy, while psychological variables are less adequate to explain energy consumption patterns, since the latter are determined by socioeconomic barriers and opportunities.

Housing characteristics such as size, type, density and envelope affect energy consumption. It has been posited that low density development, along with associated increase in housing area, increasing number of energy consuming appliances have contributed to rapid growth in energy consumption, even while efficiency standards have been tightening (Kaza, 2010), both at the household level and electrical equipment.

Dilaver (2009), in a study for Turkey, suggests that household total final consumption expenditure and real energy prices are important drivers of residential electricity demand. Despite it, Summerfield *et al.* (2010), for the UK, mentioned that energy prices are relatively inelastic with an estimated elasticity of 0.20. Azevedo *et al.* (2011) corroborate these findings suggesting that, given their analysis of the price inelastic behavior in EU regions, public policies aimed at fostering a transition to a more sustainable energy system will require more than an increase in electricity retail price if they are to induce needed conservation efforts and the adoption of more efficient technologies by households.

Kelly (2011) identified for England the number of household occupants, floor area, household income, dwelling efficiency, household heating patterns and living room temperature as the main drivers behind residential energy consumption. For Germany, Gruber and Scholmann (2006) showed that electricity consumption is strongly influenced by the number of existing equipment, household area and annual income. Bartiaux and Gram-Hanssen (2005) exposed for Belgium and Denmark that family size; household area and number of equipment are strong determinants for electricity consumption. Rhodes *et al.* (2014) work indicated that variables such as working from home, hours of television watched per week, and education levels have significant correlations with average profile shape, but might vary across seasons.

Ndiaye and Gabriel (2011) applied a principal component analysis to 221 households in Canada, found the main factors affecting household electricity consumption were: the number of occupants; the type of ownership; the average number of weeks of vacation away from the house; and the type of fuel used in space heating and air conditioning. Jones *et al.* (2015) focused their research in determining socio-economic and dwelling factors that contribute to electrical energy demand in UK residential buildings, highlighting higher consumption in

households with more children and teenagers and in households with high annual incomes. Ürge-Vorsatz *et al.* (2015) based on a Kaya identity approach disclosed the number of households, persons per household, floor space *per capita*, and specific energy consumption as drivers for residential heating and cooling.

According to Foster *et al.* (2000) social and cultural factors such as cooking habits and household characteristics may make households behave contrary to economic predictions based on income and relative fuel prices. There are; therefore, a range of non-economic variables that are important in explaining household decisions regarding energy use.

All the referred examples are illustrative of the need of looking to the variety of factors that may be responsible to high energy consumption in households. Notwithstanding these factors are deeply context dependent, which means that applied research in concrete cases is crucial to understand not only the behavior and role of these factors but also to deepening the knowledge on the combination and interrelations between these factors.

Table 1.1 presents an extensive revision of the existing literature on factors affecting household energy consumption covered by several authors for different world regions. Although these factors are presented in isolation from each other, in the real world they are closely interrelated.

According to Kowsari and Zerrifi (2011), the determining factors of household energy use can only be found at the household level (*i.e.* micro-level). The aggregated level of energy demand is made up of day-to-day decisions at the household level that are affected by a variety of socioeconomic factors. Where micro-level data is used, it has often no sufficient quality, necessary to answer many of the questions, since much of the research on household energy use in this area is based on disaggregated data taken from large-scale surveys.

Table 1.1 – Determinants behind residential energy consumption

Categories	Determinants	Authors
Endogenous Factors (household characteristics)		
<i>Economic Characteristics</i>	Income, expenditure	ESMAP (2003); Leiwen and O'Neill (2003); Elias and Victor, (2005); Zachariadis and Pashourtidou (2007) Kaza (2010); Nguyen-Van (2010), Raty and Carlsson-Kanyama (2010); Cayla <i>et al.</i> , 2011; Kowsari and Zerriffi (2011); Lescaroux (2011); Wiesmann <i>et al.</i> (2011); Brounen <i>et al.</i> (2012). Vassileva <i>et al.</i> (2012), Rhodes <i>et al.</i> (2014); Pablo-Romero <i>et al.</i> (2016)
<i>Non-Economic Characteristics</i>	Household size, type and year of construction; Occupants gender, age, education, household composition, Information, job or occupation, family dimension	ESMAP (2003); Leiwen and O'Neill (2003); Myers <i>et al.</i> , 2005; Heltberg (2004); Gruber and Scholmann (2006); Gupta and Kohlin (2006); Farsi <i>et al.</i> (2007); Antunes (2008); Ewing and Rong (2008); Schlag and Zuzarte (2008); Larsen <i>et al.</i> (2010); Kaza, (2010); Paço and Varejão (2010), Raty and Carlsson-Kanyama (2010); Rue du Can <i>et al.</i> (2010); Cayla <i>et al.</i> (2011); Ellegård and Palm (2011); Energaia <i>et al.</i> (2011); Gram-Hanssen (2011); Hamza and Gilroy (2011); Kelly (2011); Kowsari and Zerriffi (2011); Ndiaye and Gabriel (2011); Wiesmann <i>et al.</i> (2011); Brounen <i>et al.</i> (2012); Hojjati and Wade (2012); Vassileva <i>et al.</i> (2012); Bedir <i>et al.</i> (2013); Rhodes <i>et al.</i> (2014); Jones <i>et al.</i> (2015); Huebner <i>et al.</i> (2015); Üрге-Vorsatz <i>et al.</i> (2015); Risch and Salmon (2017); Seebauer and Wolf (2017); Yoo <i>et al.</i> (2017)
<i>Behavioral and Cultural Characteristics</i>	Preferences, personality, practices, attitude, lifestyle, social status, religion, ethnicity, environmental awareness and concern, values	Socolow (1978); Lutzenhiser (1993); Kempton and Schipper (1994); Wei <i>et al.</i> (2007); Gram-Hanssen (2008); Oikonomou <i>et al.</i> (2009); Üрге-Vorsatz <i>et al.</i> (2009); Santin <i>et al.</i> (2009); Raw and Varnham (2010), Larsen <i>et al.</i> , (2010); Gram-Hanssen (2011); Kowsari and Zerriffi (2011); Sutterlin <i>et al.</i> (2011); Yun and Steemers (2011); Carlo and Ahamada (2012); Vassileva <i>et al.</i> (2012); Kavousian <i>et al.</i> (2013); Blight <i>et al.</i> (2013); Bartiaux <i>et al.</i> (2016), Sonnberger and Zwick (2016); Huebner and Schipworth (2017); O'Neill and Xiu (2017)
Exogenous Factors (external conditions)		
<i>Physical Environment</i>	Geographic location, urbanization level, climatic condition	Bhatt and Sachan (2004); Elias and Victor (2005); Halicioglu (2007); Zachariadis and Pashourtidou (2007); Filippin and Larsen (2009); Kaza (2010); Raty and Carlsson-Kanyama (2010); Rue du Can <i>et al.</i> (2010), Steemers (2011); Lescaroux (2011); Wiesmann <i>et al.</i> (2011); Hojjati and Wade, (2012); Zhao <i>et al.</i> (2012), Kavousian <i>et al.</i> (2013)
<i>Policies and Energy Supply Factors</i>	Energy policies, environmental policies, subsidies, market and trade policies; Prices and affordability, availability, accessibility, reliability of energy supply.	Van Raaij and Verhallen (1983); Gupta and Kohlin (2006); Halicioglu (2007); Herter <i>et al.</i> (2007); Zachariadis and Pashourtidou (2007); Schlag and Zuzarte (2008); Alberini and Filippini (2011); Azevedo <i>et al.</i> (2011); Filippini (2011); Lescaroux (2011); Butler (2016); Yoo <i>et al.</i> (2017)
<i>Technology Characteristics</i>	Conversion efficiency, cost and payment method, complexity of operation	Kelly (2011); Lescaroux (2011); Jones <i>et al.</i> (2015)

1.2.2 The Challenges

To pinpoint how to effectively reduce energy consumption and GHG emissions, increase energy efficiency, deliver energy services demanded, it is crucial to look not just at technology but also, at the factors that drive people to consume energy, including how people interact with technology. Energy demand has many human and social dimensions that researchers need to understand, because they are likely to exacerbate in the years ahead. For example, ageing population may need more heating and other energy-dependent services and climate change could cause more buildings to overheat, leading to a greater uptake of air conditioning.

Despite the continuously increasing energy efficiency of the sector, non-technical factors have influenced the amount of energy consumption thus resulting in an overall net increase in final energy consumption for the last 25 years. Challenge: investigate the inner patterns of energy consumption in the residential sector, identifying the drivers behind energy consumption in Portugal at different scales (country, city, consumers), since changes in household behavior and other drivers governing energy service demand should be incorporated in energy analysis to have a realistic view of household energy use (Kowsari and Zerriffi, 2011).

Energy saving is; therefore, not only a matter of more efficient technology in terms of end-use or supply, but also in terms of demand (people's behavior and lifestyle, climate, etc.) While politicians express a need for a more environmental (and also economic savings) oriented attitude towards energy saving actions, the implementation of the necessary measures reaching the expected outcomes is revealing to be more difficult. Challenge: How could the determinants for energy consumption be feedforward into energy policy design and instruments definition?

However, much of the current debate regarding energy efficiency in the housing market focuses on the physical and technical determinants of energy consumption, neglecting the role of the economic behavior of resident households (Brounen *et al.*, 2012) and on the structural differences that exist behind energy consumption in different regions and from different energy consumers. For Azevedo *et al.* (2011), there is no substantial prior literature on international comparison on residential electricity consumption to highlight the importance of the underlying factors. Challenge: The knowledge on the determinants and consumer groups is of great interest to feed in future energy planning strategies both at a local/household level and at multi sectoral policies from strategic planning.

Projections of future energy needs relied on final energy consumption, usually sustained by quantitative models as namely econometric or technological. They lock future options of energy resources and technologies available to satisfy energy needs, limiting the ability to consider alternative energy paths for the future. Challenge: energy services have been approached in a simplified or absent way, which call for more studies and in depth analysis capable to project

the determinants behind future ESD. Daioglu *et al.* (2012) also identified this gap, bringing up that most energy models describe future residential energy demand supported on simple relations between energy consumption and income or GDP *per capita*.

An interlinked problem refers to the current policy framework that mainly covers the promotion of EE and partly neglects other dimensions for the reduction of energy consumption (Bartiaux *et al.*, 2016). This is somewhat justified by the lack of knowledge on the determinants of energy consumption at households, due to the underlying complexity of mixing socio-economic (*e.g.* tendency to increasing single families), cultural and lifestyles factors (urban vs. rural likely), which vary across countries and also within the same country. Several authors point out this research gap (Haas *et al.* (1998); Lopes *et al.* (2005); EMF (2011); Santin *et al.* (2009), Gram-Hanssen (2011), Huebner *et al.* (2015)). It is important to know the characteristics of target groups when devising and applying policy instruments for energy consumption reduction, increased thermal comfort and RES penetration. For example, if women and men differ regarding their energy use and emission profiles, policy instruments should perhaps be differentiated in order to achieve maximum impact (Raty and Carlsson-Kanyama, 2010), aligned with this, Huebner and Schipworth (2017) discuss the role of downsizing (*e.g.* dwelling size) as an option to the elderly.

The impact of the behavior of household members on the energy consumption of a household might be significant. Within the same buildings with the same installations, energy consumption could be reduced by an average of 37% by a more rational economic behavior (*e.g.* EURECO, (2002); Vekemans (2003); Desmedt *et al.* (2009). Gram-Hanssen (2011) have also demonstrated for Nordic countries that energy savings should go beyond EE and devote great relevance to the influence of the household occupants and how they use the technologies. A study for Netherlands also mentioned that the variation in energy consumption is still large for dwellings with the same characteristics, where occupant characteristics and behavior significantly affect energy use (Santin *et al.*, 2009). However, different conclusions may arise from other EU regions, namely southwestern countries since patterns of consumption are greatly affected by changes in geographic (*e.g.* less heating needs and more cooling needs due to expected impact of climate change), sociologic (*e.g.* different environmental awareness or lifestyles), economic parameters (*e.g.* lower *per capita* income). According to Lescaroux (2011), in terms of policy implications, a country-by-country approach is required when setting energy efficiency achievements objectives. Challenge: Identification and characterization of different consumer groups and what drive that consumption.

Several studies identified the potential and the challenges of policies looking for the reduction of energy and GHG emissions (*e.g.*, NAPEE (2008); Fraunhofer *et al.* (2009); Granade *et al.* (2009)). EMF (2011) recognized an increasingly importance in combining richness in

technology coverage with realism in market behavioral responses, being required additional research about the behavior of consumers and its weight. There is a need for an improved comprehensiveness of the city planning process towards sustainable energy use driven by integrated approaches (*e.g.*, Zanon and Verones (2013); WEF (2016)). Russo *et al.* (2016) also underscores that planning and management processes are needed to support decision making processes in order to design and operate cities infrastructures and services. Keirstead *et al.* (2012) concluded that, despite the diversity of modelling practices of urban energy systems, studies usually compartmentalize the assessments focusing on specific aspects of energy use and mostly use exogenous input data. Challenge: How to integrate consumer behavior, detailed data and all energy consuming sectors within energy system analysis?

1.2.3 The Opportunities

Electricity is a key energy carrier used around the world and across all end use sectors. It is expected to continue to grow, with a shift away from fossil fuels (IEA, 2016a). But electricity use in households is invisible being a lifestyle enabler; so, infrequent billing based upon estimations prevents awareness inside households (Abreu *et al.*, 2012). A common method to stimulate consumers to a rational energy use behavior is to measure all energy related activities. The figures help the consumers to recognize energy consumption and take control over the energy flow (Gyberg and Palm, 2009).

The technological advancement with metering, communications and computation are enabling utilities to monitor and save huge amounts of data related to their operation. The deployment of electricity meters with two-way communication capabilities is allowing the registering of high resolution data (Viegas *et al.*, 2016). In this context, smart meters have been gaining higher interest in demand-side management initiatives and are seen as an important instrument for giving energy consumption feedback to households and to be used as tools to understand consumers' behaviors. Smart meters facilitate detailed electricity consumption information to be captured, processed, and communicated at frequent intervals. As smart meters are replacing traditional electricity meters in large parts of Europe, there is now a unique opportunity to realize comprehensive consumer feedback systems, extract knowledge from the consumption patterns enabling the use of this technologies to other applications and not only as mere remote metering applications (Weiss *et al.*, 2013). The dissemination of smart meters is; therefore, of major importance and an opportunity both to promote household's occupants' awareness on electricity consumption, and to get insights on the household energy consumption profiles. Also, acknowledging the temporal aspect of electricity use is significant because electricity is expensive to store and thus is typically produced at the rate of consumption (Rhodes *et al.*, 2014).

The electricity use in households may no longer be a black box and perhaps not only a private issue just for the family to take under consideration, showing all the importance of transforming into an asset this big data that be might be seen as a burden to the electricity Distribution System Operators (DSO's). Information and knowledge may be converted into an asset for different kinds of stakeholders: consumers, energy services companies (ESCO'S), DSO's, electricity sellers, policy makers.

Several authors have already conducted some research under consumer segmentation using smart meters' data, but usually lacking such extensive and comprehensive datasets and tools (meters, surveys, energy simulation models, temperature data) to support and further inform the results (*e.g.* Kavousian *et al.* (2013); Hayn *et al.* (2014) Seo and Hong (2014); Wijaya *et al.* (2014); Mcloughlin *et al.* (2015); Ramos *et al* (2015); Zhou *et al.* (2017a); Zhou *et al.* (2017b)).

The potential of smart-meter is highly amplified when combining the high-resolution data delivered by the smart meters with other tools as surveys. This could allow to extract the main determinants and patterns of energy consumption in households. Smart meters can act as support tools for tailored feedback evaluation, policy design and intervention at smaller scales from what is currently being done (*e.g.*, consumer groups, neighborhoods). In this sense, it is underscored the importance of combining different tools to inform distinct level of policies.

The increase knowledge on energy consumption patterns, energy services, behaviors and consumers is considered herein, as an opportunity, used as entry points for improved RES integration and better energy system analysis.

All these opportunities combined are expected to inform the design and effectiveness of dedicated energy policies and instruments for the residential sector without compromising energy services demanded.

1.2.4 Case Study

This research was supported by Portugal as a case study, and the municipality of Évora in particular. As portrayed in Section 1.1.3, total and residential final energy consumption and energy intensities development, show very distinct past trends and current situation across EU countries. This calls for the need to look into different countries in the EU policy context, through case based approaches that are able to accommodate the particularities of the residential sector. The specificities of the residential energy consumption depend on distinct factors, as explained before. Notwithstanding, case based approaches can span multiple scales both spatial and temporal, since it can give insights to similar contexts. Portugal represents a proper case study due to different reasons that are described below.

First of all, Portugal has an effective potential to become a low carbon economy, already relying on a strong renewable power system and with increasing expectations due to its untapped potential specially for solar energy, which may have impact on households' energy consumption profiles. Electricity consumption in the country was fully covered by hydro, wind and solar power during 107-hour run in 2016. Besides this, there is an expected convergence to achieve comparable energy *per capita* to other EU28 countries. In EU, there is a large regional disparity in annual *per capita* residential consumption. Despite a significant increase in the last decades, from 49.8 in 1990 to 64.9 GJ in 2015 for total final energy (30% increase) and 6.5 GJ to 7.6 GJ in 2015 (17% increase) for residential sector energy consumption, Portugal has still a relatively low *per capita* consumption of energy (PORDATA, 2016). Albeit this growth, and as seen in Figure 1.2, Portugal had in 2015, a *per capita* energy consumption (both total and residential), below almost all EU countries (27% and 66% respectively below EU28 average), even when compared to countries with similar climate conditions like Spain and Italy.

As in other EU countries, last decades' energy consumption trends are very irregular, which calls for a better understanding of consumers' behavior. Since 1990, total Portuguese final energy consumption grew about 1.3% per annum, with 0.5%/year specifically in the residential buildings (PORDATA, 2016) (Figure 1.6). Though, in the last 10 years we have seen a significant reduction. Portuguese residential sector had consistently raised its final energy consumption between 1990 and 2005 (*i.e.* 33%). After this period, the final energy consumption has gone through a stabilization period and more recently (*i.e.* 2010-2015) through a significant decrease (-2.3%/year). The consumption growth followed an increase of energy services demand due to: 1) higher purchasing power that raised the standards of basic comfort and level of amenities, 2) the widespread utilization of relatively new types of loads whose penetration and use has experienced a very significant growth (Almeida, 2008) and 3) a higher number of households with larger areas and fewer people, demanding more equipment (Bertoldi and Atanasiu, 2007). The recent trends might be explained by increase energy efficiency, reduced thermal comfort levels inside households induced by higher energy prices and lower available income for energy expenses, still justified by the economic and financial crisis.

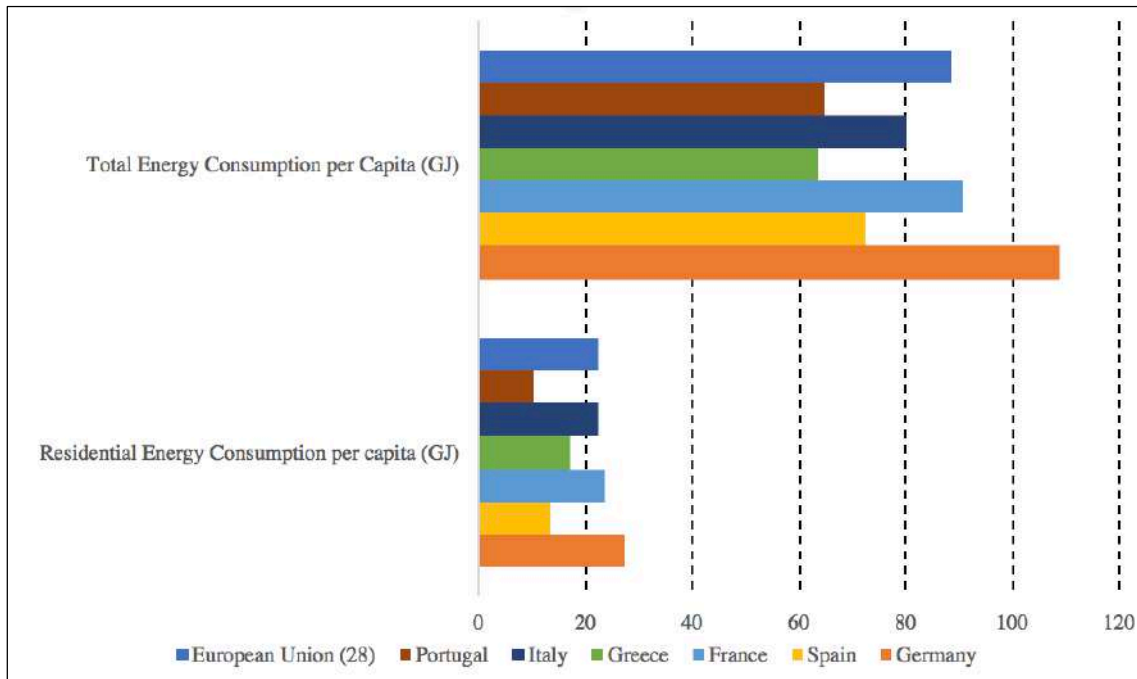


Figure 1.6 – Final Energy Consumption (Total and Residential) per capita in 2015 for selected EU countries (PORDATA, 2016)

Another important reason is the significant electrification trend. Portugal has increased its electricity consumption *per capita* 90% since 1990, while the average EU28 only increased near 20%. The Portuguese residential sector has also seen a shift in the mix of energy supply. In 1990, electricity accounted for 21% of energy consumption and natural gas was not yet consumed in Portugal. In 2015, the share of electricity increased to 41% and the natural gas share increased to 32% since its introduction in 1998. These resulted in increased efficiency in energy use but also demonstrates the recent national trends of a society of consumption with higher ownership of electrical equipment. The rising weight of electricity in residential energy consumption also justify the increased importance of analysis using electricity smart meters' data.

Despite being a warm southern EU country with mild winters, several facts point Portugal as severely endangered by fuel poverty issues; with a widespread lack of thermal comfort inside households (both for heating and cooling) across the country (*e.g.* Magalhães and Leal (2014), Palma (2017)). As a result, around 30% of the population receives social tariff support for the payment electricity and natural gas bills. These issues will be further investigated in Chapter 3.1.

Further convergence of EU patterns of living could also be expected. In 2005, Portugal had a living space per person of around 37 m², similar to United Kingdom value in 1991 (Boardman *et al.*, 2005) showing large possibilities of increasing. This determinant factor is difficult to be influenced by policy; nevertheless, trends have to be taken into consideration when the goals of a policy are formulated since they have a strong impact on demand.

On the other hand, being located in the Iberian Peninsula, targeted as one of the most likely climate impacted regions on heating and cooling energy needs, with probable impacts on energy consumption and increased uncertainty in energy services demand projections. Portugal is among one of the warmest countries in Europe with high temperatures in the summer, and generally longer summers, where heating consumptions for buildings are, on the whole, much lower than in other European countries. According to Santos *et al.* (2006), a generalized increase of monthly cooling energy demand and a reduction of monthly heating energy demand, as well as a reduction of the heating season and a consequent extension of the cooling season is likely for Portugal due to expected climate change.

Lastly, it presents high costs of energy for families. According to IEA (2016a), electricity prices in Portugal are relatively high by IEA standards and they have been increasing significantly over the past decade. From 2008 to 2013, final electricity prices increased annually on average by 8.8% for household customer. Electricity and natural gas prices for families with all taxes and levies included, were in 2016, 13% and 38%, respectively, higher compared to EU28 average (PORDATA, 2016). Much of the price increase for household customers was the result of an increase in taxes and levies, in particular with the increase of value added tax (VAT) (from 6% to 23% as from October 2011), but also the result of a set of subsidies to ordinary producers, namely compensation for stranded costs due to the liberalization process and payment of feed-in tariffs for renewables and combined heat and power (IEA, 2016b). This increase in energy prices in conjunction with the depletion of families' private consumption, explains also part of the decrease of electricity consumption observed recently in households (Azevedo *et al.*, 2011).

For all these reasons, Portugal was considered as a case study for this research, using the municipality of Évora for an in-depth analysis. This city has a smart grid project with 31 000 smart meters with registries of 15 minutes' electricity consumption (EDP Distribuição, 2016) and high solar PV potential both from rooftop (Moreira, 2016) and utility scale (Lourengo, 2014). These represent important raw data that could be analyzed and combined in order to obtain detailed information and produce knowledge to support policy development and implementation.

As stated before, residential energy sector consumption is derived from a combination of discrete and continuous choices from consumers. This work intends to address the problem of better understanding the determinants that drive energy consumption patterns at different levels in a southern European country, while acknowledging the existing bottleneck between the need for increased energy services demand fulfilment (specially for space heating and cooling) and the reduction of energy consumption through increased energy efficiency.

1.3 Research questions

The main objective of this research is to understand the differences on energy consumption arising from different socio-demographic, technologic, behavioral and economic characteristics of residential households.

To achieve this goal, four research questions were settled looking into different perspectives and taking advantage of different data sets, methods and spatial and temporal scales.

RQ#1 – What are the main determinants governing electricity consumption patterns for different types of household consumers in Southern European countries?

RQ#2 – Why to identify specific consumer groups and behaviors?

RQ#3 – How, and in what extent, the uncertainty associated with the determinants of energy consumption will impact energy services demand and final energy consumption in the long term?

RQ#4 – How multiple and detailed data and tools can be integrated to inform sustainable system planning and policy design?

The answers to these questions and all the empirical findings are expected to contribute to advance the state-of-the art on the knowledge of residential energy consumption, especially in southern European countries and to integrate that knowledge into local, regional and national energy policies, both at the short and long term perspectives, guiding the decision-makers to chalk out appropriate, effective and environment-friendly policy instruments.

1.4 Scientific outputs

The work developed in this dissertation resulted in several conferences papers and presentations and peer reviewed publications as follows:

Publications:

- Gouveia, J.P., Seixas, J. (2016). Unraveling electricity consumption profiles in households through clusters: Combining smart meters and door-to-door surveys. *Energy and Buildings*. 116, 666–676. <http://doi.org/10.1016/j.enbuild.2016.01.043>
- Gouveia, J.P., Seixas, J., Giannakidis, G. (2016). *Smart City Energy Planning: Integrating Data and Tools*. AW4City - International World Wide Web Conference 2016, April 11-15, 2016, Montréal, Québec, Canada. ACM 978-1-4503-4144-8/16/04. <http://dx.doi.org/10.1145/2872518.2888617>
- Gouveia, J.P., Seixas, J., Mendes, L., Shiming, L. (2015). *Looking Deeper into Residential Electricity Consumption Profiles: The Case of Évora*. 12th International

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- Gouveia, J.P.; Fortes, P.; Seixas, J. (2012). Projections of Energy Services Demand for Residential Buildings: Insights from a Bottom-up Methodology. *Energy* 47 (2012) 430-442. <http://doi.org/10.1016/j.energy.2012.09.042>
- Gouveia, J.P., Seixas, J., Long, G. *Combining smart meters with surveys, and buildings energy simulation to assess consumer groups: the case of fuel poverty and fuel obesity*. Submitted for publication. Under review.
- Gouveia, J.P., Seixas, J., Mestre, A. *Daily Electricity Consumption Profiles from Smart Meters - Proxies of Behavior for Space Heating and Cooling*. Submitted for publication. Under review.
- Gouveia, J.P., Seixas, J., Andrade, M., Bilo, N., Chiodi, A., De Miglio, R., Dias, L., Gargiulo, M., Giannakidis, G., Irons, D., Long, G., Nychtis, C., Nunes, V., Pollard, M., Rigopoulos, A., Robinson, D., Simoes, S., Valentim, A. *Analytical Framework to support Integrated City Energy Planning*. Submitted for publication, under review.

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- Gouveia, J.P., Dias, L., Seixas, J., Simões, S. (2017). *InSmart – Integrative Energy Planning for Cities Low Carbon Futures: Analytical Framework*. 3rd Energy for Sustainability Conference, Funchal, 8th February 2017.
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1.5 Dissertation outline

This research was developed across two different lines of thought aiming to advance the state of the art in data processing using different tools and methods to produce knowledge to inform energy policies formulation and implementation at two levels: (i) tailor-made policies and (ii) integrated policies.

Figure 1.7 represents the process of this research and how this dissertation is organized. This work is divided in six chapters that present different research contributions. Distinctive

knowledge flows are also presented. Blue arrows represent the outputs that were used as inputs in other stages of the research, the grey arrows symbolize the knowledge flows that are created by the process to inform the different policies, and the dash arrows are illustrative of the potential use of the generated outcomes for different ends.

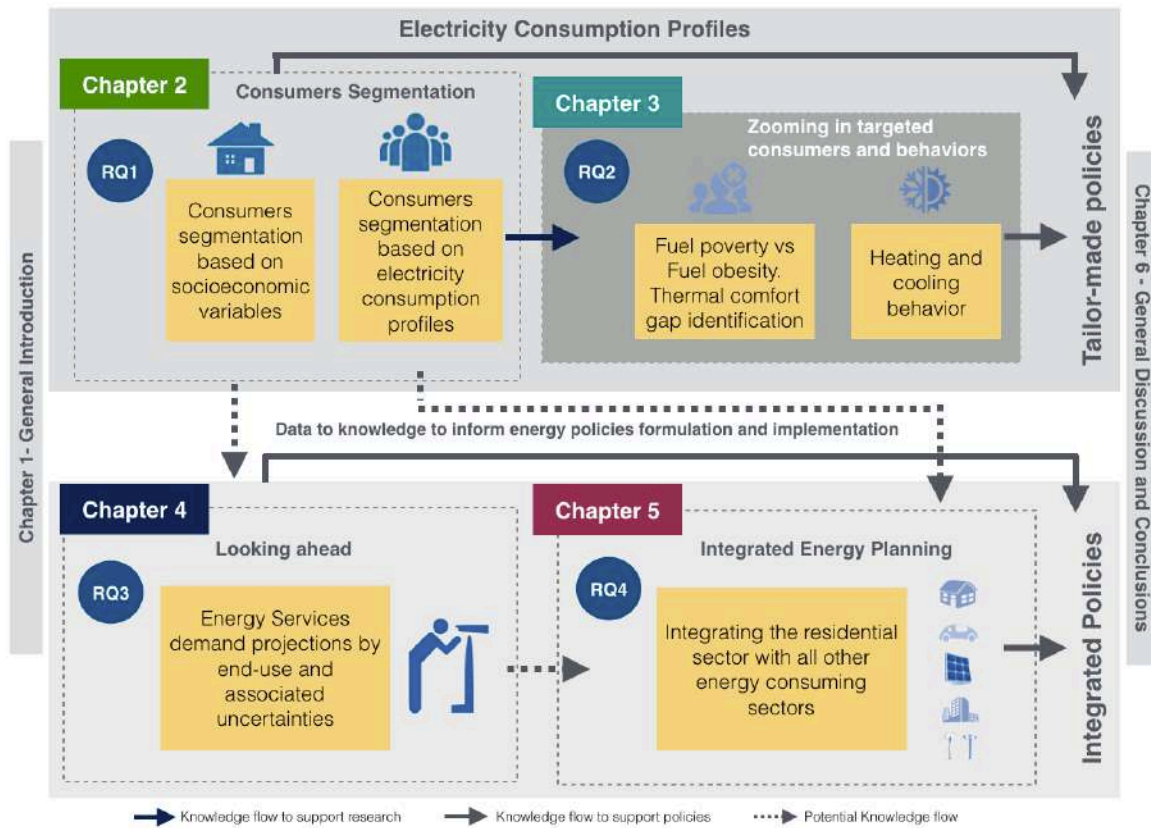


Figure 1.7 – Research Map

Chapter 1 introduces the dissertation, presenting the relevance of the study and the problem formulation while explaining the scoping and the research questions directing the work. A data analysis was conducted to set the scene on current situation and past energy consumption trends across EU28. Literature review on previous work carried out regarding the determinants of energy consumption in the residential sector is presented and the case study is justified.

Chapters 2 and 3 present the research developed in electricity consumption profiles to support tailor-made policies, while Chapters 4 and 5 develop approaches to energy services demand projections and to combine residential sector with all other energy consuming sectors, both to inform integrated and higher level policies.

Chapter 2 presents two different analysis conducted for consumer segmentation assessment and characterization that respond to the first research question. One methodology is driven firstly by a socio-economic identification of the consumers. It distinguishes important determinants of consumption previously identified in the literature, and after their electricity consumption

profiles are compared. The other methodology relies on a cluster analysis supported on annual electricity consumption profiles that are further characterized taking into account socio-economic, buildings' characteristics and equipment ownership. The two assessments show relevant distinctions that exist across consumers, justifying the need of tailor-made policies in the energy arena. The first assessment gave place to a scientific publication on the proceedings of the *European Energy Markets Conference* (2015) and the second to a paper published in *Energy and Buildings* (2016).

Chapter 3 goes deeper in the analysis of distinct types of consumers and behavior patterns for the most significant end use in households (*i.e.* climatization). In this chapter, two innovative methodologies are proposed and discussed using high resolution temporal data to assess fuel poverty and thermal comfort gap spinning-off from the work carried out in the previous chapter, and to evaluate heating and cooling behavior. Insights for policy are provided from both analysis. These two-works answer RQ#2 and have been submitted for publication and are currently under review.

Chapter 4 addresses a prospective long term analysis of several determinants of energy consumption within the different end uses. It is first presented a methodological approach to project energy services demand, evaluating the range of uncertainties of several of the parameters. These results are used as input in a country level energy system model to capture the impact of those energy services demand projections into final energy consumption, while underpinning the most significant results and policy recommendations. The work was published in *Energy* (2012) and answers RQ#3.

Chapter 5 presents an analytical framework depicting a methodological process from data collection, modelling processing and results analysis to be applied in medium to long term cities energy planning. In this work, an integration of all city energy consuming sectors is considered within an energy system model used as an integrated city energy planning tool. One submitted publication and currently under review give body to this chapter contributing to answer the formulated research question (*i.e.* RQ#4).

Chapter 6 presents the main findings of the dissertation and combines the answers for all the research questions.

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Chapter 2 | Electricity Consumption Segmentation

Part 1: Paper published in Proceedings of 12th International Conference on the European Energy Market

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2.1 Looking Deeper into Residential Electricity Consumption Profiles: The case of Évora

ABSTRACT

In order to stabilize or reduce households' electricity demand while fulfilling energy service needs, preventing harmful environmental impacts and decreasing fossil fuel imports, a growing use of decentralized renewable energy sources, coupled with energy efficiency programs, is needed. We claim that successful design and implementation of these measures will be achieved by understanding of households' electricity consumption patterns using high resolution data from smart metering coupled with the knowledge on socio-economic details. For that purpose, we analyzed daily off-peak and total electricity consumption for 2011-2013 from smart meters of 250 households in the city of Évora, for which a 110 questions door-to-door survey is also available. We concluded for significant variations on electricity consumption among different consumers' profiles, following specific socio-economic characteristics. We estimated 12.7 MW of solar photovoltaic potential for auto-consumption based on segmented daily minimum consumption. Acquired knowledge can be used to target energy consumption reduction policies and optimize self-consumption capacity investment costs and electricity production surplus.

KEYWORDS

Electricity Consumption Profiles, Évora, Households, Self-Consumption, Smart Meters

2.1.1 Introduction

The search for increased energy efficiency, greenhouse gases emissions reduction and increased share of renewable energy sources (RES), as established in the new European Union goals by 2030 (EC, 2014) requires more decisive actions. In this context, energy consumption in buildings deserves special attention since they represent a significant share of energy consumption (around 20-30%) in European Union (EU) (Eurostat, 2011). In Portugal, residential buildings consume approximately one third of total electricity, with a growth of 70% from 1995 to 2012 (DGEG, 2014). This consumption is a complex issue that can be explained by a combination of physical, technological, demographic, climatic and behavioral characteristics of a building and its occupants (*e.g.* Howden-Chapman *et al.* (2009), Kowsari and Zerrifi (2011), Sutterlin *et al.* (2011), Brounen *et al.* (2012)). For policy making processes and in order to improve the design and implementation of better measures and effective policies an in-depth analysis of electricity consumption profiles gathered from smart meters' data crossed with knowledge of the intertwined factors driving the consumption is necessary.

The tailoring of energy efficiency measures based on specific household profiles enables the change of behavior and equipment towards the ultimate goal of an effective energy consumption reduction and load curve consumption peaks minimization. Moreover, self-consumption through decentralized electricity production is an attractive option for households as it allows better control over energy costs and demand, creating resilience in the network, along with greater efficiency and innovation.

The downward trend in the price of photovoltaic (PV) solar panels (until recently one of the most expensive renewable energy technologies) has been remarkable. The reduction of the cost of solar panels had come down by a factor of five in the past six years and the cost of full PV systems, which include other electronics and wiring, by three (IEA, 2014).

Following Moore's Law (reduction of costs based on the amount produced – economies of scale), it is estimated that in 10 years, the electricity produced by solar PV systems will be as cheap as the one generated by coal (Naam, 2011). Currently, the levelized cost of electricity from solar photovoltaic systems is estimated to be between 0.13–0.14-euro cents per kWh (Talavera *et al.*, 2011). This level of production cost for solar photovoltaic indicates that *grid parity* has been achieved: a situation where the price of the electricity generated by a renewable energy system is at least equal to the price one pays for the electricity from the grid.

Nevertheless, currently in Portugal, decentralized electricity installed capacity from RES through micro generation (<5.75 kW) is still modest (93.4 MW) representing only 0.5% of total installed capacity (MEE, 2014). This is in the course of changing; grid parity along with the new self-consumption legislation for Portugal (Decree-Law no.153/2014) should support further

deployment of micro generation renewable energy. From a feed-in tariff perspective, this legislation has the potential to promote producers to consume the electricity they produce. We argue that the successful design and implementation of cost-effective self-production electricity options will be achieved through the understanding of households' electricity consumption patterns by using very high resolution data (*e.g.* hourly, daily) from smart metering.

This work advances on in-depth data analysis of electricity consumption profiles taking Évora city (Portugal) as a case study. We analyze a dataset of daily off peak and total electricity consumption from 2011 to 2013 measured by smart meters of 250 households combined with an extensive door to door 110-question survey on household data, in order to identify target groups to derive insights on the factors governing electricity consumption and to support PV integration and estimation of its potential.

The work presented here is being partly developed under the EU project InSMART, that involves four European cities (Évora, Cesena, Trikala and Nottingham) targeting innovative methods to integrative city planning, including buildings, public lighting, transport, waste, water and wastewater networks. Further description of the project can be seen in Gouveia *et al.* (2014).

This paper is organized in 4 Sections. Section 2.1.2 summarizes the methods and presents the data used. Section 2.1.3 discloses results regarding electricity consumption profiles and off peak shares using selected electricity consumption determinants. Section 2.1.4 concludes, presents the limitations of the study and further work.

2.1.2 Methodology and data

With the growing deployment of smart meters and real-time home energy-monitoring services, data that allows studying the determinants of energy consumption inside households and electricity consumers' profiles are becoming available.

In order to unveil electricity consumers' profiles (total and off-peak consumption) based on similar socio-economic characteristics to use as proxy information for future integration of RES in households for self-consumption, we combined smart meters' data with household surveys.

The survey encompassed information on dwellings' location and physical characteristics, occupants' socio-economic data (*e.g.* income, persons per household, age, gender, tenure) and ownership and use of electrical appliances. The fieldwork of the survey in the streets of Évora was carried out between July and August 2014. Due to onsite difficulties, time and transport logistics and interviewers' availability constraints, we were able to collect 389 valid surveys, representing 97% of the total expected surveys (400 were initially defined). Regarding the spatial dissemination and as planned, the surveys were made extensively along the entire

municipality in order to collect information of a representative set of households. 37% of the surveys answers were collected in the rural areas, and the remaining in urban areas.

Évora was selected as a case study since it has the first massive smart metering system (31 000 smart meters in households) in Portugal - InovCity project (EDP Distribution, 2015). Therefore, making use of this valuable information, the surveys were linked to the smart meters' database. Of the total number of surveys collected (*i.e.* 389) we were able to identify and link 64% of them with the smart meter database (275). The reasons for not obtaining a full match are twofold: 1) the interviewers were not able to identify the number of the meter so we were not able to link the survey to the smart meters' database (32%) or 2) no smart meter is installed in that household (4%).

Data from the 250 smart meters are available since 2010, but its data availability is dependent on the smart meters' rollout in the municipality of Évora. Thus, a complete database including daily off-peak (00h00 to 07h00) and total (00h00 to 24h00) electricity was retrieved from 2011 to 2013. Information on the type of tariff (dual and single tariff) and contracted power (kVa) was also obtained for improved knowledge on households.

Combining these two sets of information provides an extensive and coherent dataset on household electricity consumption. Bearing in mind that residential electricity consumption has strong temporal variation, which is not captured with low-resolution consumption data such as monthly bills, these high-resolution electricity consumption data is vital.

Statistical analysis performed over this very high temporal resolution data allows the characterization of the electricity consumption profiles as a function of several factors: dwelling location (urban vs. rural), contracted power, type of household, year of construction, occupants characteristics and other socio-economic determinants. Several electricity consumption profiles are evaluated and presented in the next section, appraising daily total and off peak electricity consumption.

We use off-peak consumption as a proxy for the minimum base load of electricity consumption of Évora households in order to find adequate PV capacity. With this, it is possible to maximize PV production without grid feed-in injection and this way preventing over estimating of capacity and investment costs. In other words, we identify the city potential from dwellings self-consumption provided by PV production. These findings are particularly relevant due to the recent publication of Decree-Law no.153/2014 which regulates PV production for self-consumption, *i.e.* no grid injection.

2.1.3 Results

2.1.3.1 Characterization of the dataset

The dataset derived from the sampled smart metered houses in Évora is characterized by a daily average consumption for the three years of 9.82kWh per day, with seasonal peaks in winter days: maximum daily average consumption of 19.98kWh (in January 2011), while the minimum daily average consumption occurred during spring (May) with 6.71kWh per day (Figure 2.1). There are no significant changes in the consumption patterns clearly distinguishing the three years of analysis; however, we can observe that the year of 2011 has had higher maximum daily consumption (during winter). Data analysis also indicates that throughout the years the off-peak consumption pattern is similar to the total (off-peak consumption period in Évora represents, in average, 35% of daily total consumption).

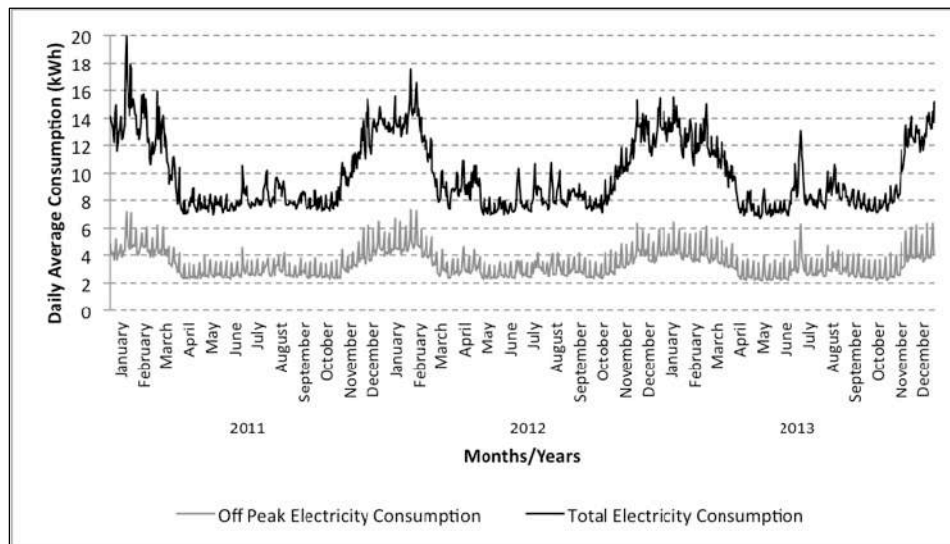


Figure 2.1. - Daily average of total and off-peak electricity consumption for the sampled meters (#250)

Looking deeper into the off-peak consumption period of the sampled houses we can conclude that the average registry of the dataset is at 3.42 kWh but the minimum is set at 2.18 kWh. As portrayed in Figure 2.2, the majority (90%) of the minimum registries of daily off peak consumption locate below 6 kWh, with 70% under 4 kWh. Using this distribution as representative for the Évora city, we can set a PV potential for auto-consumption to secure the minimum base load of electricity consumption.

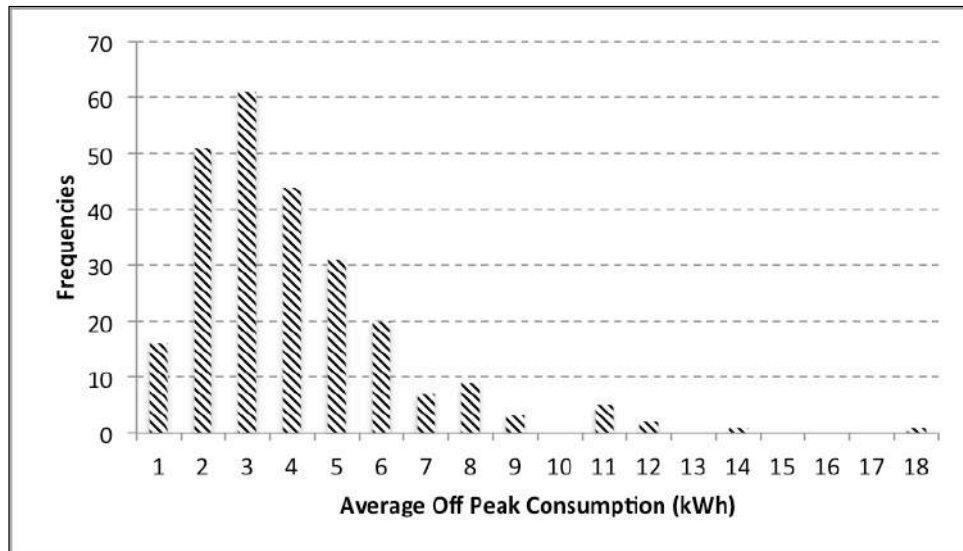


Figure 2.2. - Frequencies of distribution of the daily average off-peak consumption of the sampled meters

2.1.3.2 Detailed analysis using consumers' segmentation

In order to get an in-depth understanding on what factors govern total and off-peak electricity consumption, we present data segmentation for a set of 13 determinants of electricity use in households (Table 2.1), and two examples of total electricity consumption profiles (Figures 2.3 and 2.4).

Table 2.1- Characterization of different categories of determinants of electricity use in households

Determinants	Categories within Determinants	Annual Average Total Consumption (kWh)	Off-Peak Consumption (%)
Location	Rural	9.59	35%
	Urban	9.98	35%
Type of House	Detached	10.66	37%
	Semi Detached	10.22	34%
	Terraced	8.91	35%
Persons per Household	1 and 2	7.73	33%
	3 and 4	11.15	37%
	Higher than 5	13.67	34%
Education Levels	Until 4 th grade	7.62	31%
	From 5 th to 12 th	9.56	35%
	Graduation, MsC and PhD	13.37	39%
Contracted Power	Until 4.6 kVA	7.19	33%
	From 5.75 to 10.35 kVA	11.35	36%
	Higher than 13.8 kVA	17.24	33%
Type of Tariff	Single tariff	9.03	33%
	Dual tariff	11.43	34%
Period of Construction	Before 1945	9.37	32%
	Between 1946 and 1990	9.50	35%
	After 1991	11.33	35%
Working Status	Working	11.00	37%
	Retired	8.62	31%
	Student	9.05	36%
Monthly Income	Under 750€	7.23	31%

	Between 751€ and 1500€	9.93	35%
	Between 1501€ and 2500€	11.30	38%
	Higher than 2501€	15.63	34%
Bearing Structure	Concrete	10.47	34%
	Masonry walls of loose stone	5.77	31%
	Masonry Walls with plate	9.78	36%
	Masonry Walls without plate	9.87	33%
Type of Roof	Flat	9.63	34%
	Sloped	9.83	35%
Type of Glazing	Double	11.33	37%
	Single	9.13	33%
Household Contract	Owner	10.43	35%
	Private rented	7.45	33%
	Public rented	6.74	34%
	Tenant for free	11.15	35%

Evaluating total electricity consumption for different consumers' profiles based on their similar socio-economic characteristics, we can identify relevant differences within groups of consumers of the same determinant (both in the annual average and in the yearly profiles). The following assertions can be made:

There are clear distinctions within groups of contracted power and tariff, directly related to the amount and peaks of electricity.

- Detached houses present significant higher levels of consumption compared to terraced houses, associated with their external walls characteristics, which might suggest poor insulation.
- The period of construction categories also highlight significant differences, specially comparing houses built after 1991 with the other two groups.
- Bearing structure (mainly comparing masonry walls with loose stone and concrete) and windows glazing type are such examples. Glazing type present a 4% difference on the share of off-peak electricity consumption. It is not straightforward to link glazing type and electricity consumption since it might be a result of a combination of several factors such as occupants' characteristics and other buildings construction characteristics.

Therefore, household occupants' characteristics play an important role on electricity consumption, which is stated by the differences within education levels, working status, persons per household (Figure 2.3) and monthly income groups.

- The number of occupants has a direct influence on the levels of total electricity consumption observed by the annual average consumption and by the yearly profiles. Yet, off-peak consumption share does not behave similarly since higher number of persons per household does not mean higher levels of minimum consumption. Kaza (2010), Gram-Hanssen (2011) and Larsen *et al.* (2011) present the number and the use of appliances correlated to the

number of people living in the house; but for Kaza (2010) the space cooling and heating use is likely to be the same irrespective of number of people. Moreover, as suggested by Brounen *et al.* (2012) and Kavousian *et al.* (2013) there is a non-linear relationship between household electricity consumption and the number of occupants *i.e.* larger households having higher aggregate electricity consumption but a lower *per capita* consumption.

- There is no statistical difference between rural and urban houses, concerning off-peak consumption share and total consumption, although interesting seasonal differences arise when evaluating the yearly profile (Figure 2.4). There is a clear distinction between urban and rural houses in winter and summer months, which should guide the design of effective measures for energy efficiency to “peak shaving” and for RES implementation for self-consumption. The lower electrical consumption of rural houses in the winter is justified by the use of biomass in fireplaces for space heating purposes.

Through the evaluation of off-peak consumption as shares of total electricity consumption from Table 2.1, one might say that two very distinct off-peak profiles appear, supported on the combination of different categories of determinants; *i.e.* 1) combination of categories characterized by off-peak share average of around 32% and 2) with off-peak shares ranging from 36% to 39%.

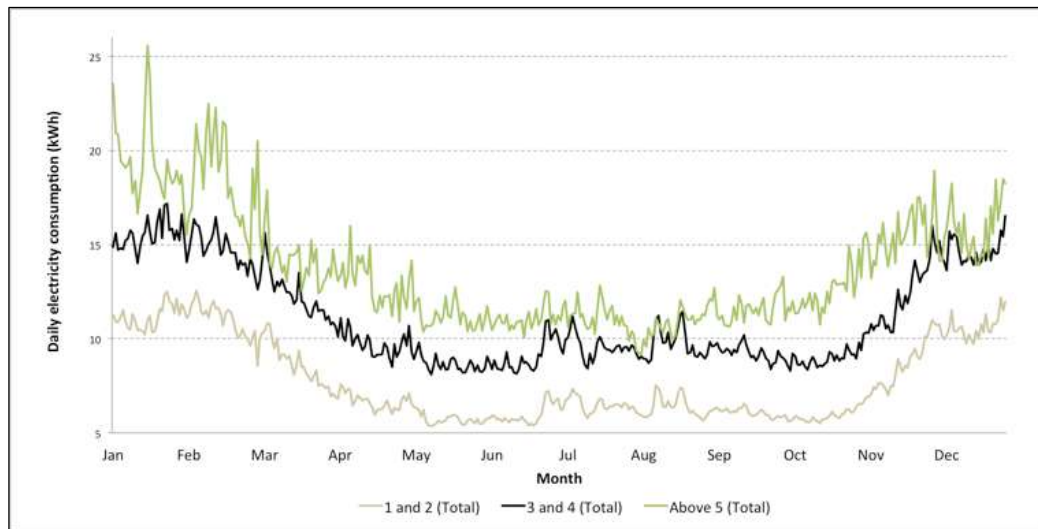


Figure 2.3 - Total Daily average electricity consumption disclosed for the number of persons per household

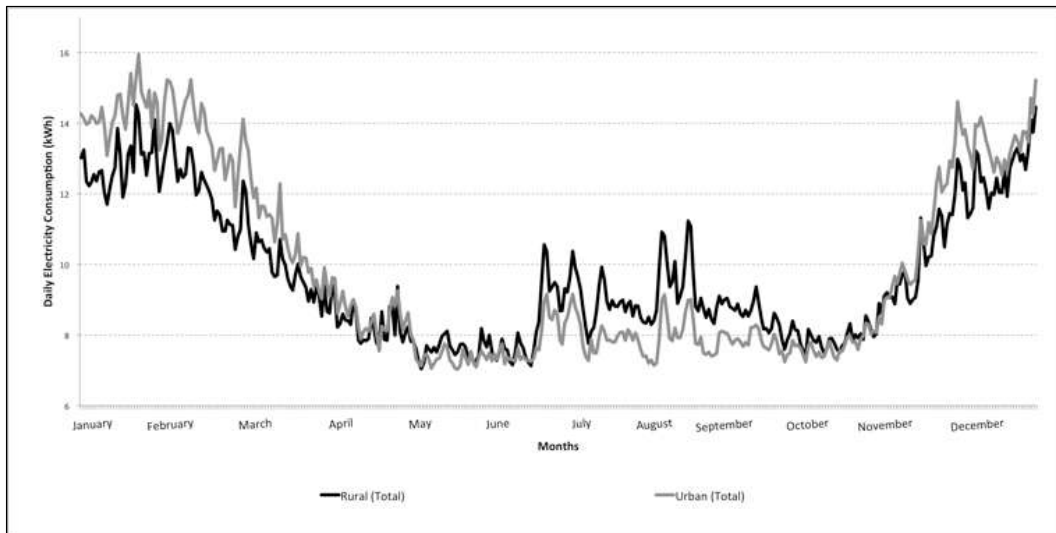


Figure 2.4. Daily average of total electricity consumption for rural and urban houses

The results on different profiles also unfolds that the population and households addressed by our survey are well distributed with different socio-economic status benefiting the outcomes of analysis. The evaluation of yearly consumption profiles and representativeness of off-peak consumption allow us to better define relevant consumers' segments to address both tailored energy reduction policies as also set the potential for RES integration in households to fulfil base load needs. Next section presents an estimation of PV potential following this, for the municipality of Évora as an example.

2.1.3.3 Photovoltaic potential based on daily off peak electricity consumption

Supported in the off-peak distribution of the sampled households of Évora, represented in Figure 2.2, we calculated PV systems' size per cluster so each household would produce up to the minimum hourly consumption. The objective is to prevent grid injection of excess produced power (with no storage *e.g.* batteries). We simulated commercially available PV panels to design PV systems' size for houses ranging from:

- Houses with minimum consumption of 0.29 kWh - 1 panel of 300 Wp.
- Houses with minimum consumption of 1.29 kWh - 1.35 kWp system (six panels of 225 Wp).

Considering the cluster distribution to be representative of the municipality of Évora and that all the households have feasible conditions to install the previous range of PV systems we applied it to the total number of residential households: 22774 (INE, 2011) to calculate the city optimal potential for PV self-consumption.

The result is that the city could produce 19 GWh per annum of PV electricity from a total installed power of 12.7 MW. This would represent 22% of current total electricity consumption

in residential households (84 GWh for 2013 (DGEG, 2015)) and circa 7% of the city total electricity consumption (261 GWh for 2013) (DGEG, 2015).

2.1.4 Conclusions

Stabilization or reduction of households' electricity consumption while fulfilling electricity service needs has been pointed out as a major goal in developed countries to prevent harmful environmental impacts and fossil fuel imports. Decentralized RES technologies coupled with energy efficiency programs are relevant options to overcome that goal.

The research presented in this paper suggests that combining electricity consumers through aggregation of similar socio-economic characteristics is a major contribution to the evaluation of different electricity profiles (total and off-peak) and to optimize self-production capacity investment expenditures and electricity production surplus when sizing electricity production systems (*e.g.* solar PV).

Major conclusions from the case of the municipality of Évora refer to very distinct profiles of total electricity consumption arising from occupants' features as income and the number of persons per house; and buildings characteristics as type of house and glazing. Furthermore, off-peak data allows estimating that 19 GWh per annum could be auto-produced for households to fulfil minimum consumption base loads.

Besides the achievements on the characterization of electricity profiles and PV potential based on minimum daily electricity consumption in Évora, this paper discloses the importance of the future widespread use of smart meters, which provide sufficient information to support the design and implementation of energy policies also delivering useful insights to those who design business models for energy at households' level, when the related socio-economic background and other electricity consumption determinants are known.

We acknowledge some limitations of this study, mainly regarding a *ceteris paribus* comparison for each determinant, and possible underestimation of PV potential due to the use of average minimum consumption profiles using off-peak period as proxy. The use of daily consumption data instead of hourly data also holds limitations for a more detailed assessment of the RES potential.

Acknowledgements

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Authors Contributions

J. P. Gouveia structured and wrote the paper, and performed all the smart meters and surveys data analysis. J. Seixas supported the design of the paper and its in-depth revision. L. M. Mendes assessed the PV potential calculations. provided the data from the electricity smart meters. L. Shiming assisted on the handling and cleansing of the smart meters' data.

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2.2. Unraveling electricity consumption profiles in households through clusters: combining smart meters and door-to-door surveys

ABSTRACT

Improvements of energy efficiency and reduction of electricity consumption could be pushed by increased knowledge on consumption profiles. This paper contributes to a comprehensive understanding of the electricity consumption profiles in a Southwest European city through the combination of high-resolution data from smart meters (daily electricity consumption) with door-to-door 110-question surveys for a sample of 265 households in the city of Évora, in Portugal. This analysis allowed to define ten power consumption clusters using Ward's method hierarchical clustering, corresponding to four distinct types of annual consumption profiles: U shape (sharp and soft), W shape and Flat. U shape pattern is the most common one, covering 77% of the sampled households. The results show that three major groups of determinants characterize the electricity consumption segmentation: physical characteristics of a dwelling, especially year of construction and floor area; HVAC equipment and fireplaces ownership and use; and occupants' profiles (mainly number and monthly income). The combination of the daily electricity consumption data with qualitative door-to-door survey-based data proved to be a powerful data nutshell to distinguish groups of power consumers, allowing to derive insights to support DSOs, ESCOs, and retailers to design measures and instruments targeted to effective energy reduction (*e.g.* peak shaving, energy efficiency).

KEYWORDS

Daily Electricity Consumption, Hierarchical Clustering, Consumers' Segmentation, Smart Meters, Household Surveys; Electricity Demand Management.

2.2.1. Introduction

Greenhouse gases (GHG) emissions will hold steady or might even increase in developed countries if effective reduction of energy consumption will not be taken (Lomas, 2010), contrary to policy goals aiming a transition towards low carbon economies. The need for energy consumption reduction is also linked to energy supply security and affordability, and climate change strategies. Therefore, increased search for energy efficiency, GHG emissions reduction and increased share of renewable energy sources, as established in the European Union (EU) goals by 2030 (EC, 2014) requires more successful and directed actions.

Energy consumption in residential buildings deserves special attention since they represent a significant share of final energy consumption in OECD (Organization for Economic Co-operation and Development) countries, 27% in EU28 in 2013 (Eurostat, 2015). In Portugal, residential buildings consume approximately one third of total electricity, with a growth of 70% from 1995 to 2012 (DGEG, 2014). This consumption is a complex issue that can be explained by a combination of physical, technological, demographic, climatic and behavioural characteristics of a dwelling and its occupants.

Understanding the determinants that govern energy consumption has thus been the subject of abundant international literature for more than 30 years (*e.g.* Van Raaij and Verhallen (1983); Bartiaux and Gram-Hanssen (2005); Gruber and Scholmann (2006); Kelly (2011)). More recently, Jones *et al.* (2015) presented a literature review of the existing research investigating the socio-economic, dwelling and appliance related factors that affect electricity consumption in the residential sector.

In this area of study, smart meters have been gaining higher interest in demand side management initiatives and for utilities, and are seen as an important instrument for giving energy consumption feedback to households and for consumers' profiles analysis (Weiss *et al.*, 2013). With growing deployment of smart meters and real-time home energy-monitoring services, adequate data allowing the study of electricity consumers' profiles in households and its determinants are becoming available.

Hayn *et al.* (2014) worked on daily electricity household profiles through segmentation based on lifestyles, socio demographic factors, and electric appliances and on new technologies for heat and electricity generation. Crossing the information delivered by the smart meters with the main determinants of energy consumption in each household, allows for market segmentation identifying consumers with similar needs and behaviors (McDonald and Dunbar, 2012). This valuable knowledge promotes individually and personalized feedback evaluation to households or groups of similar consumers being important for energy savings. Furthermore, tailoring of energy efficiency measures based on specific household profiles enables the change of behavior

and equipment with the ultimate goal of an effective energy consumption reduction and load curve consumption peaks minimization.

There are studies on the residential electricity consumption profiles using smart metering data. Seo and Hong (2014) with a 30 households sample for Daegu in South Korea characterized power consumption patterns and presented summer load profiles. Rhodes *et al.* (2014) using 103 homes for Austin in Texas determined representative residential electricity use profiles within each season drawing correlations to the different profiles based on survey data. Lee *et al.* (2014) demonstrated profiles of electricity consumption for 60 low energy-housing houses in South Australia. Ramos *et al.* (2015) identified daily load profiles of medium voltage customers applying several clustering algorithms; McLoughlin *et al.* (2015) presented a methodology for electricity load profile characterization through clusters for Ireland using 3941 customers.

The Southwest European region have not yet been analyzed in terms of electricity consumer profiles, which has been seen as a bottleneck for the identification of opportunities for energy reduction and further energy efficiency achievements. Usually, there are statistics and knowledge regarding the national level, although, for effective opportunities of policy instruments or services towards energy efficiency and reduction there is the need for data and knowledge at a more local level.

An analysis of the data available for Évora indicates that, 82% of the residential buildings are associated with single-family houses (mainly terraced houses) and only 8% with apartments (INE, 2011). This presents a relevant difference from the EU average countries with 64% of residential buildings being single-family houses and the remaining 36% being apartments (Economidou *et al.*, 2011).

A substantial share of the buildings stock in Évora, as in other European cities, is older than 50 years. More than 20% of the residential buildings have been constructed before the 1940s when energy-building regulations were very limited. A large increase in construction in 1946-1990 is also evident, with the buildings constructed in this period representing around 56% of the current city stock (INE, 2011).

This paper aims to identify, understand and explain representative yearly electricity consumption profiles of households, for the case study of Évora municipality. We applied a clustering approach to electricity consumption data, gathered from smart meters, and linked it with a dedicated survey for the same households to identify and characterize target groups of consumers.

We argue that the proposed methodology and the achieved results are useful to derive insights to support utilities, retailers and ESCO's for marketing segmentation and innovative policies for

effective energy reduction, as it is the case of tariff design, demand side management strategies, energy efficiency improvements, among others.

The paper is organized in four sections. Section 2.2.2 describes the methods and discloses the data used. Section 2.2.3 presents selected results regarding electricity profiles by consumption clusters and related explaining variables. Section 2.2.4 concludes.

2.2.2 Methods and data

This section describes the methodology used. Through the combination of the smart metering dataset provided by an electricity distribution company as in Wyatt (2013) and Bartusch *et al.* (2012); and a door-to-door survey as in Kavousian *et al.* (2013) and Gram-Hanssen *et al.* (2004); we have made an in-depth analysis through segmentation of consumers based on clustering electricity consumption, aiming to identify distinct yearly electricity consumption profiles and to characterize their determinants. Figure 2.5 explains how the work was developed and how the different steps were addressed. Each step will be described next.

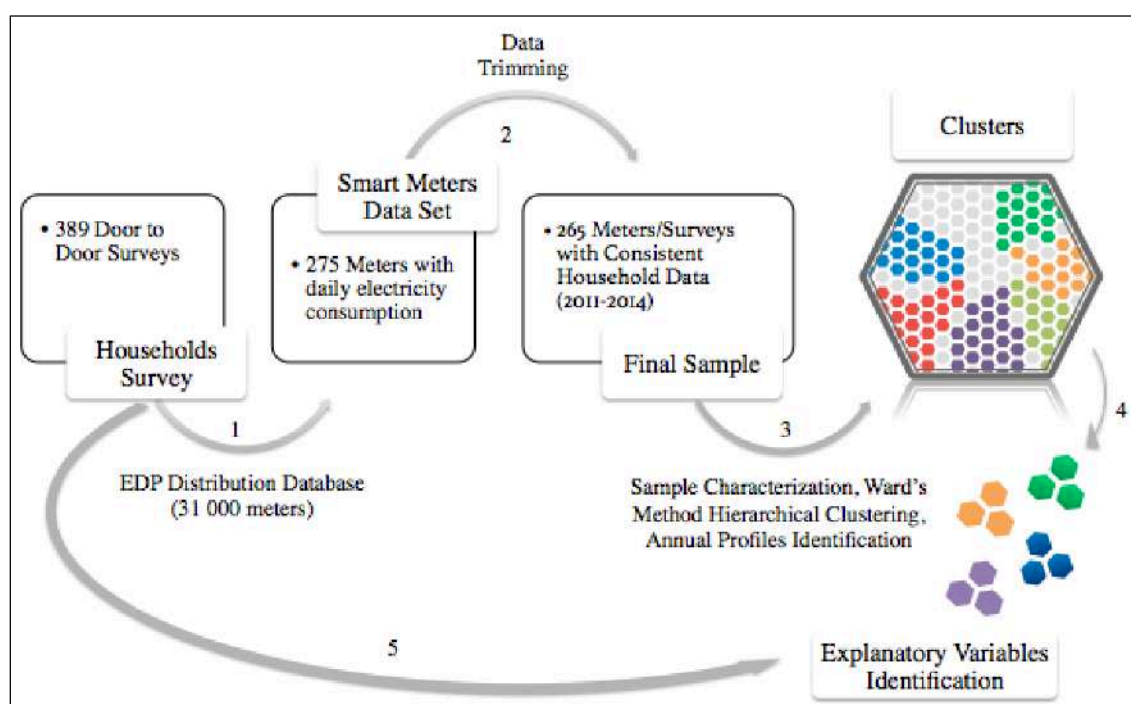


Figure 2.5 – Study Methodology

2.2.2.1 Door-to-door household survey

The door-to-door survey consisted in 110 questions and encompassed information on location, socio-economic data (*e.g.* average monthly income, family size), equipment's ownership and use (*e.g.* number of hours of use in a day) and physical characteristics of the dwellings (*e.g.* bearing structure).

The fieldwork of the survey was carried out through the municipality of Évora during July and August 2014, including urban and rural areas. The identification and selection of the locations to make interviews was supported on the existing internal districts of the municipality i.e. parishes, which are the lowest spatial unit with available statistical data. Évora municipality has twelve parishes, three in the urban area comprising around 80% of the population and nine in the rural areas. Therefore, for our purpose, four districts were identified: we combined all the rural parishes in one sector and the three urban parishes were individually kept as districts.

Due to budget limitations, we set a maximum of 400 interviews to be done. Because of onsite difficulties, time and transport logistics and interviewers' availability constraints, we were able to collect 389 valid surveys, representing 97% of the total expected surveys, being 37% of the surveys answers collected in rural areas, and the remaining in the urban area. This way we were able to capture different households' characteristics and consumer types.

2.2.2.2 Smart meters' dataset

This study also relies on data from a massive smart metering system conducted for the first time in Portugal in the municipality of Évora, within the InovCity project (EDP Distribuição S.A., 2015). It contains measurements of electricity consumption registries gathered from 31 000 household every 15 minutes since April 2010. The installed equipment's in Évora are concentrators from EFACEC and Janz meters with PLC communication (FSK modulation) in the CENELEC-A frequency band (35-91 kHz). Data collection of load diagrams from the meters to the distribution transformer controller is done on a daily basis starting at 00:00 and for every 6 hours. The InovCity project is being carried out by the main Portuguese electricity distribution company, hence the smart meters component is integrated within a full smart city philosophy, which comprises better network management, remote and centralized control stations; electric mobility and distributed generation systems (EDP Distribuição S.A., 2015).

Residential electricity consumption has strong temporal variation, which is not captured with low-resolution consumption data such as monthly bills, thus high-resolution electricity consumption data from smart meters is vital. Therefore, making use of this data, a sample was collected; the household surveys were linked to the smart meters' database through the household meter number, while preserving the confidentiality of the house owners. As mentioned by Wijaya *et al.* (2014), consumer segmentation alone is not enough. Therefore, combining these two sources of information allows an extensive and coherent household data analysis to develop effective and efficient policies better targeting different consumers.

Of the total number of collected surveys (*i.e.* 389), we were able to identify and link 64% of them with the respective smart meters (275). The reasons for the gap are twofold: 1) the interviewers were not able to identify the number of the meter so we were not able to link the

survey to the 31 000 smart meters' database (32%) or 2) no smart meter is installed in that household (4%).

Data availability is dependent on the smart meters' rollout in the municipality, since not all the meters were installed in the beginning of the project (*i.e.* 2010). For our objective, while avoiding too much granularity (by using 15-minute data), daily electricity consumption data was retrieved for the years 2011 to 2014. By excluding 2010 data we were able to collect a more complete database. Despite the information acquired from the surveys referred only to 2014 with possibilities of changes in household socio-economic details (*e.g.* tenure, number of people, income); we assumed that the characteristics mostly apply for the electricity profiles of 2011-2014.

Information on the type of tariff (dual and single) and contracted power (kVA) was also obtained for improved knowledge on the sampled households. The type of tariff is related to the costs of electricity, depending on the hours of consumption (day, night and weekends), while the contracted power (*e.g.* 1.15 kVA, 3.45 kVA, 6.9 kVA) constrains the number of electrical appliances that could be used simultaneously.

A data trimming of the electricity dataset was made. The electricity registries from the Distribution System Operator (DSO) have the information per meter of accumulated electricity consumption. To have the daily electricity consumption we had to subtract the registry of the previous day from the registry of the day. Following Torsten *et al.* (2013) meters with annual readings with less than 80% of available electricity readings were discarded. Thus, we screened the full data set of 275 meters to identify major data faults (*i.e.* missing of sporadically daily registries; missing several days/months in sequence). 10 meters were excluded in this step.

For further analysis, the daily electricity consumption data were averaged for the four years (2011-2014), preserving the intra-annual variability for each household. This approach will allow us to identify important and distinctive profiles of consumption and make typification of consumers' characteristics (*e.g.* dwelling characteristics and occupants' profiles) for each electricity consumption profile. The 265 meters remained with few days with missing data (less than 1%), for which we imputed values based on the average values of the neighboring days.

2.2.2.3 Data analysis methods

An exploratory data analysis of the final sample of 265 households' daily electricity consumption data sets from smart meters was made, as well as a clustering analysis. The cluster analysis was carried over the daily means (per household), *i.e.*, averaged over 2011-2014 for each day. After the previous explained electricity data trimming, we applied a hierarchical clustering using the Ward's Method (Ward, 1963) with a measured interval through the squared

Euclidean distance, allowing an analysis of variance approach to evaluate the distances between clusters. This method is regarded as very efficient; however, it tends to create clusters of small size (Statsoft, 2015). Therefore, through an iterative process, we evaluated the clustering results for a number of clusters ranging from 3 to 12. We concluded that still maintaining robustness and statistical significance of the clustering, only increasing the number of clusters allows to capture distinct yearly consumption patterns that would be interesting to unravel and compare, in order to create types of consumer for which different policy and energy reduction measures could be targeted. The 10 clusters option with similar means and standard deviations were selected for further profiles analysis. It met a good balance option to illustrate differences of the annual profiles with significant number of meters/surveys.

After allocating each survey to the correspondent cluster, a screening of the answers of the surveys was made in order to recognize the most relevant parameters (*e.g.* dwelling characteristics, occupants' profiles, electrical appliances ownership and use) that further explain the electricity consumption patterns and major similarities/distinctions within clusters allowing an increased knowledge on the clusters segmentation.

From the information collected in the households survey, we retain the following variables to characterize the households: (i) location (Urban and Rural) (as in *e.g.* Halicioglu (2007); Raty and Carlsson-Kanyama (2010)), (ii) dwelling type (as in Bedir *et al.* (2013); McLoughlin *et al.* (2012)), (iii) dwelling age (Wiesmann *et al.* (2011); Brounen *et al.* (2012)), (iv) dwelling total floor area (*e.g.* Baker and Rylatt (2008); Kavousian *et al.* (2013)), (v) type of glazing and windows framing, (vi) bearing structure and (vii) type of external walls. The following socio-economic variables, which might influence electricity consumption, were selected: (i) the number of occupants (according to Bartiaux and Gram-Hanssen (2005); Brounen *et al.* (2012)), (ii) education of the household responsible person (*e.g.* Gram-Hanssen (2004)), (iii) household income (Lam (1998; Santamouris *et al.*, 2007) and (iv) employment status (*e.g.* Cramer *et al.*, 1985; Yohanis *et al.*, 2008). For factors associated with electrical appliances and heating and cooling equipment we selected the following variables: (i) ownership of heating and cooling technologies (as in Bedir *et al.* (2013); Tso and Yau (2007)), (ii) ownership of white electrical appliances (as in Leahy and Lyon (2010); McLoughlin *et al.* (2012)), (iii) type of tariff and (iv) contracted power.

Statistical analysis performed over very high temporal resolution data allows the characterization of the electricity consumption profiles. Significant differences and similarities within cluster groups were assessed, which can be useful to support market segmentation and tariff design for DSOs and to improved knowledge on groups of consumers for ESCO's and for electricity retailers to feed specific energy and pricing reduction recommendations.

2.2.3. Results and discussion

In this section, we aim to explore the results from the clustering analysis portraying the different yearly consumption profiles, and its most relevant determinants gathered from survey data to explain household electricity consumption clustering. Figure 2.6 presents the daily electricity consumption for the sampled meters (265 households) averaged for the four years with consistent available data (2011, 2012, 2013, and 2014) and the corresponding daily minimum temperature. A higher daily average consumption in the winter months of December and January and in the summer month of July is apparent, presenting a strong inverse correlation with the minimum daily temperatures ($r=-0.82$) (Figure 2.6), maximum daily temperatures ($r=-0.77$) and with the daily average temperature ($r=-0.80$). These correlations show a potential direct link between electricity consumption and the use of cooling and heating systems.

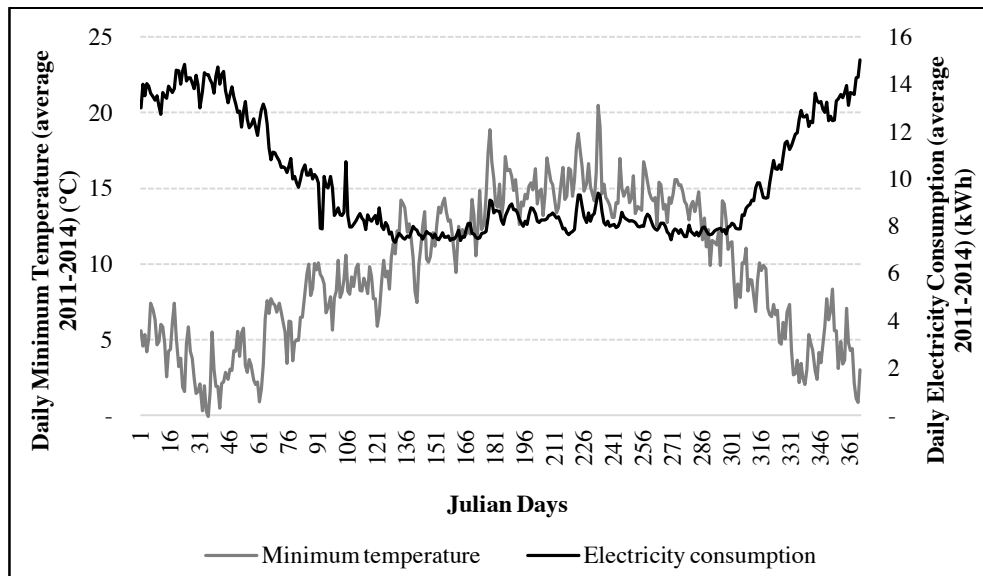


Figure 2.6 – Daily average electricity consumption for the sampled households (265) and minimum daily temperature for Évora (both averaged 2011-2014)

2.2.3.1 Electricity data clustering from smart meters

The clustering method applied split the 265 smart meters' dataset into 10 clusters, showing a distinct distribution of meters (with at least 25 meters per cluster) within clusters with mean daily electricity consumptions below 12 kWh (cluster 1 to 5), totaling 217 meters (more than 82%) and the other five clusters. The remaining 47 meters are included in clusters 6 to 10 fitting the high levels of consumption and/or variability with daily median consumption of almost 28 kWh (*i.e.* cluster 8) (Figure 2.7).

The box-and-whisker plot unveils the descriptive statistics of the clusters (C_i) regarding their dispersion and skewness, and the existing outliers. The distribution of electricity consumption data from C_1 to C_5 is similar, with C_1 presenting the lowest statistics (median 3.99 kWh and

standard deviation of 2.10 kWh) and C2 the highest variance (standard deviation of 4.26 kWh). The short box plots within these clusters (and also C9 and C10 at a certain extent) suggests that, generally, the consumption data have similar profiles. Differences within these clusters can be further evaluated in Table 2.2. Clusters C6 to C8 present tall box plots depicting significant variances (standard deviations ranging from 6 to 11 kWh) within clusters already unveiling possible differences among the seasons of the year. Cluster C7 shows the highest data variability (standard deviation of 10.87 kWh) and highest consumption. With the exception of clusters C6 and C7, all the other clusters have a consistent distribution of data within the second and third-quartile.

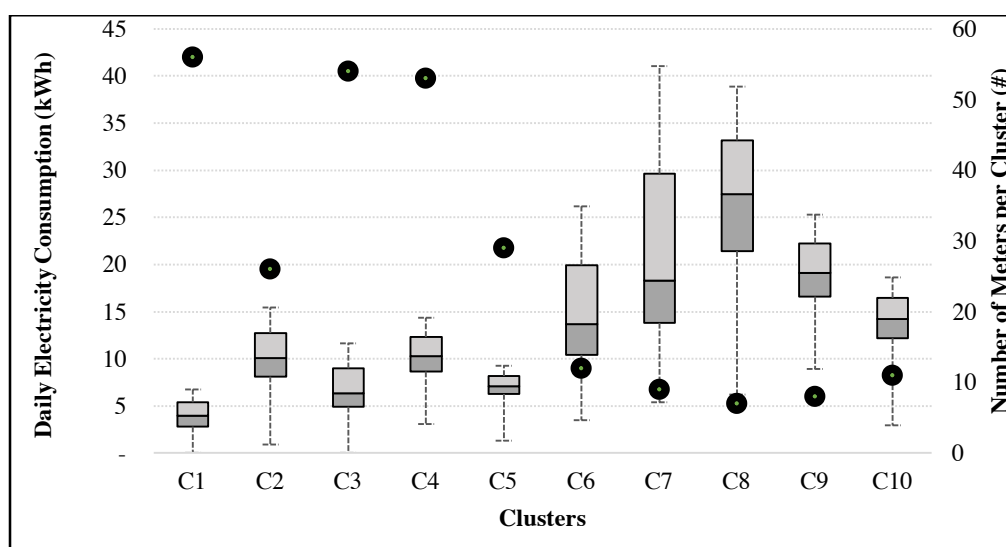
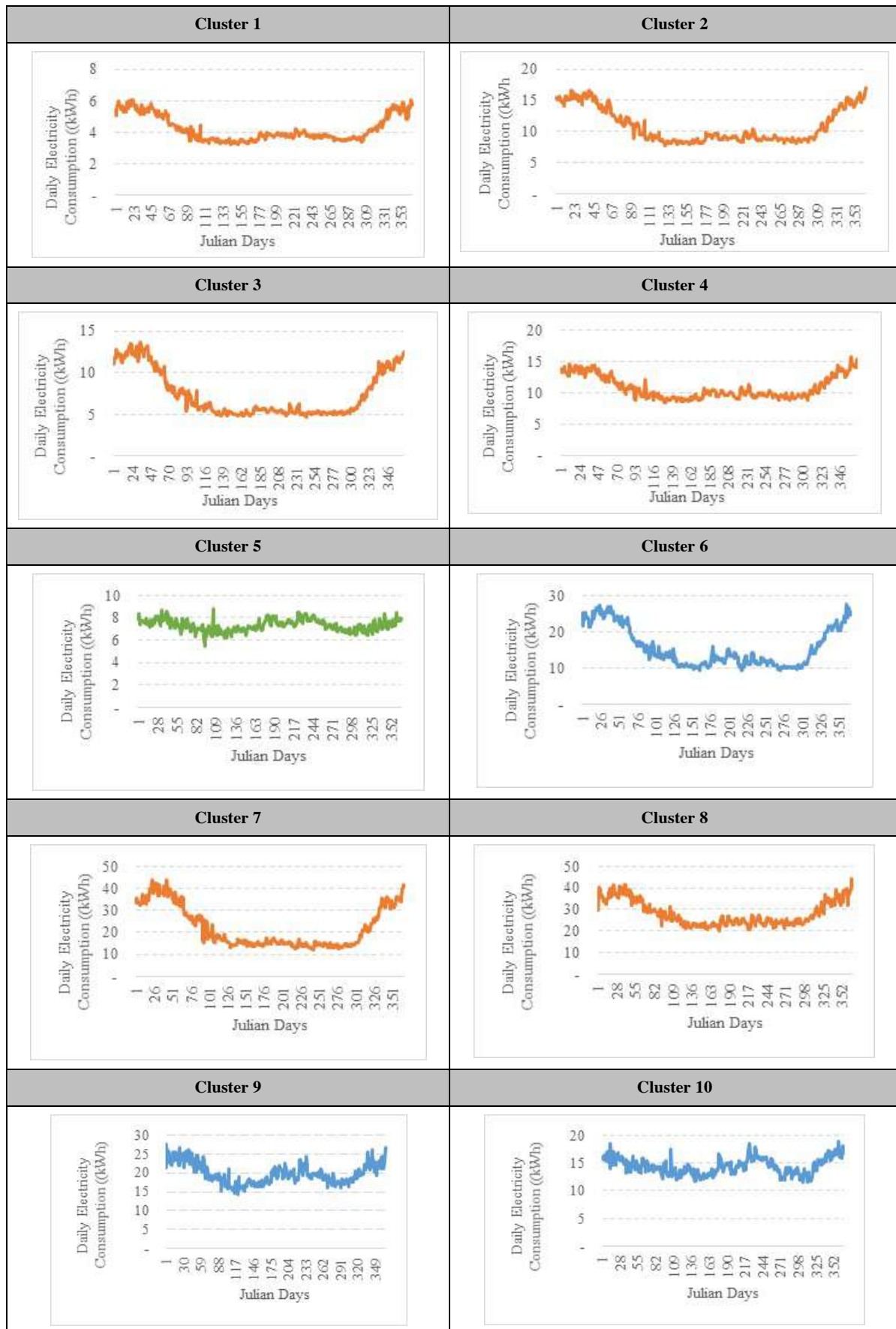


Figure 2.7 – Box and whisker plot with clusters distribution and number of meters per cluster

Table 2.2 advances on the annual electricity consumption profiles of each one of the ten clusters allowing to identify important distinctions of inter annual consumption patterns. Three distinctive profiles can be concluded, named a) U profile; b) W profile, c) Flat profile. The rationale behind this identification is a visual analysis further supported on the evaluation of the differences between the levels of electricity consumption in winter and in summer. This segmentation has the objective of acknowledging the different yearly electricity consumption patterns of household consumers and to further evaluate them.

Table 2.2 – Annual electricity consumption profiles by cluster (2011-2014 average)



Under the U Profile we include six clusters (77% of the sampled households): C1, C2, C3, C4, C7 and C8 (in orange). This profile could be further disaggregated, in the Sharp U profile (C1, C2, C3 and C7) and the Soft U profile (C4, C6 and C8) branches. Soft U profile is characterized by differences of electricity consumption on winter and the remaining seasons of the year (around 50% lower in summer) possible explained by the lower ownership and use of cooling electrical when compared to electricity-supported systems. Sharp U profiles present a higher difference on winter and the remaining seasons (around 70% lower in summer in some clusters) portraying the inexistence or low use of cooling equipment in the summer compared to a strong use of electricity-based technologies for space heating in the colder months of winter (December, January and February) which is corroborated by the findings in Tables 2.3 to 2.6.

Under the W Profile (in blue), we include clusters C6, C9 and C10 (12% of our sample), which present clear distinctions of electricity consumption between summer and winter and the inter-seasons period. These clusters with high values of daily consumption present a strong hump-shaped consumption in summer, most prominent in C9 and C10. These profiles suggest that the respective households might have high ownership rates and use of HVAC systems for cooling and low use of electrical equipment for heating in the winter (C6) or both high use of electrical systems for cooling and heating (C9 and C10). Nevertheless, we acknowledge that C6 is not a very distinct W profile, looking more as a transition profile between a Soft W and Soft U.

Cluster C5 (in green) is in the lower levels of consumption of all the sampled data, and we considered it as having an annual Flat consumption profile (11% of the sampled households) since the consumption has small intra annual variations. The minimum of electricity consumption is 62% of the maximum consumption value. This type of profile could be explained by the inexistence of electrical equipment for cooling or heating being the electricity consumption only linked to end uses like cooking, lighting, washing cloths and dishes and other electric equipment (e.g. televisions, computers) which usually do not have seasonal variations.

For an in-depth characterization of the electricity consumption of the households behind the four recognizable distinct profiles, we crossed the meters' data of each cluster with the correspondent survey results. Considering the statistical behavior and yearly patterns presented previously, three clusters are selected as examples of each profile to present the results: a) U profile - Cluster 1 and Cluster 7, b) W Profile - Cluster 9 and c) Flat profile – Cluster 5. The selection was based on distinct consumption profile of clusters regarding the mean (low, medium, high), dispersion (low and high) and annual profile (similar along the year or different in winter and/or summer months).

Van Raaij and Verhallen (1983) recognized several factors that drive household electricity consumption behavior, such as energy-related attitudes, personality, socio-demographic factors,

building characteristics, energy prices, feedback and general information about energy use. Kelly (2011) identified for England the number of household occupants, floor area, household income, dwelling efficiency, and household heating patterns and living room temperature as the main drivers behind residential energy consumption. For Germany, Gruber and Scholmann (2006) showed that electricity consumption is strongly influenced by the number of existing equipment, household area and annual income. Bartiaux and Gram-Hanssen (2005) exposed for Belgium and Denmark that family size; dwelling area and number of equipment are strong determinants for electricity consumption.

Tables 2.3 to 2.6 disclose selected variables collected in the surveys, to be compared throughout the chosen clusters. By evaluating the survey results for the households in each cluster, it is possible to identify important similarities and differences regarding socio-economic determinants, dwelling characteristics and appliances use and ownership, which could further explain the different clusters' aggregation and levels of consumption and profiles.

Table 2.3 - Summary of selected variables characterizing the Dwellings of Clusters 1, 5, 7 and 9

Shape of Annual Electricity profile	Cluster	Characteristics of Dwellings																						
		Location (%)		Type (%)			Period of Construction (%)					Avera ge House hold Area (m²)	Bearing Structure (%)			External Wall (%)				Glazing (%)		Window Framing (%)		
		Urban	Rural	Semi Detached	Terraced	Detached	<1919	1920-1945	1946-1990	1991-2005	≥2006		Concrete	Masonry Wall with and without plate	Masonry wall with loose stone	Brickwork double layer with insulation	Brickwork double layer without insulation	Brickwork single layer	Stone Masonry and Rammed Earth	Single	Double	Aluminum	Wood	PVC
U Shape (soft)	C1	61	39	30	52	18	16	20	55	9	-	90	24	70	6	6	2	72	20	83	17	38	60	2
Flat	C5	34	66	52	34	14	3	22	38	34	3	117	33	52	15	30	26	22	22	54	46	64	32	4
U Shape (sharp)	C7	78	22	33	33	33	22	-	56	22	-	149	33	67	-	33	11	45	11	67	33	56	44	-
W Shape	C9	38	63	24	38	38	-	-	25	50	25	162	50	50	-	38	12	50	-	13	87	63	37	-

Table 2.4 - Summary of selected variables characterizing the Household Occupants of Clusters 1, 5, 7 and 9

Shape of Annual Electricity profile	Cluster	Characteristics of Household Occupants																								
		Average Number of persons per household	Age of Household Members (%)					Gender of Household Members (%)		Education of the Head of the Family (%)			Monthly Average Income of the Household (%)				Employment Status (%)				Household Occupation Contract (%)			Relation of Household members (%)		
			<5 years old	5-17	18-49	50-64	≥65 years old	Male	Female	<9th grade	9th-12th grade	Graduation, MSc or PhD	≤750€	751€-1500€	1501€-2500€	≥2501€	Working	Retired	Student	Other	Owner	Rented	Tenant for Free	Family	Room Mates	Another Couple
U Shape (soft)	C1	2	-	7	32	18	43	44	56	53	35	12	60	29	11	-	32	47	15	6	60	38	2	89	9	2
Flat	C5	2.86	-	16	48	14	21	52	48	44	44	12	26	53	21	-	51	23	20	5	86	14	-	100	-	-
U Shape (sharp)	C7	2.44	-	9	32	36	23	45	55	13	24	63	20	40	20	20	43	23	17	17	89	11	-	100	-	-
W Shape	C9	4	3	19	59	19	-	56	44	-	50	50	-	17	33	50	50	9	38	3	100	-	-	100	-	-

Table 2.5 - Summary of selected variables characterizing the Appliances Ownership of households in Clusters 1, 5, 7 and 9

Shape of Annual Electricity profile	Clust er	Appliances Ownership**																								
		Heating Technologies (%)			Cooling Technologies (%)			DHW Technologies (%)		Cooking Technolog ies*** (%)		White Appliances and Other Electric Equipment (%)								Lighting (%)						
		Heating Equipment Ownership	Electric (HVAC, heaters)	Non-Electric (fireplaces, gas room heaters, heat pumps)	Cooling equipment Ownership	HVAC	Fan	Electric (electric resistance)	Non-Electric (gas, solar)	Gas Stove	Electric Stove	Desktops	Laptops	Refrigerators	Freezers	Microwaves	CWM	CDM	DWM	TV	IL	TFL	CFL	HL	LED	Lamps per household
U Shape (soft)	C1	86	88	12	46	27	73	6	94	98	5	16	52	100	61	91	96	16	29	171	20	3	72	3	2	10.1
Flat	C5	79	43	57	72	43	57	3	97	103	21	48	83	107	76	100	97	41	72	252	18	8	62	1	11	12.3
U Shape (sharp)	C7	89	73	27	67	17	83	-	100	67	67	22	11	133	100	111	100	56	89	200	9	17	68	4	2	16.0
W Shape	C9	100	36	64	75	100	-	-	100	88	38	113	225	125	113	100	113	63	88	213	1	6	84	9	-	20.3

**When percentages are higher than 100% it means that some households own more than one equipment.

***For cooking appliances, more than 100% ownership can mean twofold: a) more than two stoves per household, b) dual fuel stoves (electricity and gas)

Note: PVC - poly(vinyl chloride), HVAC - heating, ventilation, and air conditioning; DHW - domestic hot water; CWM - cloth washing machines; CDM - cloth drying machines; DWM - dish washer machines; IL - incandescent lamps; TFL - tubular fluorescent lamps; CFL - compact fluorescent lamps; HL - halogen lamps; LED - light emitting diode

Table 2.6 - Summary of selected variables characterizing the contracted power of households in Clusters 1, 5, 7 and 9

Shape of Annual Electricity profile	Cluster	Contracted Power Characteristics				
		Contracted Power (%)			Type of Tariff (%)	
		$\leq 3.45kVA$	4.6-6.9kVA	$\geq 6.9kVA$	Single	Dual
U Shape (soft)	C1	78	20	2	71	29
Flat	C5	31	66	3	69	31
U Shape (sharp)	C7	-	56	44	56	44
W Shape	C9	-	62	38	38	62

Cluster 1 is characterized by a predominance of terraced dwellings located in urban areas, in small houses (around 90 m²) built between 1946 and 1990 period. Following the period of construction, materials and techniques, the predominant bearing structure of the dwellings comprised in this cluster is masonry wall with or without plate associated with brickwork single layered in the external walls. The majority of the dwellings (83%) have single glazing and wooden window framing.

Regarding occupants' characteristics, we can say that this clusters' households are portrayed by the smallest families of all clusters (average of two persons per household), generally older than 65 years old with low levels of education (secondary level), retired and with households' monthly average income below 750€. It is in this cluster that the level of owner occupied houses is the lowest, with a relative important share of rented houses (38%).

The electricity profile of this cluster (Soft U Shape), defined by a significant difference of consumption on winter months is backed up by the survey results with predominant ownership and use of electric heating equipment (88%). Only 46% of these cluster dwellings have cooling equipment. From which, near 80% own fan coils, that consume a lot less than HVAC systems. Still, it is in this cluster that the ownership and use of fans is the lowest.

In C1, the overall smallest ownership of white appliances, computer equipment and lamps from all the clusters combined with the dominant number of houses (78%) with low contracted power (under 3.45 kVA) also explain the lowest levels of daily electricity consumption in this cluster when compared to others. 71% of the houses in this cluster still have single tariffs not taking advantage of the lowest prices at night of dual tariffs.

Being the cluster with the higher number of dwellings from our sample (21%), C1 is, as seen, characterized by the lowest electricity consumption levels and annual consumption profile portraying the lack of fulfilment of thermal comfort levels inside households both in summer and winter, suggesting a case of fuel poverty. As described in a project from EPEE (2009), by Moore (2012) and Thomson and Snell (2013), backing up our results, the combination of low incomes, low performance dwellings with defective insulation (windows, walls, roofs) and older households are enablers of fuel poverty. Also, consistent with our findings, Wand (2013), under EU fuel poverty network, pointed out that currently in Portugal, around 28% of the population is unable to keep their home adequately warm.

Cluster 5: Opposing with C1, C5 is characterized by a high share of households located on rural areas (66%), and with higher prevalence of more recent built houses of the semi-detached type. Furthermore, other characteristics describing the households within this cluster are: average size dwellings around 117m², built after 1946 but with a high share built after 1991, also shown in the higher number of concrete houses (33%). Increased share of insulation levels justified by the entrance of more restraining thermal regulations also represent important differences when compared to C1. The sampled houses of this cluster have a similar distribution of single and double-glazing but the majority of them has aluminum framing in the windows (64%).

Regarding occupation, C5 is established by higher number of occupants inside the households (2.86), contrasting with C1 concerning the age of occupants, household income, employment status and household occupation status: 64% of the occupants aged below 50 years, and 51% working full time reflected on medium levels of monthly income (*i.e.* 53% of houses earning between 751 and 1500€).

The construction characteristics combined with the very high ownership and use of non-electricity based equipment for cooking (103%), heating (57%) and DHW (97%), enable us to better understand the annual flat electricity consumption profile. When available, the space heating falls back predominantly on fireplaces, and the space cooling is majorly carried out with fans. Consistent with the increase in daily average consumption when compared to C1, C5 has 66% of the households with contracted power between 4.6 and 6.9 kVA, and a very high share of single tariff users. The electricity consumption profile of C5 portrays a standard comfort household.

Cluster 7 has the highest share of urban dwellings. It presents an even occurrence of the three considered types of houses (terraced, detached and semi-detached), thus not being an explanatory variable distinguishing the houses in this cluster compared to other clusters.

Construction characteristics (*e.g.* period of construction, external wall and glazing) of dwellings are very similar to the ones illustrating C1.

The deepest differences on the amount and the seasonality of electricity consumption between C1 and C7 include the higher average household area (40% higher in C7), and the number of persons per household (2.44), suggesting more space heating needs in winter months. In this cluster, the bulk of the age of the household members is below 64 years old, 80% of the monthly income are above 750€ and directly related to the high levels of education of the head of the family (63% have at least a graduation). These socio-economic characteristics are effective drivers of the C7 electricity consumption profile.

Regarding appliances ownership, C7 presents one of the highest levels of penetration of space heating equipment (89%), from which 73% have electric heaters or HVAC (the majority bought after the 2005 summer heat wave in Portugal). 67% of the houses in this cluster own equipment for cooling but the lion share being fan coils which once again explain the sharp difference of seasonal consumption.

Besides all the previous characteristics, the very high daily average consumption is also justified by the high penetration of white appliances and other electrical equipment. The penetration of refrigerators (133%), freezers (100%), microwaves (111%), dish washing machines (89%), electric stoves (67%) and number of lamps per household are higher than in the previous assessed clusters, showing a clear evidence of consumers with higher levels of disposable income.

Regarding contracted power, all the dwellings in C7 households have at least 4.6 kVA (72%), with once again a dominance of single tariffs contracts (56%). We may state that C7 portray what we may name as '*fat energy*' households with opportunities for potential reduction of electricity consumption, either through energy efficiency options and/or more rational energy behaviors.

Cluster 9: The electricity consumption in this cluster households follow a W profile, recognizable by the high levels of consumption in winter and summer months when compared to the inter seasons months. The dwellings are predominantly located in rural areas (63%), with a strong predominance of houses constructed after 2006 with high average floor areas (162 m²). In the research carried out by Zhao *et al.* (2012), there is a clear distinction between the patterns of energy use in urban and rural households, due to higher energy services demand in urban households. In our work this is not recognizable. Despite the important share of houses in rural areas, they are still close (less than 30 km) to the urban city environment, therefore, with similar urban patterns consumption.

Dwelling characteristics, as bearing structure, type of wall and windows (87% with double glazing and 63% with aluminum framing) arise to distinctively characterize this cluster. Similarities within other important explaining determinants of electricity consumption such as household occupants include: the average number of four persons per household; 59% aged between 18 and 49 years old; 100% of the adult members have at least the secondary level of education; 50% of the members either have full time jobs (50%) or are students (38%); 50% of the households have an income level above 2500€ per month, the highest share of all clusters.

The high income relates with the ownership of electrical equipment both impacting the quantity and quality of the appliances (*e.g.* Reiss and White (2005)). A large body of literature has also concluded that energy consumption increases with income (Kaza (2010); Cayla *et al.* (2011); Brounen *et al.* (2012)). However, the opposite has also been identified by other studies (*e.g.* Foster *et al.*, 2000). All these socio-economic features can typify middle to high-class family, with two working adults and two children, and explaining the high consumption levels throughout the year but especially in winter and summer seasons.

When evaluating the survey results for the houses in C9, we can conclude that the identical levels of consumption in winter and summer are validated by the dominance of air conditioning systems for cooling and a mix of electric (36%) and non-electric (64%) equipment for heating. The lower ownership and use levels of electrical heating equipment, as oil heaters and HVAC, closes down the gap between both seasons (*i.e.* winter and summer) consumption. Also, supporting the high daily electricity consumption is one of the higher ownership levels of white appliances, computers and lamps of all the clusters. Desktops, laptops, refrigerators, freezers, microwaves, cloth washing machines and televisions have all ownership levels higher than 100%. Cloth drying machines have in this cluster the highest penetration rate of all the clusters. This high daily consumption cluster has the double of the average lamps per household (*i.e.* 20) of the lowest consumption cluster – C1. As expected by the electricity consumption profile, 40% of the houses have a contracted power higher than 6.90 kVA with 62% taking advantage of dual tariff pricing. C9 also can be considered ‘*fat energy*’ households with a different profile, with opportunities for effective reduction of electricity consumption.

The relationship between area, persons per household and consumption portrayed in this cluster is also referred by Larsen *et al.* (2010), Kaza (2010) and Gram-Hanssen (2011) that present the number and the use of appliances correlated to the number of people living in the house; but for Kaza (2010), the space cooling and heating use is likely to be same irrespective of number of people. However, it is more energy efficient to live more people together, as families with more members consume less electricity *per capita* (Larsen *et al.* (2010); Wiesmann *et al.* (2011)).

Our analysis suggests to conclude for three major groups of determinants that influence the residential electricity consumption segmentation: (i) physical characteristics of a dwelling, especially year of construction and total floor area; (ii) electrical heating/cooling equipment and fireplaces ownership and use; and (3) occupants' profiles (mainly number of occupants and monthly income).

2.2.3.2 Insights for policy and stakeholders

The characterization of the dwellings, in terms of construction type, socio-economic factors and equipment, beneath the consumption of the clusters highlight and explain the wide range of electricity consumption profiles, within consumers of the same region. This illustrates the relevance of consumer segmentation for policies and measures design and implementation, tailored to energy reduction.

Following other studies outcomes (*e.g.* Leiwen and O'Neill, 2003), our results unfold that higher average household area also reveals higher energy consumption. However, when comparing the clusters on household occupants we can state that there is (but not on all clusters) a non-linear relationship between household electricity consumption and the number of occupants, as also suggested by Brounen *et al.* (2012), Kavousian *et al.* (2013) and Hayn *et al.* (2014).

According to these four clusters evaluation, we can say that tariff while being similar to several clusters is not a paramount explanatory variable of the segmentation. Furthermore, we might also conclude that gender, type of household occupation contract (contrary to the findings of Ndiaye and Gabriel (2011)) and relation of household members are also variables that not significantly distinct the consumption profiles. Other determinants collected in the surveys which do not make a distinction between clusters; therefore, not being group specific to tackle individually measures are: penetration of electric equipment for DHW, high substitution of incandescent lamps for compact fluorescent lamps and widespread ownership of refrigerators and cloth washing machines near or above 100%.

Our results on typification of electricity consumption profiles and description of the characteristics of the households beneath them, unfolds important results for several stakeholders in the electricity services supply chain. The DSO would benefit from better handling the peak demand, making use of seasonal tariffs and balancing changes in contracted power. Besides, in constrained budget availability and knowing the number of consumers in each cluster, it is important to target measures to the most relevant group of consumers. For example, the U and W shape consumers could benefit from changes of contracted power in the seasonal variations of electricity consumption, reducing their annual expenses with electricity.

Electricity retailers and ESCO's can also benefit from the detailed awareness of consumers' profiles at local level, in order to make tailor-made measures targeted to groups of consumers with similar needs, equipment and socio-economic profiles. In fact, there is a significant difference between groups of consumers within the same municipality, with some consumers struggling to achieve minimum comfort levels in winter and summer months, while others consuming three times the average along the year, which require a well-balanced interplay of policies and measures. For some consumers, focusing on improvement of dwelling characteristics through insulation measures, improvement of roofs, walls and window materials is decisive. For others, the ultimate goal of energy reduction coupling energy efficiency measures (*i.e.* equipment's substitutions) and behavioral changes might be the focus.

2.2.4 Conclusions

This paper examines how the combination of smart meter data and door-to-door survey information can deliver important results and meaningful knowledge regarding households' electricity consumption profiles. Exploratory analysis and hierarchical clustering were applied. The annual consumption profiles were extensively characterized and explained through socio-economic characterization of the household members, dwellings characteristics and equipment ownership.

The analysis of the electricity consumption profiles of 10 clusters, showed four distinct types of annual consumption patterns in the municipality of Évora: U shape (soft and sharp), W shape and Flat, which might bring different insights for public policies and stakeholders decisions. U shape profile is the most common one, covering 77% of the sampled houses, and is characterized by a significant difference of electricity consumption between winter and the rest of the year unraveling the low ownership levels of air conditioning system for space cooling in Évora (confirming also the pattern at national level).

Based on three major groups of electricity consumption determinants: dwelling's physical characteristics, especially year of construction and total floor area; electrical heating/cooling equipment and fireplaces ownership and use; and occupants' profiles, mainly number of occupants and monthly income), we typify and distinguish three main groups of consumers: fuel poverty, standard comfort, and "*fat energy*" households. Therefore, future policies and measures, as well as energy services companies, should take into account these differences to better serve simultaneously energy efficiency and thermal comfort levels.

The fieldwork was conducted in a southwestern European city; however, the methodology can be applied to any region equipped with a smart metering network. This paper also discloses the importance of the future widespread use of smart meters, to benefit both the consumers interest and the stakeholders of the electricity services supply chain. In fact, despite acknowledging that

such a consistent dataset of information with an extensive characterization of consumers is still rare and it is unlikely to be collected by electricity retailers or DSOs, we consider that the outcomes of our analysis could also be used as a starting point for utilities looking at peak shaving and electricity demand shifting inside households derived from market segmentation.

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Authors Contributions

J. P. Gouveia structured and wrote the paper, and performed all the smart meters and surveys data analysis. J. Seixas supported the design of the paper and its in-depth revision.

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Chapter 3 | Zooming in targeted consumers and behaviors

Part 1 - Paper submitted for publication

Gouveia, J.P., Seixas, J., Long, G. *Combining smart meters with surveys, and buildings energy simulation to assess consumer groups: the case of fuel poverty and fuel obesity*. Submitted for publication. Under review.

Part 2 - Paper submitted for publication

Gouveia, J.P., Seixas, J., Mestre, A. *Daily Electricity Consumption Profiles from Smart Meters - Proxies of Behavior for Space Heating and Cooling*. Submitted for publication. Under review.

3.1 Combining smart meters with surveys, and buildings energy simulation to assess consumer groups: the case of fuel poverty and fuel obesity

ABSTRACT

Fuel poverty is a recognized and increasing problem in several European countries. A growing body of literature covers this topic, but dedicated analysis for Portugal are scarce despite the high perception of this condition. This paper contributes to fill this knowledge gap focusing on a European southwestern city while bringing new data sets and analysis to the assessment of consumer groups and to policy discussion. We combine electricity smart meters' registries with socio-economic data, collected from door-to-door surveys, to understand the extent and the determinants of fuel poverty and fuel obesity conditions carried by two contrasting consumer groups based on the amount of electricity consumption. We complement the analysis with buildings energy simulation of typologies presented in those groups, to figure out the heating and cooling thermal performance gaps. The existence of these gaps allowed confirming and/or discarding the initial hypothesis of the poverty or obesity conditions. Our results also disclose socio-economic variables, as income, and consumers' behavior as key determinants of electricity consumption. We also identify a severe lack of thermal comfort levels inside households of both groups, either in cooling (98% for fuel poverty and 87% for fuel obesity) and heating seasons (98% for fuel poverty and 94% for fuel obesity). Major conclusion refers that electricity consumption cannot be used alone to segment consumer groups. This assessment may serve to support energy policy measures and instruments targeted to different consumers' groups. For example, distinct campaigns and differentiated incentives may apply to achieve energy efficiency and reduction while keep or improve comfort levels.

KEYWORDS

Fuel Poverty; Fuel Obesity; Smart Meters; Surveys; Buildings Energy Simulation; Thermal Comfort.

3.1.1 Introduction

The first United Nations Sustainable Development Goal refers ‘*end poverty in all its forms everywhere*’ and the seventh ‘ensure access to affordable, reliable, sustainable and modern energy for all’. Among other objectives, these goals set the background for analysis of energy equity issues and fuel poverty eradication (UN, 2015). Fuel poverty (FP) is increasingly becoming a problem in European countries as acknowledged by the European Council Directive 2009/72/EC and European Commission (2015). Atanasiu *et al.* (2014) estimate that between 50 and 125 million people are unable to afford proper indoor thermal comfort. Nevertheless, despite the pan-European dimension of the problem, no consistent and common definition of fuel poverty is used in Europe Union (EU) countries.

For the purpose of this paper, we adopt the definition used in the Republic of Ireland and United Kingdom (UK), stating that fuel poverty occurs when ‘*households are unable to afford adequate energy services in the home at reasonable cost, while spending more than 10% of its disposable income on energy services*’ (Department of Communications, Energy and Natural Resources, 2011; Department of Energy and Climate Change, 2013). This includes all uses of energy and considers the thermal comfort levels needed and not just what is effectively being consumed. For this matter, the combination of low incomes (Wright, 2004; Saunders *et al.*, 2012; Moore, 2012); low performance dwellings with defective insulation (*i.e.* windows, walls, roofs) (Shortt and Rugkasa, 2007, Morrison and Shortt, 2008), older household occupants (EPEE, 2009) and high costs of energy (Atanasiu *et al.*, 2014) are enablers of fuel poverty.

Commonly, proxy indicators have been used to estimate fuel poverty, such as the ones included in the EU Statistics on Income and Living Conditions (EU - SILC) like: inability to keep home adequately warm; arrears on utility bills; the presence of a leaking roof, damp walls, floors or foundation, or rot in window frames or floor (Thomson and Snell, 2013). For Thomson and Snell (2014) the surveys behind those indicators were not designed to measure fuel poverty and as such provide imperfect estimates of the problem and are insufficient to identify the source of the problem.

As recognized by Thomson and Snell (2013), knowledge on fuel poverty in UK and Ireland is well established, with a strong focus on heating demand (Healy and Clinch, 2002a). A lot of work has also been also carried out focusing on the impacts of fuel poverty on health (Healy, 2003; Marmot Review Team, 2011) since the impact of temperature and damp upon the body are significant (Sumby *et al.*, 2009).

Despite a growing body of literature covering several European countries (e.g. Brunner *et al.*, 2012; Atanasiu *et al.*, 2014; Pye *et al.*, 2015; Schumacher *et al.*, 2015), fuel poverty is a particular problem for southern European member states, as acknowledged by Thomson and

Snell (2013) and Wand (2013), and are expected to suffer from summer average temperature and heat waves increase, as a consequence of climate change impacts. Evaluation of countries where the heating might not be the only problem, as in EU southern countries (e.g. Portugal), has been recurrently dismissed. For Bouzarovski (2014), due to the major social and geographical differences in the incidence of energy poverty within the EU, policies tackling this issue are best delivered at the regional scale.

Despite being a warm southern EU country with mild winters, several facts point Portugal as severely endangered by fuel poverty issues. Healy and Clinch (2002b) set Portugal within the group of EU countries with the poorest housing status (as Greece, Ireland and UK) with consequences in the levels of excess winter deaths. Between 2007-2012, Portugal has ranked first or second in this EU28 ranking.

In 2014, Portugal had 27.5% of people at risk of poverty; 20.9% of people with arrears on utility bills, 28.3% of people enabled to keep home adequately warm, 35.7% living in a dwelling not comfortably cool during summer time (2012 data) and 32.8% of dwellings with leakages and damp walls (Eurostat, 2015). Portugal is one of the European countries with a high inequality of income distribution; with a GINI index of 34.5% in 2014, above the 31% for EU28 average (PORDATA, 2016a), whilst around 30% of the population receives social tariff support for the payment of the electricity and natural gas bills. A combination of these indicators sets the scene to identify the share of people at risk of poverty who are affected by fuel poverty. According to Bouzarovski (2014), Portugal ranks in the top three EU countries of fuel poverty risk, mainly justified by the lack of thermal comfort levels inside households. Simões et al. (2016) delve into this issue using CENSUS 2011 data to map vulnerable elderly people in 29 municipalities across the country. In Portugal, there is no legal definition of fuel poverty in place and data availability for analyzing is limited and with no monitoring system. Additionally, in 2016, the electricity and natural gas prices for families, with all taxes included, were respectively 13% and 38%, higher compared to EU28 average (PORDATA, 2016b). All these indicators have continuously been increasing in recent years stressing the need for an in-depth and dedicated studies on fuel poverty for Portugal.

For our analysis, two very contrasting electricity consumer groups were selected, building on earlier work from Gouveia and Seixas (2016). This paper assesses the household electricity consumption profiles of these two contrasted consumers' groups aiming to disclose fuel poverty conditions. We use a group of consumers under possible fuel obesity conditions, for a better comparison analysis while extending the validation of the methodology. Under this paper, we use the expression fuel poverty to refer to depict households characterized by typical enablers of fuel poverty as depicted above, and fuel obesity to refer a household with the highest electricity consumption of the city or region. While the former may suggest energy deprivation for basic

energy needs, the later might suggest inefficient and unsustainable energy consumption practices.

We combine electricity smart meters' registries with data collected from door-to-door surveys (e.g. socio-economic of household's occupants, dwellings characteristics and equipment ownership and use) to extract the determinants of energy consumption. We bring in additional data sources as energy simulation data for a better understanding of thermal comfort levels in consumers with significant distinct consumption levels. The Portuguese municipality of Évora is used as a case study. Numerous authors already acknowledged those parameters as important determinants of energy consumption (e.g. Kowsari and Zerriffi (2011); Ndiaye and Gabriel (2011); Bedir *et al.* (2013); Rhodes *et al.* (2014); Jones *et al.* (2015); Huebner *et al.* (2015); Ürge-Vorsatz *et al.* (2015); Risch and Salmon (2017); Seebauer and Wolf (2017); Yoo *et al.* (2017)).

The combination of those three data sources is innovative and contributes to fill the knowledge gap on contrasting energy consumer groups as in possible fuel poverty and fuel obesity conditions in Portugal, whilst assessing the heating and cooling thermal comfort performance gap to validate the hypothesis of the existence of such groups. The determinants of energy use are coupled with households' energy simulations to verify socio-economic energy behavior.

The rest of this paper is organized as follows. In Section 3.1.2, the case study, methodology and the three different datasets used are described. The results, discussion and characterization of the consumers under fuel poverty and fuel obesity are depicted in Section 3.1.3. The conclusion is presented in Section 3.1.4.

3.1.2 Methods

The methods adopted in our study combines qualitative and quantitative data from household surveys, daily electricity consumption data and energy simulation of buildings typologies to track fuel poverty and possible fuel obesity groups at a municipality level, conveying a disaggregated analysis as pointed by Scarpellini *et al.* (2015). This approach brings new data sets to the fuel poverty discussion and assessment, namely for Portugal. Figure 3.1 depicts the overall process and the specific goals and methods used. Their interactions are explained in next sections.

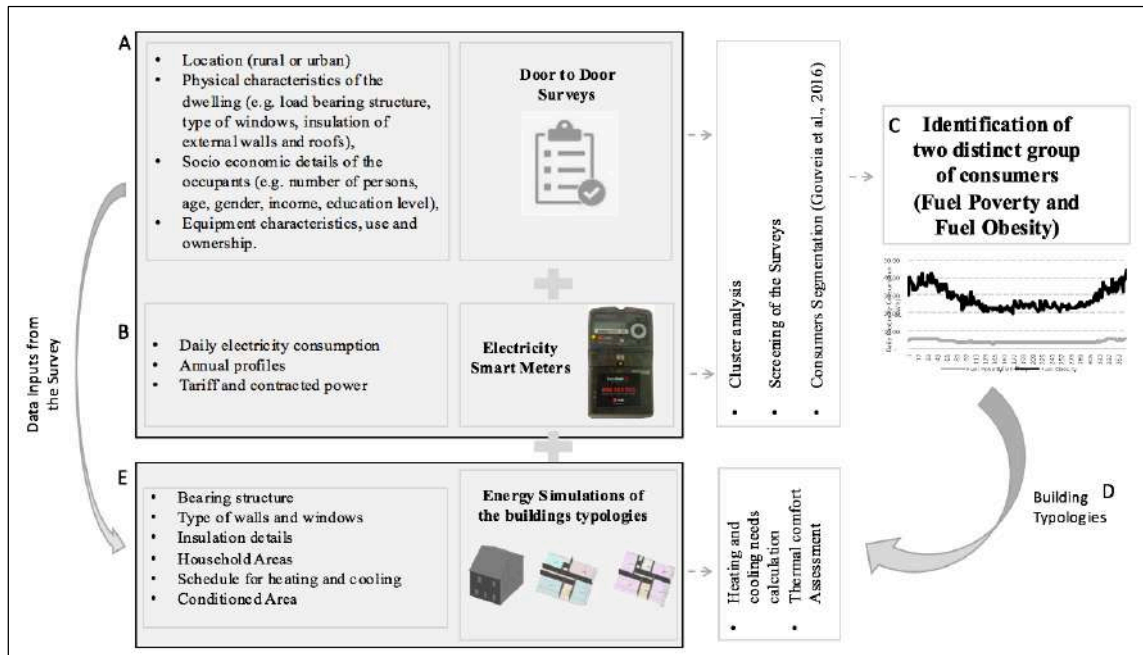


Figure 3.1 – Overall methodology to identify contrasting consumers and to assess their thermal comfort gap

3.1.2.1 Case study – municipality of Évora, Portugal

The municipality of Évora is located in Alentejo region, in Portugal, covering 1307 km², with almost 57 000 inhabitants (INE, 2011). In 2014, the residential sector represented 15% of the overall city final energy consumption. The *per capita* annual final energy consumption was around 48 GJ, which compares with 61 GJ for the average of the country (PORDATA, 2014).

Évora, with a Mediterranean climate type (Köppen-Geiger climate classification), has an annual average temperature of 15.8°C, but high monthly thermal amplitudes are observed. August presents the highest temperature monthly average (23.3°C) and January the lowest (9.3°C). The lowest temperature ever recorded was -5°C and the highest 44.5°C (IPMA, 2016). These specificities on climate require specific dwellings construction, that should foster solar gains in the winter, and restrict the solar gains in the summer, promoting strong thermal inertia and evaporative cooling (Gonçalves and Graça, 2004).

The Portuguese Decree Law n. ° 118/2013 sets the conditions for the energy performance of residential buildings in Portugal, and defines a heating season indoor thermal comfort temperature of 18°C and for the cooling season of 25°C. The difference between the two indoor temperatures (the one from the energy balance and the comfort temperature) drives the existence of space heating and cooling needs, depending on the season. In turn, the temperature difference between the air inside and outside a dwelling lead to heat flows between these two places.

3.1.2.2 Door-to-door surveys (A)

Data for buildings and households' characterization is available in the EU at the CENSUS each 10 years. Surveys on households' energy are increasingly available in several developed countries and carry significant knowledge on energy related issues (*e.g.* EIA, 2009; INE and DGEG, 2011). However, most of these studies and statistics are presented at national or multi regional level, with no city spatial detail. Therefore, the information cannot be combined for a comprehensive analysis, missing the characterization of the determinants of energy consumption and of groups of consumers at municipal/city scale.

We conducted 389 door-to-door surveys during summer 2014 (Gouveia *et al.*, 2015) aiming to characterize the residential buildings and to identify distinct groups of electricity consumers of the municipality of Évora, within the EU INSMART project (www.insmartenergy.com). The survey included 110 questions covering information about location, physical characteristics of the dwelling (*e.g.* load bearing structure, type of windows, insulation of external walls and roofs), socio-economic details of the occupants (*e.g.* number of persons, age, gender), appliances characteristics, use and ownership.

Thomson and Snell (2014) proposed a survey exclusively dedicated to evaluate fuel poverty, which allowed us to follow some of their recommendations to the EU SILC survey and for a future EU28 household survey on fuel poverty. Our survey therefore included questions regarding the heating and air conditioning equipment, energy efficiency questions concerning insulation and window glazing, the type of energy sources used for primary and secondary heating and socio-economic details, as income and age of occupants.

3.1.2.3 Electricity smart meters (B)

Évora was the first region in Portugal (in 2010) equipped with a massive electricity smart metering system (around 31 000 meters delivering 15 minutes' registries) (EDP Distribuição, 2015), which brought new, high resolution and big data sets on electricity consumption. The increasing availability of detailed and high granular power consumption data makes it easier to assess of how energy is being used in households.

Cross referencing survey and smart meter data makes it possible through analytical processing, data mining and data visualization to identify and highlight relevant consumption profiles, portray vulnerable consumers, assess potential role of energy efficiency measures and possible energy equity issues in energy use. After a data wrangling and cleansing to identify missing of sporadically daily registries; missing several days/months in sequence, a final sample of 265 meters with electricity consumption data averaged daily for four years (2011-2014) was used, preserving the intra-annual variability for each household (Gouveia and Seixas, 2016).

3.1.2.4 Consumers segmentation and characterization (C)

From the two data sets, an in-depth analysis and identification of different consumers was made through segmentation, using clustering analysis of electricity consumption, applying Ward's Method. The objective was the identification of distinct yearly electricity consumption profiles and daily consumption levels, to uncover distinct groups of electricity consumers. The door to door surveys were used to support and explain that segmentation and to characterize the households within the groups. Data from the surveys portray the determinants driving energy consumption and the characteristics (e.g. dwelling characteristics, occupants' profiles, electrical appliances ownership and use) of each group, allowing to isolate key consumers to consider for policy development and implementation.

From the information collected with the households' survey, we retain the following variables to characterize the households in each group: (i) location (Urban and Rural), (ii) dwelling type, (iii) dwelling age, (iv) dwelling total floor area, (v) type of glazing and windows framing, (vi) bearing structure and (vii) type of external walls. The socio-economic variables, which might influence electricity consumption, were selected: (i) the number of occupants (ii) education of the household responsible person (iii) household income and (iv) employment status. Factors associated with electrical appliances and heating and cooling equipment were also selected: (i) ownership of heating and cooling, (ii) ownership of white electrical appliances, (iii) type of tariff and (iv) contracted power.

From the analysis previously developed in Gouveia and Seixas (2016), ten clusters of consumers were established, two groups are highlighted and deeper analyzed in this paper due to their significant different average daily consumption (*i.e.* 4 kWh vs. 28 kWh) and different monthly electricity consumption levels portrayed in the annual profile. One of the two consumer groups, is recognized to be in fuel poverty due to their consumption levels and socio-economic characterization, while the other group, present high average daily consumption levels (total and per square meter) suggesting obesity patterns of electricity use including inefficient equipment use or redundant consumption. Therefore, in the context of this research these two designations are used to convey those two contrasting groups.

3.1.2.5 Energy simulation of buildings (D and E)

This paper describes a more detailed assessment, cross validating these results of consumer groups with energy simulations of heating and cooling needs for those households' building typologies. This allows levels of indoor thermal comfort, for both heating and cooling, to be confirmed. It also enables the testing of whether they are being effectively delivered and at what

extent the results from the electricity consumption profiles are reliable while used as a method for tracking fuel poverty and fuel obesity patterns and consumers.

The city residential building stock was characterized with a selection of relevant building typologies based on building form (*e.g.* detached, semi-detached and terraced houses), period of construction (*e.g.* pre-1945, 1946-1990, after 1991), number of floors (*e.g.* one or higher) and roof types (*e.g.* sloped, flat) using statistical information from the CENSUS 2011 (INE, 2011). Relevant criterion for the selection of typologies was the frequency of more than 5% representation in each civil parish and the availability of data for its characterization.

Therefore, 10 representative residential buildings typologies were defined (Gouveia *et al.*, 2015), as presented in Table 3.1. The majority of the residential buildings in the city were constructed in the 1946-1990 period (TP2, 5, 8 and 9), which account for over 60% of the stock. Of this group, TP8s, terraced houses built between 1946 and 1990, are the most common type of housing found in the city representing over a quarter of the stock alone. The older (pre-1945) and more modern (post 1991) properties each represent just under 20% of the stock each. Most of the older and newer buildings are terraced properties, TP7 and TP10 respectively. The 10 typologies were expanded into 26 sub-types, to include additional characteristics collected in the surveys. The sub-typologies were then allocated to each consumer group according to the building type presented.

Table 3.1 –Representative buildings sub typologies identified for the city of Évora

Typology Code	Building Type	Period of Construction	Number of Floors	Roof type	Room in roof	Wall Material	Roof Insulated
TP1.1_1	Detached	Until 1945	1	Pitched	No	Brick Single	No
TP2.1_1	Detached	Between 1946-1990	1	Pitched	No	Brick Single	No
TP2.1_14	Detached	Between 1946-1990	1	Steep	No	Brick Single	No
TP2.2_1	Detached	Between 1946-1990	2	Pitched	No	Brick Single	No
TP2.2_12	Detached	Between 1946-1990	2	Pitched	Yes	Brick Single	No
TP3.1_1	Detached	After 1991	1	Pitched	No	Brick Single	No
TP3.2_1	Detached	After 1991	2	Pitched	No	Brick Single	No
TP4.1_1	Semi-detached	Until 1945	1	Pitched	No	Brick Single	No
TP4.2_7	Semi-detached	Until 1945	2	Pitched	No	Stone	No
TP5.1_1	Semi-detached	Between 1946-1990	1	Pitched	No	Brick Single	No
TP5.2_5	Semi-detached	Between 1946-1990	2	Pitched	No	Brick Double	No
TP5.2_52	Semi-detached	Between 1946-1990	2	Pitched	No	Brick Double	No
TP6.1_1	Semi-detached	After 1991	1	Pitched	No	Brick Single	No

TP6.1_11	Semi-detached	After 1991	1	Pitched	Yes	Brick Single	Yes
TP6.2_5	Semi-detached	After 1991	2	Pitched	No	Brick Double	No
TP5.2_51	Semi-detached	After 1991	2	Pitched	Yes	Brick Double	Yes
TP7.1_1	Terraced	Until 1945	1	Pitched	No	Brick Single	No
TP7.2_1	Terraced	Until 1945	2	Pitched	No	Brick Single	No
TP8.1_1	Terraced	Between 1946-1990	1	Pitched	No	Brick Single	No
TP8.2_1	Terraced	Between 1946-1990	2	Pitched	No	Brick Single	No
TP9.2_13	Terraced	Between 1946-1990	2	Flat	No	Brick Single	No
TP10.1_1	Terraced	After 1991	1	Pitched	No	Brick Single	No
TP10.1_12	Terraced	After 1991	1	Pitched	Yes	Brick Single	No
TP10.2_1	Terraced	After 1991	2	Pitched	No	Brick Single	No
TP10.2_11	Terraced	After 1991	2	Pitched	Yes	Brick Single	Yes
TP10.2_13	Terraced	After 1991	2	Flat	No	Brick Single	No

The energy simulations to assess heating and cooling of the buildings typologies were carried out using Design Builder (DB, 2015) and EnergyPlus (DOE and NREL, 2015), building upon the data collected on the surveys to fully characterize each residential typology; delivering results for energy services demand on space heating and cooling. The simulation of the energy use of the housing stock of Évora was carried out in accordance with the methodology described in Long et al. (2015).

The World Health Organization provides guidance on what temperatures should be achieved in homes, to ensure that occupants feel comfortable and remain healthy. Temperatures between 18°C and 24°C are generally agreed to be the ‘comfort zone’ and pose little risk to health (WHO, 1987). Following these recommendations and the Portuguese regulation (i.e. Decree Law n. ° 118/2013), we defined the set point temperatures for the energy simulation during heating and cooling season as 18°C and 25°C, respectively. National legislation considers to be applicable across the whole of the dwelling and throughout the heating and cooling seasons. A lower level of thermal comfort for a reduced time schedule and conditioned dwelling area was modelled in order to better consider real conditions in Évora. The time schedule and the conditioned area used in the simulations differ by sub typology, based on the survey results. An average conditioned household area of 71%, 3.8 hours of heating systems operating hours and 1.8 of cooling operating hours were considered per day.

3.1.2.6 Thermal comfort performance gap

Following the methodology presented in Simões *et al.* (2016), we estimated the thermal comfort performance gap per square meter (kWh/m²) for the two distinct consumer groups. This was based on the difference between the daily electricity consumption for heating and cooling, in the heating season (5.3 months – 162 days) and cooling season (4 months – 122 days) and the final energy (i.e. electricity) that would be needed to ensure the indoor thermal comfort levels to meet the indoor reference temperatures.

We estimated the daily electricity consumption per square meter for space heating and cooling considering the share from total electricity use, consumed for space heating (9.1%) and cooling (1.6%), following the national survey carried out to residential dwellings in Portugal (INE and DGE, 2011). The final energy (electricity) associated with the energy services demand output from the sub typologies simulation work was calculated using electrical heating (*i.e.* 90%) and cooling (100%), from the door to door surveys; the ownership rate of heating and cooling technologies per consumer group from the surveys and average energy efficiencies of space heating and cooling technologies obtained from ETSAP (2012); *e.g.* open fireplace=0.35; air conditioner= 2.38.

The next section presents the results achieved for the different steps. We intertwine it with a wider discussion about potential fuel poverty and fuel obesity in the studied consumer groups, uncovered by the datasets and methodologies used.

3.1.3 Results and discussion

In this section, we present and explore the results for the two selected consumer groups, from the three datasets, door-to-door surveys, smart meters and building's energy simulation. We aim to understand how to characterize those groups of consumers that may be useful to guide researchers and electricity market stakeholders to capture such consumers' group from smart meters. Moreover, such characterization is of high interest to suggest the integration of renewable energy sources, and to propose energy efficiency or/and energy reduction measures, based on the thermal comfort performance gap gathered in the heating and cooling season.

3.1.3.1 Smart meters and surveys

Primary objectives of the combination of residential buildings survey and electricity consumption data analysis were twofold: 1) aggregate groups of consumers based on their annual consumption profiles and 2) highlight the main differences and similarities amongst the determinants of consumption of the households of each group. This first assessment allows us to use an eagle eye into fuel poverty and possible fuel obesity issues.

The clustering method applied in Gouveia and Seixas (2016), split the sample in 10 clusters. For the purpose of this paper, we extracted the two extreme consumer groups that may represent households possibly under fuel poverty (FP) and under fuel obesity (FO). The box-and-whisker plot (Figure 3.2) discloses the descriptive statistics of those consumer groups (regarding their dispersion and skewness), and the outliers. The distribution of electricity consumption data from the two groups is very distinct, with the Fuel Poverty group presenting the lowest statistics with a very low daily average, standard deviation, minimum and maximum levels of daily consumption (Table 3.2). All the descriptive statistics of the Fuel Obesity group are around sevenfold higher than Fuel Poverty group, except the annual consumption per square meter, which is still four times higher in the FO group.

Since the households are located in the same city, being similarly impacted by climate conditions, we exclude weather as a determinant that justifies the differences of the consumption profiles of the two groups. Nonetheless, the electricity consumption profiles (Figure 3.3) and its comparison with average daily temperatures indicate seasonal patterns of consumption due to energy consumption for climatization, mostly noticeable in the heating season where the role of electricity for climatization is clear. The correlation of FP daily load profile with the average daily temperature, points to -0.72 while of FO to -0.82, meaning that the impact of heating season (*i.e.* low temperatures with high electricity consumption) prevails over the cooling season.

Both groups present around twofold increase in electricity consumption in winter compared to summer. This might be portraying the inexistence or low use of space cooling equipment in the summer compared to a higher use of electricity-based technologies for space heating in the colder months of winter (December, January and February).

Table 3.2 – Descriptive statistics of daily electricity consumption for both consumer groups

Consumer Group	N	Minimum (kWh)	Mean (kWh)	Maximum (kWh)	Standard Deviation (kWh)	Annual Consumption (kWh)	Annual Consumption per square meter (kWh/m ²)
Fuel Poverty	366	3.2	4.2	6.1	0.82	1541	17.1
Fuel Obesity	366	20.3	28.2	44.2	5.8	10314	61.4

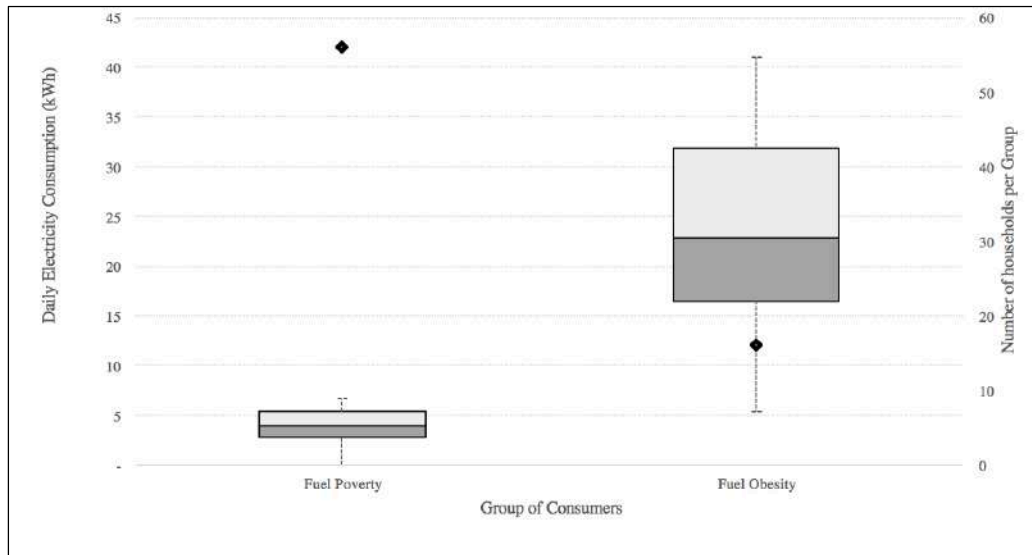


Figure 3.2- Daily electricity consumption (box and whisker plot) and number of households (black squares) per consumer group

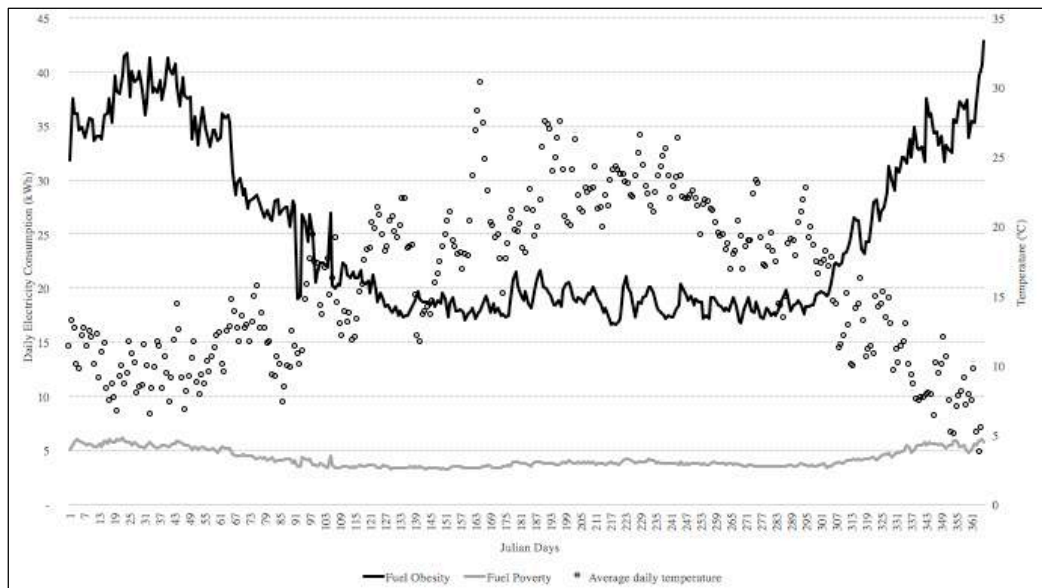


Figure 3.3 – Electricity consumption profile along the year for the two distinct consumer groups and average daily temperatures (both averaged 2011-2014)

A number of authors identified determinants of energy consumption for diverse regions based on different datasets and methodologies: Hojjati and Wade (2012), presented heating and cooling use as very sensitive to living space, while Vassileva *et al.* (2012) indicated surface area as the variable closest to energy consumption. Also for Rue du Can *et al.* (2010), the growth of floor space per household is one of the major drivers explaining the increase in energy consumption in developed countries. In mild climates, however, floor space may be of less importance as a driving force of energy consumption, as Kaza (2010) and Kowsari and Zerriffi (2011) showed for larger households with higher total energy consumption, but have lower *per capita* energy consumption due to economies of scale and volume to surface ratio.

The survey results allow to better understand the consumption levels and patterns of both consumer groups portrayed in the previous figures. As depicted in Table 3.3, several dwellings characteristics arise as significant determinants of the differences in the households' electricity use.

While the majority of households in both groups are located in urban areas ($\approx 60\%$), there are significant differences in type of houses - detached houses (18% in FP vs. 44% in FO), dwelling size (90m^2 in FP vs. 168m^2 in FO); age of construction (91% previous to 1990 in FP vs. 75% in FO); bearing structure (76% masonry walls in FP vs. 57% in FO) and wall (brickwork single layer, rammed earth and stone represent 91% in FP vs. 53 in FO) and windows materials (83% have single glazing and wooden window (60%) framing in FP vs. 71% of aluminum and single glazing (75%) in FO. All these variables *de per se* might explain the different levels of electricity consumption between both groups, since each of them plays a significant role in energy needs for heating and cooling, affecting the thermal comfort of occupants.




From our results, when addressing occupants' characteristics, we also identify important variables that explain the sevenfold difference in consumption between the two consumer groups. The consumers under fuel poverty can be styled by small families (2 persons per household), with older members (42% over 65 years old) and low levels of education (64% under the 9th grade with zero graduates). 47% are retired with only 30% working full time, resulting in 60% of the households with an average monthly income of less than 750€. The potential Fuel Obesity households are characterized by a higher number of persons per household (2.8), less elderly people but with more children (27% over 65 years old and 14% of occupants under 18 years old). The household members have higher levels of education and with full time jobs - 62% graduated, 46% working full time while only 30% are retired which is a significant contrast to the other group, resulting in 33% of the households' average monthly incomes being above 2501€.

Our assessment is in line with other authors' assessment on the role of occupants on energy consumption. According to Brounen *et al.* (2012), the age of the head of the household is significantly related to gas consumption, but age is not monotonically related to electricity consumption. The elderly may spend more time at home, but they seem to have fewer energy-consuming appliances— elderly households consume about two to four percent less electricity than middle-aged married couples do. The small difference between single elderly households and elderly households with two or more people may result from the fact that all elderly households typically spend more time in their residence, which obviates any economies of scale that are more common among families (Brounen *et al.*, 2012). Ellegård and Palm (2011) also identified occupant age as an important aspect influencing the use of appliances.

Energy conversion technologies also play a key role in household energy use, explaining differences, both in the amount and variability, in consumption throughout the year. Comparing the two groups, once again significant differences of ownership and type of equipment arise. For space heating, only 46% of the households under fuel poverty have heating equipment and the bulk (i.e. 90%) are electrical. The households under the FO group have almost 90% of heating equipment ownership (with 71% electrical and the remainder being fireplaces). Despite a lower share of electrical equipment in these households group, the energy use is still much higher. Regarding cooling equipment, the difference is also meaningful, not only in the ownership levels (46% FP vs. 75% FO) but also in the type of equipment (73% fans in FP vs. 75% air conditioners in FO). Nonetheless, a disparity can be recognized in the yearly consumption profile in both groups to the information on ownership collected from the survey, which identifies that the existence of the equipment does not mean that it is being used. This is especially true for air conditioning systems, as also shown in national statistical consumption data for space cooling representing just 1.6%.

Contrasting ownership of white appliances and other electrical equipment (as televisions, computers, lighting systems) is also identified, with the group under FP not reaching saturation in several uses (67% owns computers; dish washer 29%, freezers 61%), while in the FO group, a saturation in several end-uses and equipment (*e.g.* microwaves, washing machines) is observed. For this group, there might be an excess ownership of several appliances, with households having more than one (1.6 computers; 1.14 refrigerators, 2.3 televisions).

Table 3.3 – Survey variables related to dwellings and occupants' characteristics and equipment ownership

	Equipment ownership 	Occupants characteristics 	Dwellings characteristics 
Fuel Poverty Group	<ul style="list-style-type: none"> Space heating equipment ownership 46% <ul style="list-style-type: none"> ► 90% electricity Space cooling equipment ownership 46% (75% fan coils and 25% AC) Domestic hot water 94% non electric Low penetration of several white appliances (dish washing machines (29%) and freezers (61%)) Lighting spots per household - 9.4 (2% LED) Installed power lower than 3.45kVA 79% Single vs dual tariff (71%/29%) 	<ul style="list-style-type: none"> Average of 2 persons per household Occupants older than 65 years old 42% Occupants younger than 18 years old 7% 60% owner occupied houses Level of education: 64% under 9th grade, 0% graduated Occupation: retired (47%), working full time (30%) monthly income (average) below 750€ (60%), 0% above 2501€ 	<ul style="list-style-type: none"> Urban houses 61% Terraced houses 52% Period of construction) 55% between 1946 and 1990; 36% before 1946 House size (average) 90 m2 Masonry walls 76% Brickwork single layer, rammed earth or stone walls 91% Single glazing 83% Wooden framed windows 60%
Fuel Obesity Group	<ul style="list-style-type: none"> Space heating equipment ownership 88% <ul style="list-style-type: none"> ► 71% electricity Space cooling equipment ownership 46% (77% fan coils and 73% AC) Domestic hot water 88% non electric High penetration or saturation of almost all white appliances Lighting spots per household 18.1 (9% LED) Installed power higher than 6.9kVA 94% Single vs dual tariff (50%/50%) 	<ul style="list-style-type: none"> Average of 2.8 persons per household Occupants older than 65 years old 27% Occupants younger than 18 years old 14% 88% owner occupied houses Level of education: 23% under 9th grade, 62% graduated Occupation: retired (30%), working full time (46%) monthly income (average) below 750€ (11%), 33% above 2501€ 	<ul style="list-style-type: none"> Urban houses 63% Terraced houses 19% Period of construction) 50% between 1946 and 1990; 25% before 1946 House size (average) 168 m2 Masonry walls 57% Brickwork single layer, rammed earth or stone walls 53% Single glazing 75% Aluminium framed windows 75%

The approach anchored on the use of daily electricity consumption data evaluated by a cluster analysis, proved to be a powerful tool for consumer segmentation (Gouveia and Seixas, 2016).

The combination with survey data has proved effective to characterize the two groups of interest for the analysis in this paper. The socio-economic data combined with the annual consumption profiles uncovers potential lack of thermal comfort levels inside households both in summer and winter for the FP consumer group, but it is not clear for the FO group and needs further enlightenment. The high levels of daily electricity consumption (over 40 kWh/day) together with its descriptive socio-economic variables could indicate fuel obesity patterns. Yet, when looking deeper in the two distinct annual consumption profiles, different conclusions might be drawn. In a region with very hot summers (average temperature around 23°C) that might require high cooling demand, substantial differences in summer and winter months' electricity consumption might suggest lack of thermal comfort levels, in summer months.

3.1.3.2 Energy simulation of buildings typologies and thermal comfort performance gap

From the predefined 27 buildings sub-typologies, 15 are present within the Fuel Poverty group; while 10 exist in the Fuel Obesity group, showing a wide diversity of buildings characteristics among similar electricity consumers profiled groups. A breakdown of the results of the EnergyPlus simulations for the energy services demand for regulated heating and cooling (i.e. heating and cooling under temperature set points according to the current regulation), shows differences in annual energy services demand for climatization per square meter across the sub typologies of the same group (Figure 3.4), as expected. This is explained by the different bearing structures, construction materials and other dwelling variables extracted from the door to door surveys. However, the similar average heating (77 kWh/m² for FP group dwellings and 81 kWh/m² in FO) and cooling demand (5.7 kWh/m² for FP group dwellings and 6 kWh/m² for FO) suggests that, for our case study, behavior and socio-demographic characteristics are more significant determinants of energy consumption than building construction characteristics.

Following the methodology described in section 3.1.2.5, we assessed the thermal comfort performance gap for both consumer groups, calculating the difference between the final electricity consumption required to fulfill the regulated thermal comfort level and the real electricity consumption, derived from the meters for space heating and cooling. As depicted in Figure 3.5, the results reveal a severe thermal comfort gap within the fuel poverty consumer group namely 98.5% for space heating and 98% for space cooling, even in a very reduced climatization schedule. These outcomes backup our previous conclusions from the annual consumption profile and survey results, which pointed for characteristics of fuel poverty conditions. The simulation results further stress the conclusions from the annual electricity profile analysis, where fuel poverty issues related to cooling demand are also of utmost importance, particularly in countries/regions expected to suffer from average temperature

increase due to climate change, as the case study. We conclude that fuel poverty is prevalent amongst the households in this group though a detailed appraisal of individual households could suggest that not all households might be under fuel poverty in equal measure.

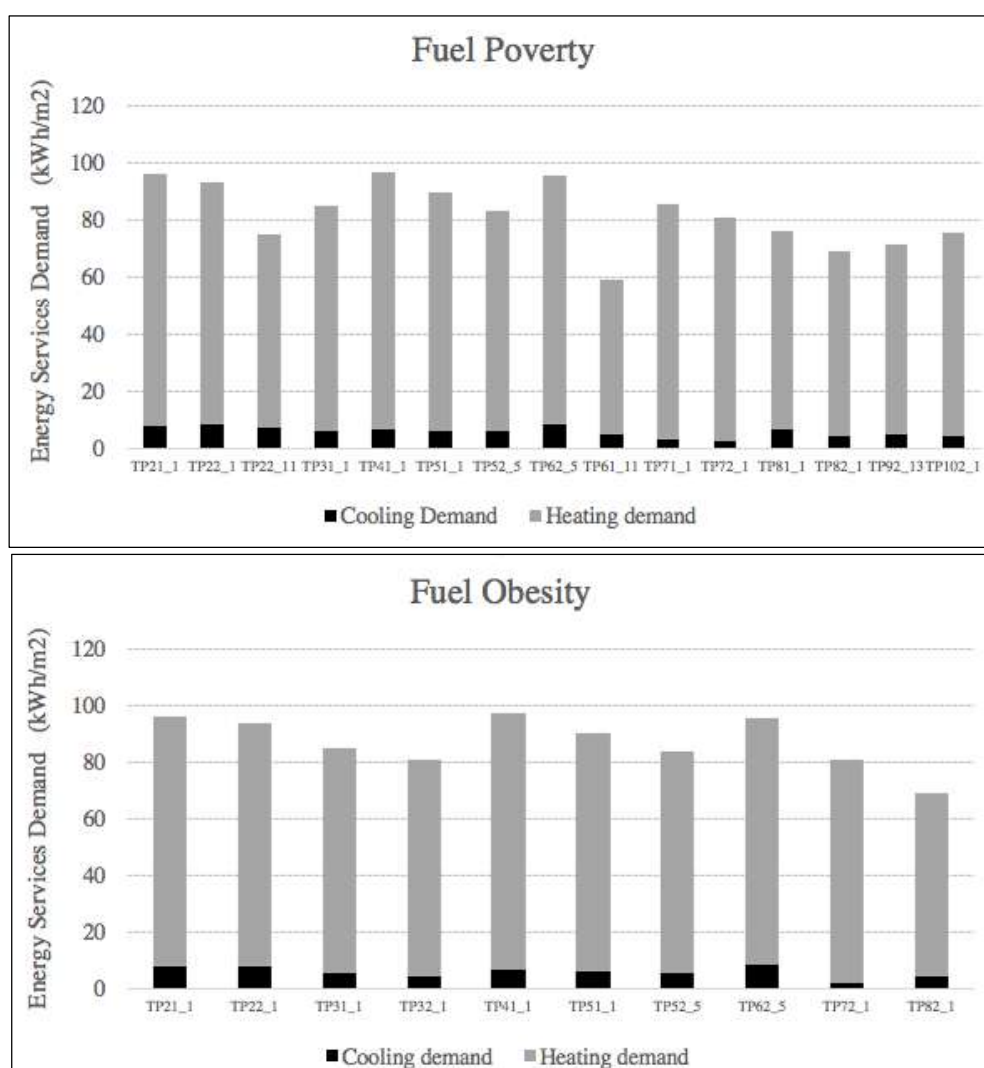


Figure 3.4 – Heating and cooling annual energy demand for the typologies of the two consumer groups: fuel poverty (top) and fuel obesity (bottom)

In the case of the potential fuel obesity group, and contrary to what could be expected from the annual consumption profiles and socio-economic determinants, the thermal comfort performance gap appears still very high. Despite the levels of consumption in this group are around sevenfold the other consumers group, the calculated gap is 94% for space heating and 87% for space cooling, still high values and close to the other group. This is due to the similar average demand for space heating and cooling between the two groups, but bigger households in the FO group. Real measured consumption is still far from fully satisfaction of “ideal” indoor thermal comfort levels and was also revealed by the substantially lower consumption in summer identified in the annual consumption profiles. But these conclusions can only be straightforward applied to the cooling season, since we are assessing just electricity for climatization. For space

heating, in households with both electric and non-electric climatization, the use of e.g. fireplaces, may partly bridge this gap, presenting this estimations as conservative. Nonetheless, these performance gaps are aligned with the results from Palma (2017), where a widespread lack of thermal comfort across the majority of Portuguese civil parishes was assessed (*i.e.* 88.2% gap for space heating and 94% for space cooling in the city of Évora), under less conservative schedules and household conditioned areas.

The thermal comfort performance gaps for both groups allow to derive some important conclusions for this region and sample. The results stress the importance of addressing the fuel poverty problem and the need for increased awareness and policy support. From the surveys, we identified the ownership of both space cooling and heating equipment, but these results clearly show that having the equipment does not mean it is used. This can be partly justified by the high costs of energy for families, as stated in Section 1, when compared to EU28 average. According to IEA (2016), electricity prices in Portugal are relatively high by IEA standards and they have been increasing significantly over the past decade. From 2008 to 2013, final electricity prices increased annually on average by 8.8% for household customer.

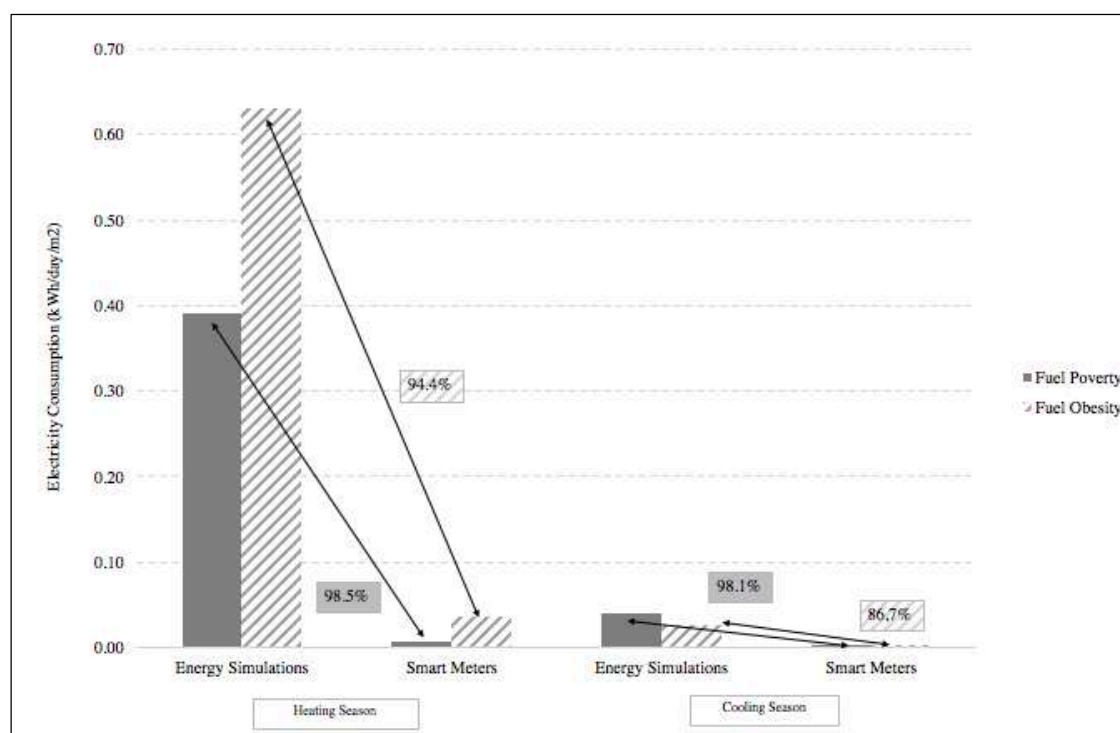


Figure 3.5 – Heating and cooling thermal performance gaps for both consumer groups

Another important outcome from the results is the significance of behavior and of socio-economic details (as income). Therefore, income is a relevant determinant that explains the consumption differences from both groups. Seebauer and Wold (2017) identify the influence of income on electricity consumption, highlighting that instead of influencing daily electricity consuming routines, the income level could drive appliance purchases, setting a household's

base electricity load, which is also aligned with the idea of bringing for discussion the fuel obesity group.

Energy prices and a general low ownership of cooling equipment in the city (and country) partly explain the high thermal performance gap for both consumer groups in the cooling season. However, in Portugal, as other Mediterranean countries, the use of traditional cooling techniques (opening windows during the night, shading device) are very common, allowing the occupants to minimize higher indoor temperatures. We argue that these cultural habits partly explain the high values of thermal comfort gaps, also in the Fuel Obesity group. Further analysis should be carried, for example based on direct inquiries of the occupants on their thermal comfort, instead of assessing it through energy consumption analysis.

We acknowledge some boundaries to our performance gaps results derived from the assumptions used, as follows: a) despite supported by information of ownership and use of other energy sources from the door to door surveys, our methodology only address electricity consumption, b) we assume average equipment efficiencies for the conversion of energy services calculated from the simulations to final energy demand; and c) due to lack of local information, we use national indicators on the electricity consumption used for heating and cooling.

However, despite these limitations, we were able to draw important conclusions on consumer segmentation groups, deepening the understanding on consumers under fuel poverty conditions and the main drivers for that. But it becomes evident that our first perception in defining the second group of consumers, as a fuel obesity group, based on the electricity consumption levels, can be understood as panglossian after an accurate analysis of the actual thermal comfort gaps. This raises the importance of combined assessments supported by multiple datasets for robust conclusions.

Therefore, despite the differences in electricity consumption patterns, both consumer groups still need to increase their consumption to achieve a better indoor comfort and reduce related health problems. To overcome this thermal comfort gap, a strong increase in energy consumption should be expected, which will affect the EU policy goals on energy consumption and emissions reduction. Therefore, we consider of utmost importance that tailor-made policies and information campaigns addressing (i) high-income households should focus on support increased use of more efficient equipment, lifestyle changes and adoption of renewable energy sources, and (ii) low-income households should focus on incentives either for efficient equipment or renewables use, or either to burden energy costs. Energy policies and measures can help to tackle the expected energy consumption in the future, but with clear differences on how to approach and target each consumer groups.

In Portugal, energy subsidies (named as social tariff) have been provided for the fuel poor households minimizing the high-energy costs but they do not provide a sustainable long-term solution not addressing the root causes of the problem. On the opposite, energy renovation measures of households at fuel poverty risk can give a long-term sustainable answer improving the energy performance of buildings. These solutions can compete with higher energy consumption from e.g. heaters and air conditioners in providing space heating and cooling services demand. Though, while insulation measures can be used as a protective measure in buildings, insulation by the interior increases the risk of overheating. Note that in a country like Portugal and at Évora specifically, some measures, such as external insulation, might cause much more thermal discomfort in the summer worsening the problem.

Modernization and retrofit of buildings and energy equipment is therefore an effective solution for energy poor households as presented by Bouzarovski and Petrova (2015), but identifying and funding those households might be an issue, even in high income countries, with the ability for extensive data collection. Our methodology presents an alternative approach for such identification.

Another alternative solution to overcome the thermal comfort gap is the increase of use of locally produced electricity from renewable sources. Évora has a high solar PV rooftop potential (40MW) (Moreira, 2016). Therefore, this strategy could be very important to help increase thermal comfort levels without an increase in energy costs to both groups of consumers. Also, green and cool roofs, smart glazing, thermochromics materials inducing changes in the color of the building's façade that reduce heating and cooling needs are solutions that will overcome the thermal comfort needs without increasing energy consumption.

3.1.4 Conclusions

This paper presented an approach to characterize distinct groups of consumers, shedding the light on how to track fuel poverty and understanding the existence or not of a fuel obesity group. Combining electricity smart meters' dataset with socio-economic data, building structure characteristics and equipment use from household surveys and comparing this data with building energy simulations allowed the identification of key energy consumption determinants. Our research illustrates the relevance of consumer segmentation to derive different consumer groups' characteristics, which should be taken into account by policies and measures. Acknowledging the differences of consumer groups, and the determinants behind them, the design and implementation of measures and instruments may be tailored to ensure its goals, as energy reduction, increase of indoor thermal comfort levels, energy efficiency increase and renewable energy integration into buildings.

Our approach and methodology delivered results compatible with fuel poverty group and with potential fuel obesity group, regarding electricity consumption. Different consumption profiles were explained by the socio-economic details and climatization behavior of the households' occupants. Though, just looking to levels of consumption might be misleading in addressing the broader picture of thermal comfort and energy consumption for space heating and cooling, as also underscored by the energy simulation of the building typologies of both consumer groups.

Despite focusing on electricity consumption, these results provide policy makers and relevant stakeholders, such as ESCOS, energy utilities, and the general population with highlights to recognize both problems (i.e. fuel poverty and lack of thermal comfort) and include them in current policies and measures whilst also providing a comprehensive picture of its evolution over time.

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Authors Contributions

J. P. Gouveia structured and wrote the paper, defined the buildings typologies and performed all the smart meters and surveys data analysis. J. Seixas supported the design of the paper and its in-depth revision. G. Long carried out the energy simulation modelling of buildings typologies.

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3.2 Daily Electricity Consumption Profiles from Smart Meters - Proxies of Behavior for Space Heating and Cooling

ABSTRACT

Daily electricity consumption profiles from smart meters are explored as proxies of active behavior regarding space heating and cooling. The influence of the environment air temperature (multiple maximum and minimum daily thresholds) on electricity consumption was explored for a final sample of 19 households located in southwestern Europe (characterized by hot, dry summers and cool, wet winters), taking the full year of 2014. Statistical analysis of the deviations from hourly average electricity consumptions for each temperature thresholds was performed for each household. Firstly, these deviations could act as proxies highlighting possible lack of thermal comfort on space cooling, and partially on space heating, supported by door-to-door survey data, on socio-economic details of occupants, buildings bearing structure and equipment's ownership and use. Secondly, meaningful differences of consumers' behavior on electricity consumption pattern were identified as a response for space heating and cooling to the environment air temperatures thresholds. Additionally, statistical clusters of active and non-active behavior groups of households were assessed, showing the electricity use for space heating. This paper illustrates the importance of the widespread use of smart-meters data on the increasingly electrified buildings sector, to understand whether and how thermal comfort could be achieved through active climatization behavior of its occupants. This is particularly important in regions where automatic HVAC systems are almost absent.

KEYWORDS

Daily Load Profiles; Smart Meters; Residential Sector; Household Surveys, Heating and Cooling; Cluster Analysis.

3.2.1 Introduction

Much attention has been given to the potential strategic role of renewable energy in the transition to a clean energy future. However, increased end-use energy efficiency and energy conservation offers comparable, if not greater, such potential in the short-term. Demand side actions are key for the reduction of energy consumption, with impacts on energy supply security and affordability, and climate mitigation and adaptation. Notwithstanding, this should be addressed carefully since, in some cases, consumers may not be in a favorable position for a direct reduction of consumption.

Different dimensions of household energy use have been explored by researchers, to design and implement strategies to provide secure access to energy services and to facilitate the transition to modern fuels, eradicate fuel poverty, address environmental concerns and mitigate greenhouse gas emissions. Yet, despite more than three decades of effort, our understanding of household energy use patterns and the variables underlying them still have a large potential to be improved (Kowsari and Zerriffi (2011); Wiesmann *et al.* (2011)). This is particularly valid when taking into account very high temporal resolution data, as electricity consumption from smart meters, allowing the identification of detailed consumption patterns. Research carried out by a large plethora of authors already identified several determinants that drive energy consumption at the household level (e.g. Leiwen and O'Neill (2003); Elias and Victor (2005); Ellegård and Palm (2011); Hamza and Gilroy (2011); Kowsari and Zerriffi (2011); Lescaroux (2011); Hojjati and Wade (2012)). We contribute for this discussion harnessing a comprehensive dataset, which includes smart meter registries and a household door to door survey from a southwestern European region.

Increased availability of smart meters' data plays an important role in the understanding of household energy use, since it allows a deeper knowledge on how different consumers deal with electricity consumption along the day to fulfil their multiple energy services. Smart meter data mining to compute electricity consumption profiles for different time granularities is a tool to identify few distinct and representative clusters of consumers from a huge number of users (Kang and Lee, 2015). When a lot of consumers exist in a smart grid environment, it is certain that there are many consumers who share similar characteristics and load patterns. Clustering analysis is an important tool in data mining, intelligent decision-making, and pattern recognition (Cios et al., 1998). Several authors already evaluated electricity consumers' segmentation through different methods, e.g. ant colony clustering (Chicco et al., 2012, 2013), normal (Ramos et al., 2015) and fuzzy k-means (Tsekouras et

al., 2007), neural methods, self-organizing maps (Beckel et al., 2012), while using different time frames (i.e. hourly, daily, seasonal, annual). Kwac et al. (2014) segmented household energy consumption using hourly data for the United States; McLoughlin et al. (2015) characterized diurnal, intra daily, seasonal into a series of profile classes of electricity use for Ireland. Macedo *et al.* (2015) typified load curves for demand side management in Brazil.

Consumption and consumers' profiles have been key for many purposes, namely electricity tariff design; consumers' segmentation to target specific energy efficiency and energy consumption reduction measures; generation of real time alerts; indoor thermal comfort assessment, among others (Ardakanian et al., 2014). However, this type of analysis usually relies only on electricity consumption data (e.g. Beckel et al., 2014) while missing other fundamental data, like the socio-economic details of the consumers and the weather conditions affecting directly cooling and heating demand. Rhodes et al. (2014a, 2014b), Wijaya et al. (2014), Cetin et al. (2014), Cetin and Novoselac (2015), Kipping and Tromborg (2015), Gouveia and Seixas (2016), Viegas et al. (2016) already combined electricity consumption profiling with survey data. Pampuri et al. (2016) states the difficulty of relating the summer electricity surplus with space cooling because often data do not cover a full year.

Weather conditions are one of the main determinants for residential energy consumption, driving annual fluctuations in energy use for space heating and cooling demand (Hojjati and Wade, 2012) and, to some extent, of other uses, like water heating (Kaza, 2010). Residential power demand can range in magnitude from a few hundred of watts to lower tens of kilowatts, and can be two times larger in a cold country than in a 'moderate' one, and half in a hot country (Lescaroux, 2011). A cooler year in a warm climate region will reduce overall energy consumption, as the demand for space cooling will be reduced. Residential electrical use patterns fluctuate differently during the day due to space-conditioning setpoints, time of year, weather, occupant behavior and schedules (Rhodes et al., 2014a). Occupant behaviors (e.g. adjust thermostat) have a big impact on buildings energy consumption. However, the occupant behavior in buildings is still not well understood. According to O'Neill and Niu (2017), the occupants' expectation of comfort or satisfaction in the built environment drives the occupant to perform various controls that have a big impact on building energy consumption.

Different authors have been showing the relation between climate temperature, behavior and electricity consumption. For example, Zachariadis and Pashourtidou (2007) conducted a study in Cyprus, showing that weather fluctuations seem to be the most significant cause of short-term

variation in electricity consumption (albeit with small elasticity values), while the effect of income and prices is not significant. Yun and Steemers (2011) also identified climate as the single most significant parameter for cooling demand, followed by behavioral issues. Ali et al. (2011) found that both temperature and humidity were significant indicators of energy use and were able to accurately forecast the aggregated load. Wiesmann *et al.* (2011) acknowledged, through top-down models, regional and climate effects significantly related to electricity consumption. Hart and Dear (2004) showed that heating and cooling devices have a strong impact on energy consumption. Parker (2003) exposed the relationships between consumption and temperature for different months and during the day, using a large sample located in a region with mild winters (Central Florida). Lee et al. (2014) and Fischer et al. (2016) point out the role and link of outside air temperature to total and peak power demand. Models from Perez et al. (2017) for Texas describe that energy consumption with relation to outdoor dry-bulb temperature is negligible up until a change-point, after which air conditioning energy use increases linearly. However, Elexon (2013) stated the relationship between environment temperature and energy services demand is fairly straightforward: when temperatures fall, heating load increases, when temperatures rise, load decreases until any cooling load (air conditioning perhaps) is applied. Though, for Ardakanian et al. (2014), the relationship between energy consumption and external temperature is not exact, making it difficult to estimate the consumption of temperature-sensitive appliances from whole-house smart meter data.

We argue that these assessments apply primarily to households with high levels of climatization and subsequent thermal comfort provided by centralized sources, like district heating or buildings' boilers. For regions where among others, climate conditions, type of dwellings, income levels and operation and maintenance of the systems do not justify the investment in centralized equipment, as Portugal or Spain; individual devices, as fans and electric heaters, are wide adopted as space cooling and heating providers. In these cases, energy consumption depends primarily of individual decisions along the day, which is a function of different factors as the environment air temperature, economic conditions and buildings' characteristics.

We consider that smart meter detailed data are key to capture when and under what conditions heating and cooling devices are used in those regions. Crossing electricity consumption data sets with other data sources focused on buildings' characteristics and socio-economic conditions provide insights to fully understand the different profiles and consumer groups. In this paper, we explore the potential of

smart meters' data for a different purpose of its mainstream use. The main objective is to conclude if detailed (hourly) electricity consumption data at the household level can be used as a proxy of active consumer behavior regarding space cooling and heating, as a response to outside temperature thresholds. We go deeper on understanding how residential electricity daily consumers' profiles respond to a range of daily minimum and maximum environment air temperature from a nearby weather station (IPMA, 2016), while taking households' members socio-economic details, buildings bearing structure, equipment ownership (collected in a door to door survey). Active vs. non-active consumers' behavior are key for different purposes, for example the identification of thermal comfort gaps, and peak loads expectations, as a function of environment air temperature peaks in summer and winter, and thus its management through demand side.

We conducted an analysis of hourly electricity registries from smart meters at households for the full year of 2014 for the city of Évora, in Portugal according to six distinct environment temperatures thresholds ($\leq 5^{\circ}\text{C}$, $\leq 10^{\circ}\text{C}$, $\leq 15^{\circ}\text{C}$, $\geq 25^{\circ}\text{C}$, $\geq 30^{\circ}\text{C}$, $\geq 35^{\circ}\text{C}$). Évora has a Mediterranean climate type, according to the Köppen-Geiger climate classification (characterized by hot, dry summers and cool, wet winters). This city is one of the Portuguese cities with higher thermal amplitudes (both daily and yearly) (further information in Section 2.2., Part B).

A clustering analysis was performed over households' consumption focusing on heating season to extract similar active behaviors. The analysis novelty refers to the profiles analysis and clustering of differences between daily and average consumption profiles for the extraction of heating/cooling behavior as a function of outside temperature. Such results are significant contributions for southern European countries that rely mostly on individual devices and passive measures, and then are much dependent from other factors than only from environment air temperature, namely for policy makers and ESCOs.

The paper follows with a section on the methods and datasets used to the development of the work (Section 3.2.2). Section 3.2.3 presents the results and section 3.2.4 discusses and section 3.2.5 concludes presenting the final remarks.

3.2.2 Methods and data

This section depicts the overall methodological process and presents the datasets used to conduct the study. We combine results from a household door-to-door survey data, a smart metering dataset and

registries of minimum and maximum daily outside temperatures. Figure 1 illustrates how the data was collected, divided in two different parts: I - datasets on household electricity consumption and characterization, and II - datasets on daily temperatures. Daily load profiles are explored according to temperatures thresholds and electricity consumption deviations are computed to typify groups of consumers with distinct active behaviors for climatization. Within this paper, we use the concept of deviation as variations of electricity consumption from each household hourly average.

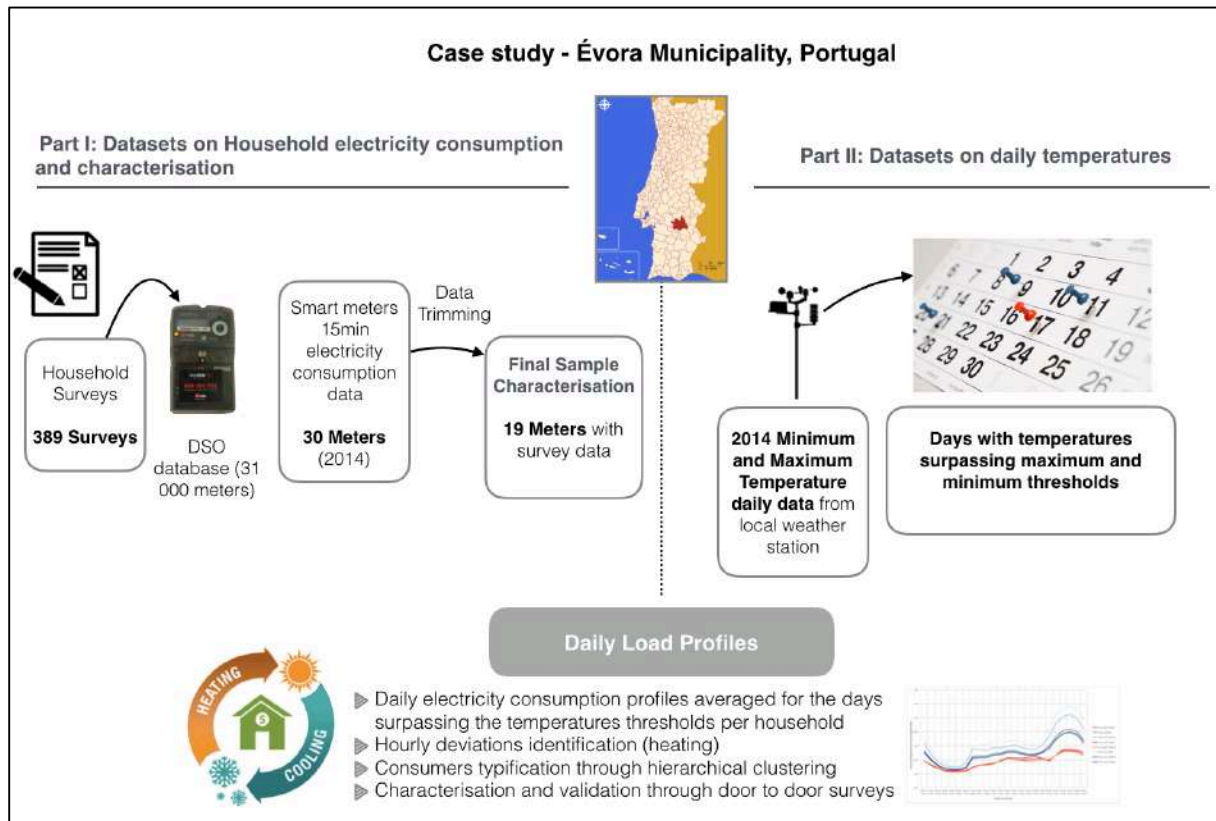


Figure 3.6 – Overall Methodology and data used

3.2.2.1 Case study

This study was conducted in Évora municipality in Portugal, chosen as a case study fourfold: 1) the existence of a smart grid project with high resolution registries on electricity consumption (EDP Distribuição, 2015); 2) the Mediterranean climate type, according to the Köppen-Geiger climate classification with an annual average temperature of 15.9°C, but with high monthly thermal amplitudes; 3) the low national ownership of air conditioners and centralized heating systems making

more significant the consumers behavior influence; and 4) the location in the Iberian Peninsula, targeted as one of the most likely impacted regions on thermal comfort due to climate change, namely on energy consumption.

In 2014, the residential sector represented around 15% of the total final energy consumption of the municipality (DGEG, 2016). No regional statistics are available by end uses, but extrapolating the national average applied for the city with the survey results, space heating represents 8% (of which, near 90% supplied by electricity) and space cooling just 0.8% (all electricity) (DGEG and INE, 2011). This indicates that other forms of energy are also used for heating, as gas in boilers or biomass in fireplaces, however for cooling all technologies, if available, are solely electric.

3.2.2.2 Characterization of data

Part 1 - Household electricity consumption datasets and characterization

As depicted in Figure 3.6, this study relies on smart-metered electricity consumption data and a door-to-door household survey data for thirty households. Our sample was retrieved from a larger database of households where door-to-door surveys were conducted in Évora during July and August 2014.

Door-to-door household survey

The survey included 110 questions covering information about location, physical characteristics of the dwelling (e.g. load bearing structure, type of windows, insulation of external walls and roofs), socio economic details of the occupants (e.g. number of persons, age, gender, income), appliances characteristics, use and ownership. For our purpose, the survey allows to evaluate the ownership and, if existing, the identification of the type and use of heating and cooling equipment (e.g. fireplaces, electric heaters, A/C, gas boilers, fans) and to characterize the socio-economic details of the inhabitants to better frame and discuss our results. The sample used herein considers different type of buildings, family structures, tariff scheme (which relates to electricity costs) and contracted power (e.g. 3.45 kVA, 6.9 kVA) to evaluate their daily load profiles.

Smart meters data

Detailed electricity registries are derived from the InovCity project, implemented by the Portuguese DSO (EDP Distribuição, 2015) since April 2010, for the first time in Portugal, in the municipality of Évora. A massive smart metering system (i.e. 31 000 meters) provide electricity consumption data

every 15 minutes for different economic sectors (i.e. residential, services, public lighting, industries, and others).

The household surveys were matched to the smart meter's database through the household meter number, while preserving the confidentiality of the house owners, resulting in an initial sample of 30 households. Electricity consumption data from the DSO database for the full year of 2014 was retrieved for the sampled households.

In order to obtain representative and robust profiles per household to be easily visualized and interpreted, we performed a data validation and trimming for the sample of 30 households. The first step was to assess the percentage of missing registries per household for the full year, with households discarded if missing data was above 20%. This validation procedure reduced our sample to 19 households that will be used in this research, with an average percentage of missing data of 14% of the 15 minutes' data (ranging from a minimum of 8% to a maximum of 19% by meter). Missing data in the dataset is in general a consequence of communication/readings problems (e.g. GPRS) and did not had a specific daily or monthly pattern.

To handle the missing data, in order to have a complete dataset for these households, the approach was to impute missing 15 minutes' registries based on a mean imputation method of the observed values for neighbouring periods. When 15 minutes' registries existed in a given hour, the imputation used the mean of the previous and next 15-minute timestamp. If a full hour or a full day was missing in the dataset, we used the mean of the available data of 15 minutes' registries electricity consumption from the next and previous corresponding hours or days. After having the full dataset of 15 minutes' registries (i.e. 35040 values) per household, these data were integrated to hourly data (i.e. 8760 values) to reduce unnecessary granularity for the purpose of our work.

Final sample characterization

Figure 3.7 depicts a box and whisker plot characterizing and showing the descriptive statistics and variability of the final 19 sampled households' hourly electricity consumption regarding dispersion and variability, as well as outliers. The households' sample is characterized by an hourly average consumption of around 0.30 kWh, while the maximum hourly consumption is registered to 6.6 kWh. The average maximum hourly consumption was 4.1 kWh, whilst the average annual electricity consumption is of 4263 kWh, above the national average of 3673 kWh (DGEG and INE, 2010).

The distribution of electricity consumption data is very diverse across the households: households #2, #4, #21 and #23 present the lowest medians (near 0.16 kWh) and household #12 depicting the highest value, of almost 0.7 kWh. The variance is also very distinct within the sample, households #2 and #11 showing the lowest hourly consumptions standard deviations (i.e. average of 0.23 kWh) and household #9 presenting the highest standard deviation (0.9 kWh). These differences will be further evaluated in the section of the results.

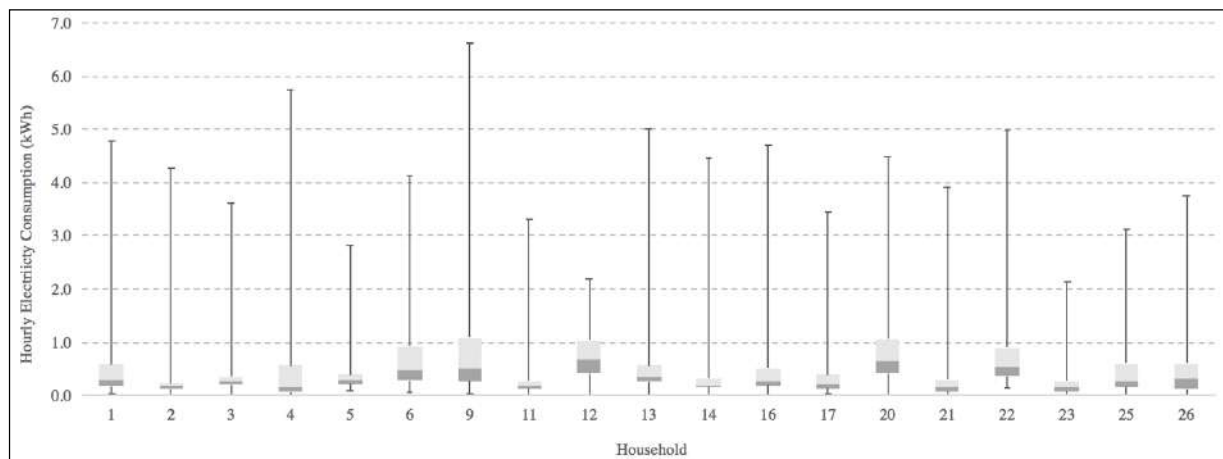


Figure 3.7 – Box and whisker plot describing the 19 final sampled households' hourly electricity consumption for the year 2014

The door-to-door surveys reveal that the sample is represented by a majority of semi-detached houses (63%) and terraced houses (26%) in the urban area of the municipality. The bulk of houses were constructed after 1991 (63%) when building regulations started to be applied and have average household areas of 114 m². 68% of the houses have concrete as the load bearing structure with external walls of brickwork double layer, only 47% have insulation (extruded polystyrene of 3 cm). The windows framing is mainly represented by aluminum (74%) and 67% present double-glazing. Almost 90% of the houses are owner occupied and the remaining private rented. The households have an average of 3.2 members, 18% are elderly people older than 65 years and 21% of the members have less than 18 years of age. Near 50% of the household members work full time, 23% are retired and the remainder are students or have other working status. These households have an average monthly income distributed as follows: 16% above 2 501€, 21% between 1 501€ and 2 500€ and 63% have an income between 751€ and 1 500€. Our sample do not have any household significantly poor, with a monthly income of less than 750€.

This sample tend for newer and more semi-detached houses when compared to the type of houses in the region (i.e. Alentejo) as shown by the CENSUS (INE, 2011), with 37% terraced, 14% semi-detached and 28% detached houses; 41% of the houses constructed after 1991 and 32% with concrete bearing structure. In the region, the number of persons per household is 2.5 and 66% of the houses are owner occupied.

Regarding the equipment ownership, 100% of the households have some type of heating equipment while for cooling the rate is more modest, 64% (11% of them have only fans, which have very different implications for buildings performance). All the households use gas for domestic hot water, 95% have gas stoves, thus with no influence in the analysis for electricity consumption profiles. Regarding other electric equipment, all the houses have either a desktop computer or a laptop (over 200% ownership) and televisions (274%). The ownership of white appliances is also saturated: refrigerators (116%), freezer (100%), microwaves (100%) and cloth and dish washing machines (100%).

Part 2 - Dataset on daily temperatures

As presented in Figure 3.6, we assess the daily external temperatures for the city of Évora. The highest monthly average occurs in August (24.1°C) and the lowest in January (9.6°C). The climatological normal (1971-2010) points the lowest temperature ever recorded at -2.9°C and the higher at 46°C (IPMA, 2016), portraying this city has one of the Portuguese cities with higher thermal amplitudes (both daily and yearly).

We use daily temperature data from Évora station (Latitude: 38°32'11.55" N, Longitude: 7°53'16.65" W and altitude: 246 m) for the period between 1st of January to the 31st of December 2014. For this year, the average daily minimum temperature was 10°C and the average daily maximum temperature was 22.7°C (IPMA, 2016).

For the purpose of our analysis, we select six distinct environment temperatures thresholds (5°C, 10°C, 15°C, 25°C, 30°C, 35°C), as well as the days that surpassed these thresholds (Figure 3.8 and Table 3.4). We use extreme outside temperatures instead of using HDD and CDD, as a pre-step to inform this work. We privilege the use of daily extreme outside temperatures (maximums and minimums) since we want to evaluate the use of whole-house electricity smart meters' data as proxies of active climatization behavior. The days under the thresholds are considered to belong in the same bin and are analyzed together being used to further assess the daily load profiles of the households' sample. Those

thresholds were chosen to reflect successive potential indoor thermal discomfort (i.e. in 5 °C steps) that could trigger active space heating and cooling behavior. Minimum temperatures above 15°C (i.e. 60 days) and maximum temperatures under 25°C (i.e. 214 days) are not considered.

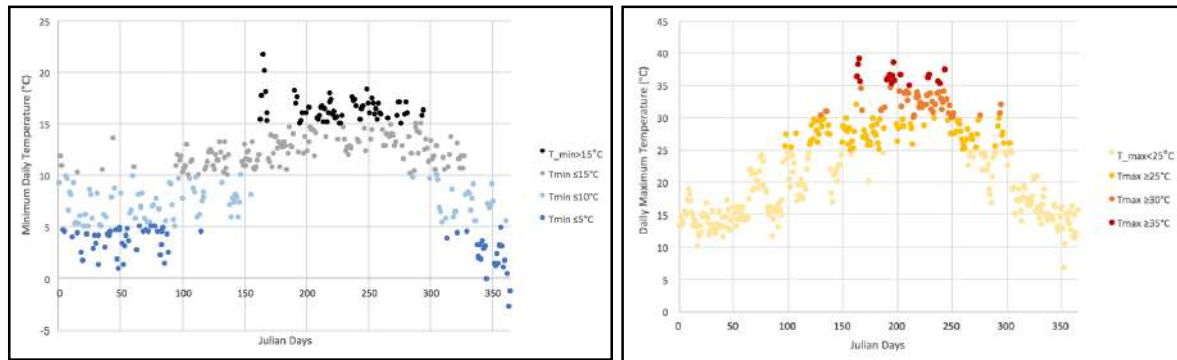


Figure 3.8 – Daily minimum (left) and maximum (right) temperatures in 2014 for Évora, Portugal

Table 3.4 – Number of days in 2014 with the minimum and maximum temperatures surpassing the thresholds

Daily Minimum Temperature (°C)	Number of Days (#)	Daily Maximum Temperature (°C)	Number of Days (#)
$T_{min} > 15^{\circ}\text{C}$	60	$T_{max} < 25^{\circ}\text{C}$	214
$T_{min} \leq 15^{\circ}\text{C}$	305	$T_{max} \geq 25^{\circ}\text{C}$	151
$T_{min} \leq 10^{\circ}\text{C}$	162	$T_{max} \geq 30^{\circ}\text{C}$	67
$T_{min} \leq 5^{\circ}\text{C}$	68	$T_{max} \geq 35^{\circ}\text{C}$	19

3.2.2.3 Assessment of load profiles and consumer groups by temperature thresholds

We compared the daily load profiles of the electricity consumption hourly averages from 365 days per each household with the load profiles averaged over the hourly electricity consumption registered in the 305, 162 and 68 days for the heating season and to the 151, 67 and 19 days in the cooling season, that surpassed the temperature thresholds (Table 1). This will allow to identify if and when the electricity consumption react to different daily temperature thresholds in the heating and cooling seasons. The temperature setpoints of major reaction were identified as a trigger for active climatization behavior. The results are illustrated by a combination of individual analysis of selected

households' average daily electricity consumption profiles and aggregated average profile of the whole sample.

The hourly consumption deviations were calculated for each household, by subtracting the hourly average consumption in a specific temperature threshold from the hourly annual average consumption. An analysis of the deviations of hourly electricity consumption was conducted for all the temperature thresholds in order to group and distinguish consumers that actively consume electricity for heating and/or cooling purposes, from those that do not. We performed a cluster analysis over the hourly deviations for the most extreme temperatures thresholds (i.e. $T_{min} \leq 5^{\circ}\text{C}$ for heating season and $T_{max} \geq 35^{\circ}\text{C}$ for the cooling season). A hierarchical clustering was applied using Ward's Method (Ward, 1963) with a measured interval through the squared Euclidean distance, which increases the importance of large distances, while weakening the importance of small distances. This clustering method allows for an analysis of variance approach to evaluate the distances among clusters, thus identifying homogenous groups of cases. Ward's method uses the F value (like an ANOVA) to maximize the significance of differences between cluster, however it is prone to outliers and the creation of small clusters that in this case do not apply since we have chosen to have only two clusters, since we wanted to confront consumer profiles with active and non-active behavior (Statistics Solution, 2016).

Finally, a complete understanding of the households and the determinants that might be influencing the active behavior of its occupants for climatization purposes was supported by the analysis of the answers of the corresponding surveys per cluster. This process allows for the recognition of the most significant similar/distinct parameters (e.g. dwelling characteristics, occupants profiles, electrical appliances ownership and use) that further explain the electricity daily consumption patterns and climatization practices.

The combination of statistical data analysis of high resolution (hourly) electricity consumption data as a function of external temperatures along the year, with an extensive survey on the households' characteristics provides a comprehensive dataset for consumers' segmentation with active climatization behavior. This knowledge may be used either by policy makers on policies targeting fuel poverty, thermal comfort levels and energy efficiency measures; and by ESCO's and energy providers for direct consumer feedback and tailor-made initiatives of tariff design, energy efficiency recommendations and equipment substitution.

3.2.3 Results

In this section, we aim to unfold the major results that address the objectives of the paper, presenting electricity consumption profiles for the different temperature thresholds assessed, the hourly temperatures change that drive the consumers' segmentation and the survey results to support the characterization of the different consumer groups.

3.2.3.1 Electricity consumption profiles

As depicted in Figure 3.9, we developed profiles aiming to understand the different electricity consumption behavior that could arise from different external temperatures. Daily consumption follows a typical residential profile, with a small rise in the morning increasing until lunch hours, the largest peak occurring at the end of the afternoon, and the lowest consumption observed during the night. We recognize the differences of the daily electricity load profiles with changes on the external temperature, by comparing them with the hourly averaged load curve for the year 2014 (Figure 3.9, in green). Table 3.5 depict the hourly standard deviation for the 7 different daily load profiles under analysis for a better understanding of the hourly data variation.

To look for the active behavior of households, we will focus the analysis on the impact of lower daily minimum temperature and higher maximum temperatures. From Figure 3.9, we may conclude that consumers have higher electricity consumption levels for heating (above the average) than for space cooling (below the annual average), revealing a predominance of active behavior for heating. Looking deeper in the heating behavior (blue lines), we can see that for the days with $T_{min} \leq 5^{\circ}\text{C}$, as stated in Table 1, the average minimum increase of hourly consumption is 25% (between 2 a.m. and 7 a.m.) and the average maximum increase is almost 50% (between the 6 p.m. and 11 p.m.), corresponding to a daily average increase of 38%. For the days with temperatures lower than 10°C , the hourly consumption increases between 14% and 33%. Taking the daily average, the increase of the electricity consumption is around 23%. For temperatures lower than 15°C , the difference of electricity consumption is less significant with an annual hourly average increase between 2% and 6%, and an average increase of 4%.

The increase of electricity for the $T_{min} \leq 5^{\circ}\text{C}$ and $T_{min} \leq 10^{\circ}\text{C}$ is substantiated through the surveys of the sample households, since near 47% of the households have exclusively electric equipment for space heating purposes, 16% use a mix of electricity (i.e. A/C and electric heaters) with fireplaces, and

the remaining use just fireplaces for heating. For space cooling provision, 53% of the households have air conditioners, 11% have only fans and the remaining 36% have no equipment at all for space cooling.

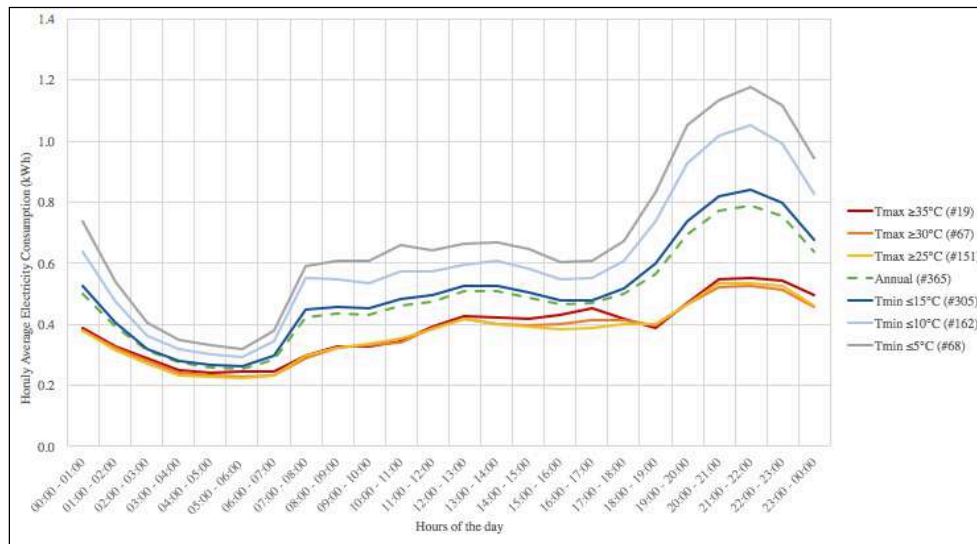


Figure 3.9 – Daily average load profiles of the 19 households for the full year, for the six temperature thresholds

Table 4.5 – Hourly standard deviation for the 7 different daily load profiles

Hours/temperatures	Tmax ≥ 35°C	Tmax ≥ 30°C	Tmax ≥ 25°C	Annual	Tmin ≤ 15°C	Tmin ≤ 10°C	Tmin ≤ 5°C
00:00 - 01:00	0.21	0.19	0.18	0.26	0.27	0.37	0.46
01:00 - 02:00	0.19	0.17	0.16	0.23	0.23	0.31	0.39
02:00 - 03:00	0.15	0.15	0.14	0.17	0.17	0.23	0.28
03:00 - 04:00	0.14	0.13	0.11	0.15	0.16	0.23	0.27
04:00 - 05:00	0.14	0.12	0.11	0.15	0.15	0.23	0.27
05:00 - 06:00	0.15	0.11	0.10	0.14	0.15	0.22	0.26
06:00 - 07:00	0.13	0.11	0.10	0.16	0.17	0.26	0.31
07:00 - 08:00	0.10	0.10	0.10	0.22	0.24	0.37	0.43
08:00 - 09:00	0.13	0.13	0.13	0.21	0.22	0.31	0.37
09:00 - 10:00	0.16	0.15	0.15	0.23	0.25	0.34	0.41
10:00 - 11:00	0.18	0.15	0.15	0.25	0.27	0.37	0.43
11:00 - 12:00	0.20	0.16	0.16	0.25	0.26	0.36	0.39
12:00 - 13:00	0.27	0.22	0.20	0.28	0.29	0.38	0.43
13:00 - 14:00	0.25	0.20	0.18	0.27	0.28	0.38	0.47

14:00 - 15:00	0.21	0.19	0.17	0.24	0.25	0.33	0.38
15:00 - 16:00	0.24	0.20	0.18	0.23	0.23	0.30	0.33
16:00 - 17:00	0.27	0.22	0.19	0.23	0.24	0.30	0.36
17:00 - 18:00	0.23	0.20	0.18	0.25	0.26	0.34	0.39
18:00 - 19:00	0.21	0.19	0.17	0.28	0.30	0.42	0.50
19:00 - 20:00	0.23	0.22	0.19	0.31	0.33	0.48	0.58
20:00 - 21:00	0.29	0.25	0.24	0.37	0.39	0.55	0.65
21:00 - 22:00	0.24	0.22	0.21	0.33	0.36	0.51	0.62
22:00 - 23:00	0.22	0.21	0.21	0.32	0.35	0.49	0.60
23:00 - 00:00	0.28	0.23	0.21	0.29	0.31	0.42	0.51

Since the cooling demand is only supplied by electricity, it would be expected that visible changes of consumption (active behavior) could be identified, although it is not the case. Besides, no significant changes of consumption are identified between moderate-maximum temperatures ($T_{\max} \geq 25^{\circ}\text{C}$) and extreme temperatures ($T_{\max} \geq 30^{\circ}\text{C}$ and $\geq 35^{\circ}\text{C}$), around 4%. Different explanations may be found, such as the very low ownership of cooling equipment; the non-use of the equipment although the households have it (i.e. air conditioners or fans), due to electricity prices (15% higher in Portugal compared to EU average) or other constraints; the exclusive use of fans with low electricity consumption, not identified on the profiles. On another perspective, one may say that the households have different indoor temperature, which the occupants are most likely to feel comfortable, particularly in free-running buildings.

Figure 3.10 presents two selected examples of households' load profiles with different levels of consumption illustrating distinct behaviors for heating and cooling that could drive for a typification of consumers. These examples show households with different occupation schedules, while also depicting different consumption behaviors along the day for heating and cooling, with different setpoints temperatures for active climatization behavior. Household #12 has a fairly similar use of electricity all day long with a small peak at the evening period (21-23h). This household has four members (two of them retired) explaining the high consumption along the day. Despite being a household with dual tariff it is not portrayed in its daily profile. This household clearly reacts more to heating demand needs than cooling, mainly when outside air temperature is beneath 10 degrees Celsius. The survey results corroborate these findings since this household only have heating equipment (i.e. electric heater).

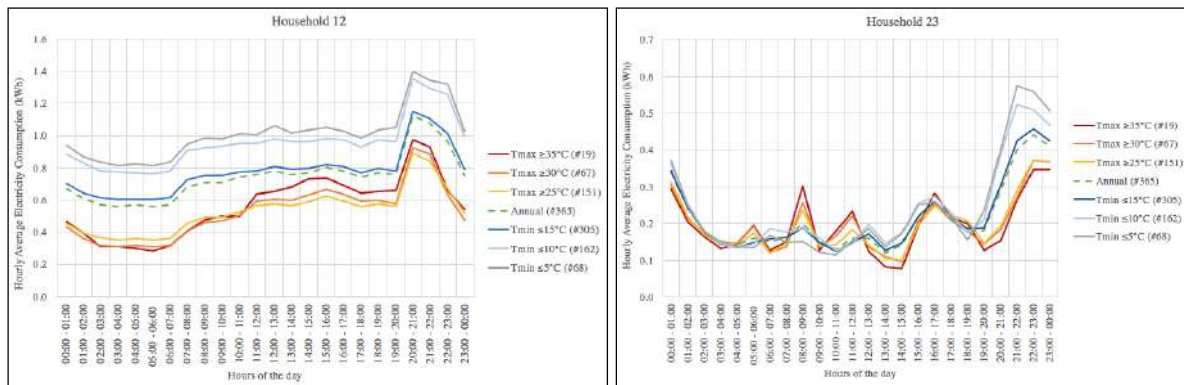


Figure 3.10 – Average daily load profiles of two selected households for the six temperature thresholds

On the right (household #23), evaluating the different profiles, it seems that this household reacts (in different amounts) both to heating and cooling demand with active consumption of electricity, with slightly higher consumption for cooling during the day and more for heating during the night period. The survey once again backs up our results since this is a household with an air conditioning system that is used for both heating and cooling. The variations of electricity consumption along the day might be clarified by its members' individual routines since it is a household with two students and two full time workers. The knowledge of other factors like income, age of household and construction materials from the surveys also allows us to refine this analysis.

From this first part of the study, it becomes evident that according to this sample, it is difficult to state that the households present a widespread active behavior for cooling due to the small hourly variations of electricity consumption to the average. Variations could also be related to other kind of equipment as washing machines. Within this context, and justified by the abovementioned reasons, for the high external temperatures thresholds, electricity consumption profiles, the hourly deviations and consumers clustering that follow on the next sections will not be performed since the differences to the average consumption would be difficult to explain by active cooling behavior. Therefore, we will focus on low temperature thresholds towards active behavior assessment for space heating.

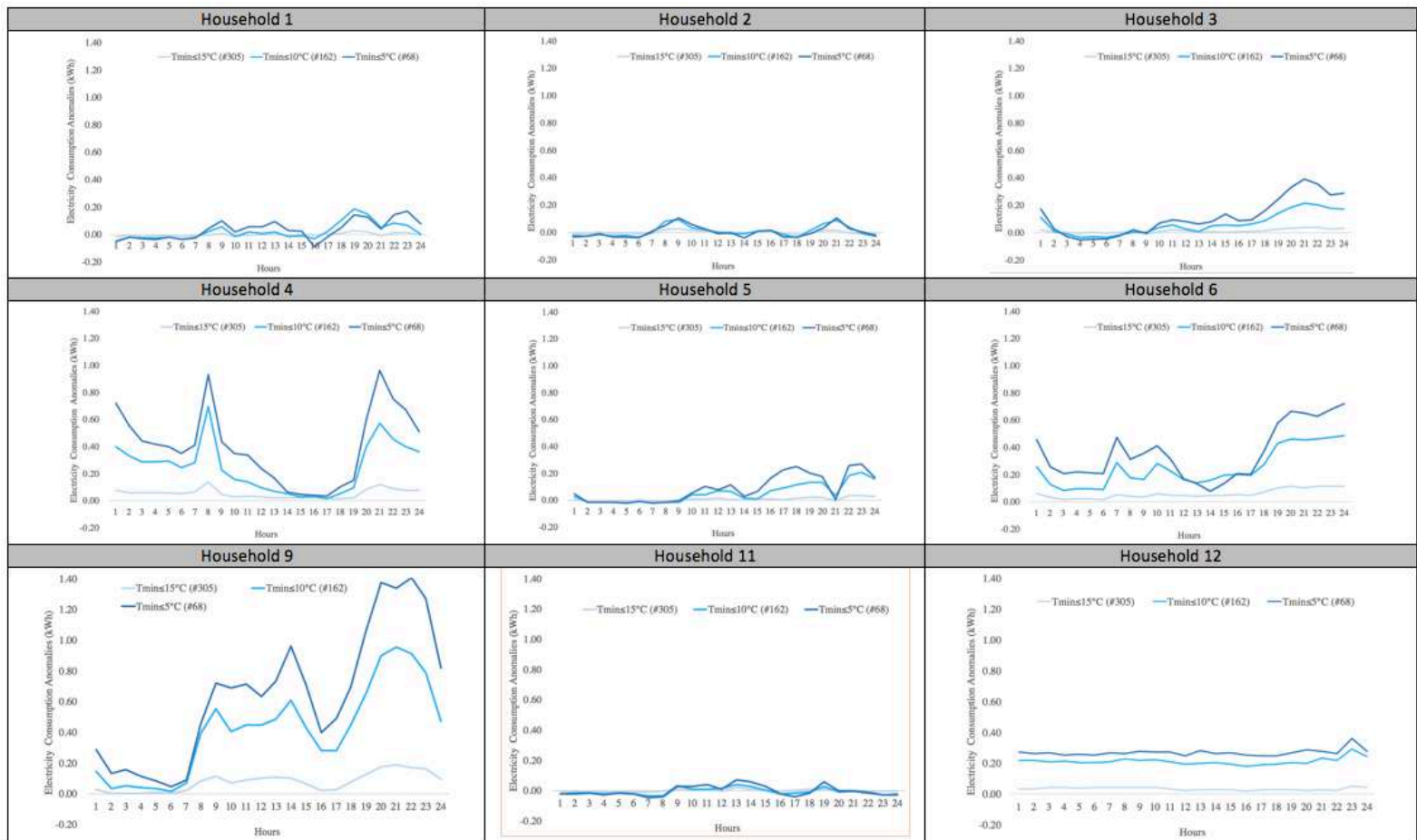
3.2.3.2 Hourly electricity consumption anomalies for consumer typification

In this section, we proceed with a deeper analysis for the heating season, based on the hourly electricity consumption anomalies, aiming to understand the variability among consumers and have a first look towards the aggregation of consumers according to their apparent climatization behavior.

Figure 3.11 presents the graphs of hourly temperature anomalies for the 19 households in the days corresponding to the three minimum temperatures thresholds (as stated in Table 3.4). With this approach, it is possible to observe the variability among households either (i) the amount of consumption, with several houses not consuming much more than the hourly averages; and (ii) the time of consumption along the day, with some households depicting two peaks of consumption while others have a trending peak around dinner time. This points to the need of typifying consumers in order to inform different levels of policies, improving energy efficiency, possibilities of demand shifting, complementary with solar systems, among others.

The average hourly consumption anomalies per household were used for the hierarchical cluster analysis results splitting the nineteen sampled households into two clusters (active vs. non-active behavior): (1) six households (#4, #6, #9, #14, #20, #25) with visible active electricity consumption behavior on space heating, and (2) thirteen households (#1, #2, #3, #5, #11, #12, #13, #16, #17, #21, #22, #23, #26), with apparent non-active electricity behavior. Figure 3.12 presents the dendrogram for the heating season with low temperatures (*i.e.* T_{min}) household clusters, displaying the distance level at which there was a combination of households and clusters.

Comparing the daily load profiles illustrated in Figure 3.13, we can clearly observe a difference between both clusters, showing that these two groups of consumers have a distinct behavior on electricity consumption along the day, reflecting a climatization active behavior for very extreme minimum temperatures (under 5°C). The active household cluster (yellow line) presents two daily peaks, one during the morning and the highest during the evening, where our results suggest that is likely due to the use of electrical equipment for space heating. The hourly consumption increase in the active household cluster compared to the annual average hour of the all sample ranges from a lowest of 35% increase in the middle of the afternoon (16:00-17:00) to 82% during the night (20:00-21:00) when it is colder and the occupants are not sleeping yet. Comparing the two clusters, the hourly consumption varies from 51% to 171% in similar periods of the day.





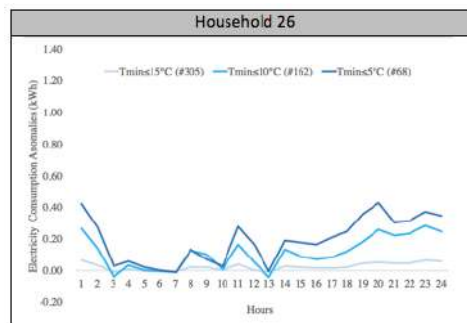


Figure 3.11 – Heating season hourly consumption anomalies for the sampled household

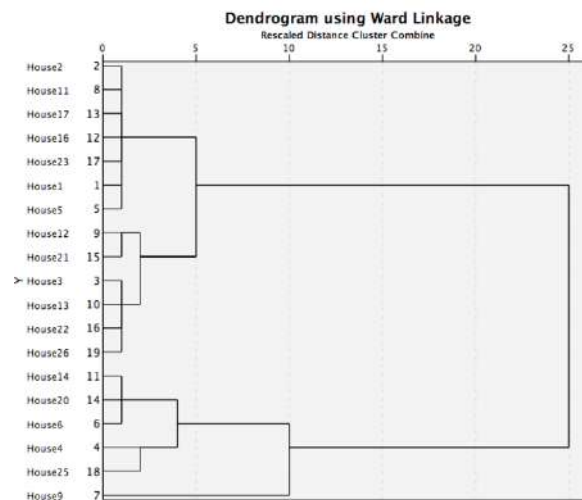


Figure 3.12 – Dendrogram from the cluster analysis of 19 households for heating season

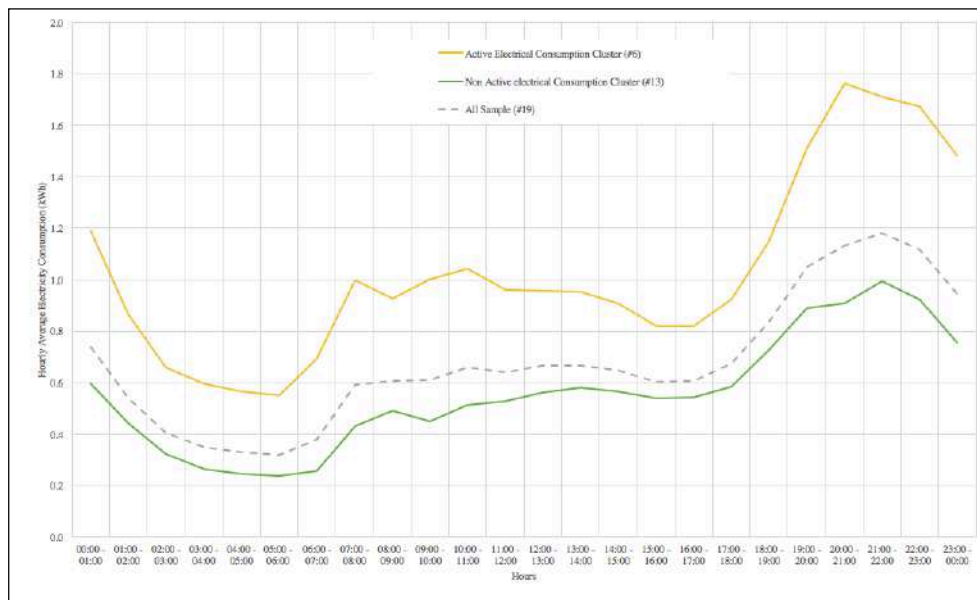






Figure 3.13 – Daily load curves for the two clusters of consumers, compared to the average of all sampled households for the heating season, with temperatures below 5°C

3.2.3.3 Understanding the drivers for consumers' behavior

For the reduction of energy consumption without disregarding the thermal comfort in the households, we have to address not only the profiles and levels of consumption at different temporal resolutions but also to track the main determinants of that consumption. Combining the clustering groups results with surveys allows for an in-depth characterization of the households behind the daily load profiles that, as aforementioned, may instigate lessons for different groups of stakeholders to deliver customized communication strategies and actions. Table 3.5 systematizes the main results from the correspondent surveys of the two clusters concluded previously, allowing to draw several insights.

Table 3.6 – Insights on the determinants characterizing the two clusters regarding active heating behavior from the respective door-to-door surveys

	Cluster 1 (Active behavior)	Cluster 2 (Non-active behavior)
Dwellings characterization 		
Type of house (%)	83% semi-detached houses 17% terraced houses	54% semi-detached houses; 31% terraced houses, 15% detached houses
Year of construction (%)	50% constructed before and 50% after 1990	31% constructed before and 69% after 1990
Average house area (m²)	116 m ²	113 m ²
Load bearing structure of the building (%)	67% masonry walls; 33% concrete	15% masonry walls; 85% concrete
Insulation (%)	50% without insulation; 50% with extrude polystyrene	46% without insulation; 54% with extrude polystyrene
Average external wall thickness (cm)	35 cm	30 cm
Framing material of windows (%)	67% aluminum, 17% PVC, 17% wood	73% aluminum, 8% PVC, 15% wood
Glazing type (%)	67% double glazing, 33% single glazing	62% double glazing, 38% single glazing
Household members' characterization 		
Household occupation contract (%)	83% owner; 17% private rented	77% owner; 23% private rented
Number of household members	3 persons per household	3.3 persons per household
Age of household members (%)	11% of members under 18 years old; 66% with ages between 18 and 64 years old, 17% with more than 65 years;	26% of members under 18 years old; 56% with ages between 18 and 64 years old, 19% with more than 65 years;
Relation of household members (%)	100% families	100% families
Schooling degree of the head of family (%)	83% with Graduation, MsC or PhD; 17% under 6 th grade	23% with Graduation, MsC or PhD; 46% with the 9 th or 12 th grade; 31% under the 6 th grade
Working status of the occupants (%)	56% full time workers; 26% retired; 17% students	47% full time workers; 21% retired; 23% students; 4% in another situation (e.g. unemployed)

	Cluster 1 (Active behavior)	Cluster 2 (Non-active behavior)
Average monthly income of the household (€)	60% above 2501€; 17% between 1501€ and 2500€; 33% below 1500€	23% between 1501€ and 2500€; 77% below 1500€
Equipment ownership and use 		
Heating equipment ownership (%)	100% ownership (67% with only electrical equipment; 33% with a mix of electrical equipment and fireplaces)	100% ownership (38% with only electrical equipment; 15% with a mix of electrical equipment and fireplaces and 38% with only fireplaces)
Heating equipment use (%; hours)	The 33% households with multi-systems estimate 80% split of consumption time by electrical equipment and 20% by fireplaces. The perceptions of the household members indicate an average of 3.5 hours of use per day on the cooler days	The 15% households with multi-systems estimate 50/50 split of consumption time by electrical equipment and fireplaces. The perceptions of the household members indicate an average of 2 hours of use per day on the cooler days.
Cooling equipment ownership (%)	67% AC either split or central; 33% do not have any cooling system	38% AC either split or central; 15% only use fans, 44% do not have any cooling system
Cooling equipment use (hours per day)	The perceptions of the household members indicate an average of 2.5 hours of use per day on the hottest days	The perceptions of the household members indicate an average of 1.5 hours of use per day on the hottest days
Domestic hot water equipment (%)	100% gas systems	100% gas systems
Cooking Stoves (%)	86% have exclusively gas stoves and 14% have a mix of gas and electricity stoves	92% have exclusively gas stoves and 15% have a mix of gas and electricity stoves and 8% have exclusively electric stoves
Renewable energy source microgeneration systems (%)	None of the households have microgeneration systems	None of the households have microgeneration systems
Electricity consumption and related characteristics 		
Daily average electricity consumption (kWh)	15.3 kWh/day	10 kWh/day
Type of Tariff (%)	67% single tariff, 33% dual tariff	54% single tariff, 46% dual tariff
Contracted Power (kVA)	83% equal or higher than 6.9 kVA	77% equal or higher than 6.9 kVA

Notes: The type of tariff relates to the costs of electricity during the day, depending on the hours of consumption (day or night), while the contracted power (*e.g.* 3.45 kVA, 6.9 kVA, 10.35 kVA) constrains the number of electrical appliances that could be used simultaneously.

Table 3.5 is divided into four groups of characteristics. The first one, ‘dwellings characterization’ reveals that all the constructive features may indicate that the houses in the ‘active behavior’ cluster consume more since they have worst building constructive characteristics. The percentage of older houses is higher and only half of the sample has insulation. Notwithstanding, with regard to the other determinants in this part, the two groups are very similar. Santin *et al.* (2009) for the Netherlands already identified that building characteristics could determine near 42% of variation in space and water heating, leaving more than 50% of the changes for user practices. Gram-Hanssen (2011) also shed the light on the

importance of consumers in the heat consumption, where identical houses could have a heat consumption varying with a factor of 3. This suggests the importance of also identifying socio-economic details, that may be crucial for the identification of the determinants for active climatization behavior.

The second part refers to ‘householder members’ characterization’, to highlight the potential risk alert of some consumers in the cluster of ‘non-active behavior’. In fact, this cluster has a higher percentage of vulnerable consumers that should be theoretically be consuming more electricity for heating such as children and elderly people. In the same line of thought, this is also the group with more retired and unemployed people, which could be spending more time at home, and consequently consuming more electricity, which is not the case. The ‘active behavior’ group includes consumers with higher education and monthly average incomes.

Analyzing the equipment ownership and use (third part of the table), we can see that the ‘non-active electrical heating behavior’ has more houses with fireplaces, on the contrary there are more houses using electrical equipment for heating in the “active behavior” cluster, which means that if we supported this typification with regard to the total energy consumption it would be better conclusions could be highlight regarding the thermal comfort level inside the households. The estimated hours of use by the household members’ backup our cluster results, showing that people perceptions are aligned with their effective consumption.

The ownership of several other electrical equipment such as lamps, refrigerators, computers, televisions, microwaves, cloth washing and dryer machines, dish washing machines, is similar across the households of both clusters and its use does not relate to outside temperature; therefore, are not presented as potential determinants of active consumption for heating. None of the households have microgeneration systems, which shows the potential of the integration of PV and solar thermal panels a recommendation in order to fulfil the needs for an increased use of electricity consumption or space heating bridging the gap on the lack of thermal comfort.

The last part of the table, ‘electricity consumption and related characteristics’, shows the lower or inexistent active behavior for heating is also portrayed in the lower average daily consumption. On the other hand, the type of tariff and the contracted power across the groups are very similar, which shows the need for diverse type of information for DSO and energy retailers, since the ones currently available are not enough to assess the type of consumers and the patterns of consumption for tailor made policy and measures design.

3.2.4 Discussion

The deployment of a smart grid environment generates large volume of data that carries important knowledge to support new functions and models. Transforming big data into useful

information to improve efficiency in the management, planning and operation of the power grid, to evaluate the potential for residential demand response programs as well in resolving the issues of sustainability and energy conservation is a key scientific challenge. Our focus on thermal comfort compared to other end-use energy services is justified by its importance on peak electricity demand.

From our analysis, we identified that consumers in this region have higher electricity consumption levels for space heating than for space cooling, revealing a predominance of active behavior for space heating. This might suggest that electrical cooling is unnecessary much of the year, and thus adoption of capital-intensive air conditioning systems is significantly lower but it might also indicate significant unmet demand for indoor thermal comfort services as discussed by Waite et al. (2017) while comparing different cities.

Therefore, this study offers more quantifiable insights into heating patterns rather than cooling, understanding electricity load patterns in a Mediterranean climate zone. The lowest temperature setpoint ($T_{min} < 5^{\circ}\text{C}$) impacts hourly electricity consumption deviations from 25% to 50%; while in the highest temperature days' profiles ($T_{max} \geq 35^{\circ}\text{C}$) it is only identified a 4% deviation. Lee et al. (2014) presented lower threshold temperature of electricity demand for heating and cooling of around 27°C and 19°C of daily maximum temperature for houses in a village in South Australia. Perez et al. (2014) indicate 25°C and Perez et al. (2017) a lower figure - 19.8°C , as the temperature threshold in their sampled houses in Austin, Texas, where after which the energy consumption increases fairly linearly related to maximum outdoor temperature. In Perez et al. (2014), in some cases, daily energy use from A/C for individual houses increased by a factor of 8.

In our analysis, the two distinct clusters derived from hourly electricity consumption deviations associated to extreme lower temperature and combined with the door-to-door surveys enabled for a better understanding and typification of households' climatization behavior regarding space heating.

The first level of heating and cooling consumption inertia towards outside temperature changes is due to the thermal inertia associated with building type and structure (i.e. house or multi apartment; type of wall, insulation, bearing structure) which minimize the impact of variations of outside temperatures, providing less changes in the indoor temperature (Silva, 2006).

Also, the adaptive comfort of different households could explain the second level of energy consumption inaction when outside temperatures tend to rise or fall. Adaptive comfort builds on the principle that people experience differently and adapt, up to a certain extent, to a variety of indoor conditions, depending on their clothing, their activity and general physical condition (BUILD UP, 2009). Usually the use of passive

adaptive measures is the first option (e.g. natural ventilation, shades), therefore not reflected on energy consumption. From our results this seems to happen until reaching very high outdoor temperatures.

The Portuguese legislation (i.e. Decree Law 118/2013), derived from the recast of Energy Performance of Building Directive of 2010 (EC, 2010), defines setpoint temperatures to calculate heating and cooling demands regarding thermal comfort levels. Several authors argue the problems of these analytical methods on overheating because they do not contemplate the household occupants' ability to adapt. This aspect is especially important in southwestern European countries, where a large proportion of households still rely on natural ventilation for cooling and shading devices (e.g. Oliveira et al. (2015); Barbosa et al. (2015); Mulville and Stravaravdis (2016)).

Despite acknowledging that the sample include households with different type of buildings, bearing structures, insulation levels, family structures that directly impact on indoor temperature, we can state that there is a general lack of thermal comfort inside households for both space heating (mainly in the households that do not have neither electrical or other type of space heating equipment) and space cooling; explained in some extent by recognized fuel poverty issues in the country (e.g. Bouzarovski, (2013); Gouveia and Seixas (2016); and Simões et al. (2016)).

Our knowledge on the low ownership of cooling equipment and the outcomes of the analysis conducted pointed that, according to this sample, the use of electricity for space cooling is negligible. This reinforces the lack of thermal comfort inside households, in face of maximum temperatures registered in several days above 30°C and 35°C. The theoretical thermal comfort inside households is far from being achieved portrayed in the gap between cooling and heating needs and effective final energy consumption. This problem has already been disclosed for Portugal by Gouveia et al., (2012) and Palma (2017); but also for other countries (e.g. Sunniko-Blank and Galvin, 2012; Wilde, 2014; Majcen et al. (2015) and Calì et al., (2016)) portraying the inability to keep households adequately warm/cool.

The knowledge produced with this analysis can be used to support the assessment of thermal comfort levels and adaptive comfort inside households, while understanding the impact of external minimum temperatures on load profiles due to active climatization actions. Regarding the analysis on maximum temperatures, we consider that the methodology presented herein may be applied for the case of high ownership rates and use of cooling equipment.

On another perspective, southwestern European countries are expected to be a region highly impacted by climate change and extreme weather events. According to Santos *et al.* (2006), a generalized increase of monthly cooling energy demand and a reduction of monthly heating

energy demand, as well as a reduction of the heating season and a consequent extension of the cooling season, is likely for Portugal, exacerbating the problem of lack of thermal comfort.

The results highlight the importance of policies targeted to different socio economic contexts and climate conditions, instead of the current one-fits-all energy policy measures and instruments. It is the case of effective reduction of energy consumption, taken as necessary to accomplish energy and climate targets, which should go further over energy conservation practices. It is not possible to prescribe policy measures and instruments to reduce energy consumption in regions with proved lack of thermal comfort, which is the case of the sample houses in the region analyzed in this study, and the lion share of Portuguese households. Our results suggest it is crucial to pay higher attention to the specificities of the countries and vulnerable consumers (e.g. old people, poor, ill people, single parents with small children) to address fair and tailor-made designed policies and measures towards energy efficiency and energy consumption reduction.

Compared with the European Union (EU28), Portugal had in 2014 still a relatively low final energy consumption per capita (1698 MWh, i.e. 27% below EU28 average) and electricity consumption per capita (4.3 MWh, i.e. 20% below EU28 average) (Pordata, 2016). The per capita energy consumption was below even when compared to countries with similar climate conditions like Spain (-11%) and Italy (-18%). Therefore, it becomes paramount to highlight that Portugal still need to promote the conditions to increase thermal comfort inside households, which may imply the increase of the energy consumption.

The following limitations are recognized in this study, namely: a) smart meters' data include cumulative consumption for all the end uses in a household (e.g. lighting, cooking, heating, washing machines) which could hamper our conclusions, though none of the other uses are consistently correlated with extreme outside temperature, as cooling and heating demand; b) the number of households may be considered low to extrapolate the results, but still enables to test the methodology; c) even though we have survey data to complement the average load profiles assessment, this might be limiting since not all the households fully use electricity for climatization purposes. A full assessment of thermal comfort would only be possible with comprehensive information on gas and biomass use.

3.2.5 Final remarks

In this paper, we investigated if high-resolution electricity consumption variations over the course of a typical day for different external temperatures thresholds can be interpreted as a proxy for active behavior of the households' occupants regarding space heating and cooling. Data analysis was supported on hourly electricity consumption registries of 2014 for a final sample of nineteen households located in Évora municipality, Portugal.

We evaluated the influence of different external air temperature thresholds, namely maximum daily temperatures (25°C, 30°C and 35°C) and minimum daily temperatures (15°C, 10°C and 5°C), on daily electricity consumption profiles. The assessment of temperature-driven daily load curve changes as proxies for active cooling and heating demand behavior shed the light on important issues on energy use for indoor thermal comfort. Hourly consumption deviations, stated as deviations of electricity consumption from average, were used to evaluate and highlight changes in consumption on the daily profiles, allowing the clustering of households with similar active climatization behavior.

The load curve (either as a total, per household or cluster of households) may be explained by the ownership of heating and cooling equipment, the income level, the house bearing structure but also from consumer behavior for climatization purposes during the day. Our results reveal that there are three types of consumers, ones that may not consume energy for space cooling and heating, others that only at very high outside temperatures consume energy and still others that may have a more active behavior.

These findings have high value for a wide range of applications within smart grids, namely for the forecasting of peak loads based on weather extremes and grid optimization. Moreover, the combination of smart meters with surveys produces knowledge on how, when and why people consume electricity, to inform policy makers and distinct energy stakeholders. It is important to know the characteristics of the target groups when devising and applying policy instruments for energy savings. Identify the active from the non-active behavior consumers is a crucial step to select where policy instruments on energy efficiency and reduction must apply. The combination of those two data sources enables in-depth analysis of the consumers' profiles, the demand side management alternatives, energy efficiency measures and also, the impact of changes in pricing tariffs. This could be particularly important for large groups of stakeholders, for example those dealing more directly with people, such as the municipalities and social support institutions, but also for ESCOS, DSO.

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Authors Contributions

J. P. Gouveia structured and wrote the paper, performed all the smart meters and surveys data analysis. J. Seixas supported the design of the paper and its in-depth revision. A. Mestre assisted on the handling and cleansing of the smart meters' data.

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Chapter 4 | Looking Ahead

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Projections of Energy Services Demand for Residential Buildings: Insights from a Bottom-Up Methodology

ABSTRACT

Projections of energy demand are important for energy security supply and low carbon futures, and usually rely on final energy consumption trends methods, limiting the opportunity for future options. Methods supported by energy services are much preferred to estimate future energy demand, since they are better suited to accomplish end-users needs. Final energy can then be assessed through complementary tools, as technological models, resulting in deeper knowledge on the relation between energy services and technology options. This paper presents a bottom-up methodology to project detailed energy end-uses demand in the Portuguese residential buildings until 2050, aiming to identify the parameters governing energy services demand uncertainty, through a sensitivity analysis. The partial equilibrium TIMES (The Integrated MARKAL-EFOM System) model was used to assess technology options and final energy needs for the range of parameters variations for each end-use, allowing to conclude on the impact of uncertainty of energy services demand in final energy. Main results show that technology can overweight behavioral practices and lifestyle changes for some end-uses as in space heating and lighting. Nevertheless, important focus should be given to uncertain parameters related with consumer behavior, especially those on heating and other electric end-uses, as thermal comfort and equipment's use.

KEYWORDS

Energy Services Demand; Residential Buildings; Portugal

4.1 Introduction

Energy demand projections are a very complex topic depending on several factors, from socio-economic, to behavioral, technological and climatic. Under or overestimating energy demand may cause energy scarcity or redundancy in resources (Ünler, 2008) emphasizing the importance of a reliable long-term energy planning.

Projections of future energy needs mostly rely on final energy consumption, usually sustained by quantitative models, namely econometric (*e.g.* Anderson (1973); Boucinha *et al.* (2006); Amarawickrama and Hunt (2008), Dilaver and Hunt (2011)) or technological (*e.g.* Strachan *et al.* (2007), Schulz (2007), IEA (2011)). An extensive review on energy models for demand projections is provided by Suganthi and Samuel (2012), while methods targeting the residential energy demand are focused in Madlener (1996) and Labenderia *et al.* (2006).

We support that projections of energy demand based on final energy greatly locks future options of energy resources and technologies available to satisfy energy needs, limiting the ability to consider alternative energy paths for the future. By focusing on final energy, there is the perception that fuels and technologies are the only important elements of energy systems (Sovacool, 2011). But since final energy consumption is driven by the demand for the services it provides, like cooking and heating (Haas *et al.*, 2008) we argue that energy projections should be driven primarily by Energy Services Demand (ESD).

An extensive portfolio of modeling techniques (bottom-up and top-down) to project energy needs is reviewed in Sartori *et al.* (2009). Projections supported by ESD following a bottom-up approach ought to provide better predictions than trend analysis of historical values (Schipper *et al.*, 1985). A bottom-up approach extrapolates the estimated energy consumption of a representative set of individual houses to regional and national levels explaining much better the changes in energy use (Swan and Ugursal, 2009). Furthermore, estimates from bottom-up tools can be used to feed more encompassing energy models to replicate baseline projections. Brounen *et al.* (2012) identifies that although acknowledged as important, social and demographic characteristics of households are often ignored in the engineering literature about energy efficiency, due to a lack of detailed data. As stated by Ruijven *et al.* (2010), energy demand is a crucial point factor in model uncertainties but despite its relevance, medium to long-term studies on energy and climate policy devote small effort and attention on ESD.

Energy services have been approached in a simplified way (*e.g.* Van Regemorter and Kanudia, (2006) and Gomez *et al.* (2011)) or absent (*e.g.* IEA (2011) and WWF (2011)), which call for more studies and in-depth analysis capable to identify and assess the drivers behind future ESD. Daioglou *et al.* (2012) also identified this gap, bringing up that most energy models describe future residential energy

demand supported on simple relations between energy consumption and income or GDP (Gross Domestic Product) *per capita*.

In this paper and following the definition by Haas *et al.* (2008) and Reister and Devine (1981) energy services refer to a measure of the service provided to final consumers by their own use of energy in any of its forms; it encompasses the short and long term components of service demand (*e.g.* consumer behavior and area of households) but only the direct component of service demand (*e.g.* lighting, cooking); therefore, not considering the range of indirect (embodied) energy services (*e.g.* food, furniture).

Energy consumption in buildings deserves special attention since they represent a significant share of energy consumption in Organization for Economic Co-operation and Development (OECD) countries (*e.g.* 20 to 30% in European Union (EU) (Eurostat, 2011). In the last years (*i.e.* 2000-2009), energy consumption in EU buildings has almost not changed, but has been increasing in the southwestern European countries (Eurostat, 2011), highlighting the importance to understand and assess the drivers of ESD in those countries.

This paper presents a bottom-up methodology to project detailed end-uses energy services demand in the Portuguese residential buildings up to 2050, aiming to identify the parameters governing energy services demand uncertainty, through a sensitivity analysis. The partial equilibrium TIMES (The Integrated MARKAL-EFOM System) model was used to assess technology options and final energy needs for the range of parameters variations for each end-use, allowing to conclude on the impact of uncertainty of energy services demand in final energy consumption. Final goal is to identify in what end-uses, and in what parameters in particular, should policies target for an effective energy consumption reduction.

This paper advances the state of the art by presenting valuable knowledge on relevant and highly uncertain drivers supporting ESD and related final energy projections in the long term. The case study application improves the understanding of the energy demand specificities for European southwest region, aiming to contribute to identify where efforts in energy policy should focus either at national and regional level.

The paper is structured in four Sections. The next section describes the general framework used to estimate both ESD and final energy for the residential sector up to 2050, presenting also the case study. It introduces the parameters used and the variations considered on the sensitivity analysis performed. The results are described and discussed in Section 4.3 and Section 4.4 concludes.

4.2 Modeling framework

In order to achieve the above-mentioned goal, research work was developed in two steps:

1) Applying a bottom-up methodology to project ESD for the different end-uses of the residential sector, namely space heating and cooling, water heating, lighting, cooking, refrigeration and electric appliances (*e.g.* dishwashing, cloth washing, among others) (Section 4.2.1.1). A Reference scenario (REF) was built, serving as a benchmark for the analysis of future ESD. A range of plausible variations of the parameters defining the REF scenario end-use services demand was assessed, resulting in around 140 ESD sensitivity analysis scenarios.

2) Selecting a set of 21 scenarios corresponding to the highest and lowest variation of each parameter for each end-use plus da REF, serving as input for the technological optimization model TIMES_PT to estimate final energy demand and technology portfolio (Section 4.2.2).

As mentioned by Pachauri and Spreng (2003), energy services themselves cannot be measured in energy units but it is possible to measure energy requirements for energy services through the consumption at the level of useful energy. The starting point for developing projections for future energy services is establishing the useful energy demand for the different end-uses in a base year (2005). This is generally estimated as a function of the energy input (*i.e.* final energy) and the efficiency of the technologies (Eq. 1).

$$\text{Useful energy demand}_n = (\text{Final energy Consumption}_n \times \text{Efficiency}_n) \quad (1)$$

For the future, the demand for a particular energy service is generally related with a consuming unit. The common projection driver to generate the demand for energy services is the evolution of number of households until 2050 ($HouT_n$), which depends on total population expectation (Pop_n) and on the evolution of the number of persons per household (PH_n) as follows:

$$HouT_n = Pop_n / PH_n \quad (2)$$

4.2.1 Energy services demand

4.2.1.1 Methodology projection by end-use

Howell *et al.* (2005) underlined that energy use in the residential sector can be best understood by focusing on specific end-use functions and their drivers. The relevance of each end-use in the overall energy consumption is highly dependent on climate, physical dwelling characteristics, appliances and system characteristics, ownership, and occupancy behavior (Sartori *et al.*, 2009). We computed ESD projections for 10 different end-uses of the residential sector and these variables were taken into account in the methodology to some extent.

Space Heating and Cooling

Household characteristics as the size, age and climate related location of the estimated households ($HouT_n$) governs its energy needs (Lombard *et al.*, 2008). We considered four categories: 1) single house in the North of the country, 2) multi-apartment in the North, 3) single house in the South and 4) multi-apartment in the South. To accommodate differences on construction techniques and on the building envelope, we breakdown the stock of households into three periods regarding the year of construction: “pre-1990”, “1990-2005” and “post 2005”. This buildings typology describes the original state of the buildings and does not take into consideration later renovation measures.

Since an integrated building design considering the high number of requirements and building components that influence energy performance, is an inherently difficult problem to formulate and solve (Jaffal *et al.*, 2012), we used the steady state approach presented in Decree Law n. ° 80/2013 resulting from the Energy Performance of Building Directive and its recast on 2010 was applied to estimate the useful energy demand for heating and cooling. Useful energy demand for heating refers to the useful energy required to maintain the temperature of the inner space at 20°C during the heating season, while useful energy demand for cooling refer to the useful energy required to maintain the temperature of the inner space at 25°C during the cooling season, considering 50% of relative humidity. Construction characteristics as type of insulation, glass fraction, and solar factor of glazing depending upon the age of the house are considered in this methodology. Heating needs (kWh/m²-year) (Nic) was obtained (Eq. 3) through the balance between:

- Heat lost by the envelope (Qt) (kWh/year);
- Heat lost by air exchange (Qv) (kWh/ year);
- Total net gains (QGU) (kWh/year) = internal gains + solar gains.

$$Nic = (Qt + Qv - QGU) / S_n, \quad (3)$$

where S_n = net floor area (m²). The methodology to compute the cooling needs (Nvc , kWh/m²-year) (Eq. 4) is very similar. For the heating needs, the Heating Degree-Days (HDD) parameter was used (Popescu *et al.*, 2009); while for the cooling needs, we applied the air–sun temperature (fictitious temperature that represents the combined effect of solar radiation in the environment and the heat exchanges by radiation and convection between the surface and surroundings). These methodologies can be stated as complementary, because while for the winter the gains minimize the needs and the losses increase them, for the summer it is the opposite.

$$Nvc = [Qg \times (1-\eta)] / S_n, \quad (4)$$

where Qg = total gains (kWh/year), defined as the sum between gains by air exchange and the total net gains, and $(1-\eta)$ is utilization factor of solar and internal gains in the cooling season. Differences

in features like HDD, average monthly solar radiation (kWh/m².month) and months of heating season result in different needs of households depending on the location. Generally, the residential buildings stock is not equally distributed in a country; accordingly, the HDD were weighted based on the population distribution in the different Portuguese areas.

We derived the total heating ESD for the residential buildings in year n (NiT_n , kWh/year) as described in Eq. 5, and for cooling energy demand (NvT_n , kWh/year) by Eq. 6.

$$NiT_n = \sum (Nic_{[N,S;SH,MA;<1990,1990-2005,>2005]} \times S_{n[N,S;SH,MA]} \times HouT_{n[N,S;SH,MA;<1990,1990-2005,>2005]}), \quad (5)$$

$$NvT_n = \sum (Nvc_{[N,S;SH,MA;<1990,1990-2005,>2005]} \times S_{n[N,S;SH,MA]} \times HouT_{n[N,S;SH,MA;<1990,1990-2005,>2005]}), \quad (6)$$

where $S_{n[N,S;SH,MA]}$ states for the households average area (m²) according to location (N – North, S – South) and type (SH – single house, MA – multi apartment) and $HouT_{n[N,S;SH,MA;<1990,1990-2005,>2005]}$ refers to the number of households in the year n for each location, type and age.

Water Heating

Energy for water heating refers to the useful energy needed to heat Domestic Hot Water (DHW) until 60°C, for bathing and washing and primarily depends on the number of persons per household. We estimated the energy needed for DHW per household for the year n (Dhw_n , kWh/year·household) through Eq. 7:

$$Dhw_n = [PH_n \times CR_{dhw} \times \Delta T \times n_d \times 4187] / 3600000, \quad (7)$$

where CR_{dhw} refers to the daily average water consumption for DHW (liters), ΔT states to the temperature increase needed (45°C) to reach the reference temperature in hot water, and n_d the number of consumption days. The total ESD for DHW ($DhwT_n$, kWh/year) can be written as (Eq. 8):

$$DhwT_n = \sum (Dhw_n \times HouT_{n[N,S;SH,MA]} \times Odhw_n), \quad (8)$$

where $Odhw_n$ is the ownership rate of DWH equipment in year n (%); $HouT_{n[N,S;SH,MA]}$ is the number of households in the year n by location and type.

Cooking

The energy service demand for cooking in year n (C_n , kWh/year) was estimated through (Eq. 9):

$$C_n = Cook \times Ocook_n \times HouT_n, \quad (9)$$

where $Cook$ is the useful energy needed for cooking per household (kWh/year·household) and $Ocook_n$ the ownership rate of cooking equipment (%).

Refrigeration and Washing Machines

The method to estimate the energy demand for refrigeration and washing machines (RWM_n) can be described as a function of four elements: ownership of each appliance a in year n (*i.e.* refrigeration equipment, cloth washing and drying machines and dishwashers) (O_{an} , %), ownership of equipment per efficiency class (O_{en} , %), useful energy needed per equipment efficiency class e in year n (E_{en} , kWh/year) and number of households (Eq. 10):

$$RWM_n = \sum_a [O_{an} \times HouT_n \times (\sum_e O_{en} \times E_{en})]. \quad (10)$$

Lighting

The number of light bulbs is the main condition for the demand of lighting services (L_n , kWh/year); therefore, we take into account the number of bulbs per household and their market share (*e.g.* LED (Light-Emitting Diode), incandescent light bulbs) (LB_n) as well as its efficiencies to obtain the specific useful energy per light bulb in the base year (E_l , kWh). With this value and considering it constant for the future, we obtained ESD for lighting from Eq. 11:

$$L_n = E_l \times HouT_n \times LB_n. \quad (11)$$

Other Electrics

The Other Electrics (OE) end-use in residential households includes electric appliances like televisions, computers, audio equipment and others. In recent years, the OE had increasing trends due to high penetration of small electric devices. Since there is no detailed data on these equipment ownerships and its efficiencies, we considered a simplified method stating the final energy consumption for OE equal to the useful energy needs. Useful energy per household for the base year (OE_{n0} , kWh), from which the projections are made, is defined by Eq. 12, where Eoe_{n0} is the final energy for other electrics.

$$OE_{n0} = Eoe_{n0} / HouT_{n0}. \quad (12)$$

For the future, an annual growth rate was considered to increase the OE energy demand (Eq. 13), where OE_n (kWh) represents the useful energy demand in the year n for OE appliances and te_n the growth rate of OE energy consumption from year $n-1$ to year n .

$$OE_n = [OE_{n-1} \times (1 + te_n)] \times HouT_n. \quad (13)$$

4.2.1.2 Assumptions for Portugal

Energy services can differ widely between countries due to cultural and social drivers (Sovacool, 2011). Portugal was used as a case study, fourfold: 1) the location in Southern Europe, targeted as one of the most likely climate impacted regions on thermal comfort; 2) the expected increasing energy needs to achieve comparable energy *per capita* to other EU countries - Portugal had in 2009, a *per capita* energy consumption below almost all EU countries (23% below EU₂₇ average), even when

compared to countries with similar climate conditions like Spain (12%) and Italy (15%); 3) the absence of comprehensive energy demand studies for Portugal, or with a focus only on electricity demand (*e.g.* Boucinha *et al.*, 2006); 4) the publication of a recent study (*i.e.* DGEG, 2011b) showing profound changes in energy consumption habits in the Portuguese residential buildings, which makes this study very timely.

Since 1990, total Portuguese final energy consumption has been steadily growing (about 2.5%/year), with 1.0%/year specifically in residential buildings (DGEG, 2011a). Residential sector is the third most consuming sector after transports and industry, representing 17% to 19% of the total final energy consumption from 1990 to 2010.

Energy demand projections usually assume different population scenarios to accommodate future uncertainty (*e.g.* Auffhammer and Aroonruengsawat, 2011). Variations of population or number of households affect all the end-uses in a similar way. Despite acknowledging the importance of the role of population evolution in future energy demand (Brounen *et al.*, 2012), we considered only one population scenario in our analysis once the scope of this paper is to focus on drivers that are usually not assessed in ESD projection.

The population scenario until 2050 resulted from an update of the 2010 value from the new census (INE, 2011a) and the growth rates were taken from the central scenario of the Portuguese National Statistics (INE, 2009). It is deemed an increase of population until 2035 reaching almost 11 million people, followed by a decrease afterwards, achieving a value around 2050 similar to current values. It is expected a decrease in the number of persons per household in line with the trend since 1990, justified by a greater number of single-parent families and increasing income and urbanization of the population (Price *et al.*, 1998). The scenario is characterized by the trends presented in Table 4.1, where the projections of GDP *per capita* are presented only for illustrative purposes.

Table 4.1 - Demographic and economic variables evolution for Portugal until 2050

Parameter	2005	2010	2020	2030	2040	2050
Annual population (thousands)	10570	10556	10725	10791	10768	10588
Persons per household (Inhabitant /household)	2.70	2.59	2.42	2.26	2.11	1.96
GDP <i>per capita</i> (1000€ ₂₀₀₀ /person)	12.75	12.41	14.20	18.50	24.19	31.93

Although the Portuguese dwelling stock comprised near 5.47 million in 2005 and 5.88 million housing units in 2010 (INE, 2011b) only households were considered in this work due to its effective occupancy. Hence, 3.92 million households in 2005 growing to 4.08 million in 2010 were considered. To classify the households by location, type and age for 2005 we firstly compiled data from the Portuguese National Statistics (INE, 2001; INE, 2008) with available information on type and

location. This was updated for 2010 with recent information from DGEG (2011a). Due to lack of studies, the 2010 shares were considered to be constant over the period of study, possibly omitting substantial future lifestyle changes. The estimation of the residential households' stock for the time horizon, following Eq. 2 and according to the expected evolution of demographic variables (Table 4.1) resulted in a 38% growth of the number of households from 2005 to 2050.

To calculate the future stock of existing households by typology, an approach based on demolition and renovation rates was used. We assumed that only “pre-1990” households are properly subjected to demolition and renovation. After renovation, the household is considered to be as new, having the characteristics of a “post 2005” household. We applied the renovation and demolition rates for dwellings available in National Construction and Households Statistics (INE, 2011b) (0.019%/year and 0.053%/year respectively) to the existing household stock until 2020, and doubled rates afterwards, following the average European value (Anström *et al.* 2010). Table 4.2 presents the number of households per category for the base year and 2050. When compared with the rates mentioned by Anström *et al.* (2010) for Portugal, calculated as a mean value of France and Spain (0.082%/year), we found them smaller, probably explained by the existence in Portugal of policies promoting the construction of new households.

Table 4.2 – Portuguese households grouped by age, location and type for 2005 and 2050

		Households Stock per category (thousands) 2005 2050						
Year	Household Typology	Households pre-1990 existing in year n (2005 2050)	Proportion on total households' stock (2005 2050)	Households built between 1990-2005 existing in year n (2005 2050)	Proportion on total households' stock (2005 2050)	Households built post 2005 existing in year n (2005 2050)	Proportion on total households' stock (2005 2050)	Total (2005 2050)
n= 2005 2050	Single House North	1158 904	30% 17%	352 352	9% 7%	- 552	0% 10%	3915 5389
	Multi-Apartment North	482 593	12% 11%	147 147	4% 3%	- 362	0% 7%	
	Single House South	745 524	19% 10%	227 227	6% 4%	- 320	0% 6%	
	Multi-Apartment South	616 758	16% 14%	187 187	5% 3%	- 463	0% 9%	
	Total	3002 2779	77% 52%	913 913	23% 17%	- 1697	0% 31%	

The average household size (m²) by type of household and location were obtained in DGEG, 2011b). In 2005, Portugal had a living space per person of around 37m² similar to United Kingdom value in 1991 (Boardman *et al.*, 2005) showing large possibilities of increasing. For the future, we used

differentiated growth rates for households in the North and South, following past trends (Table 4.3). The annual rate of change is constant over the years assuming that the trend in household's sizes growth will remain stable.

Table 4.3 – Household average size by type and location in 2005 and 2050

Household type and location	2005	2050
Single House North (m ²)	101	121
Multi-Apartment North (m ²)	80	95
Single House South (m ²)	97	118
Multi-Apartment South (m ²)	92	112

As stated in the beginning of Section 4.2, ESD estimations rely on the useful energy demand in the base year (2005). The computation of the useful energy provided according to Eq. 1 used reverse engineering, where the estimation of the useful energy was supported by the best available data through a decomposition of the Portuguese national energy balances (DGEG, 2011a) apportioning final energy consumption at the initial year to the various end-uses and using the performance characteristics of the existing technology stock compiled from several sources (*e.g.* ADENE (2006), INE (2008), REMODECE (2008), DGEG (2011b)) Figure 4.1 presents the share of final energy consumption per end-use in the Portuguese residential buildings in 2005. “Other Electric Equipment” include refrigeration ($\approx 8\%$), washing and drying machines ($\approx 4\%$) and other small electric appliances ($\approx 10\%$), which consider computers.

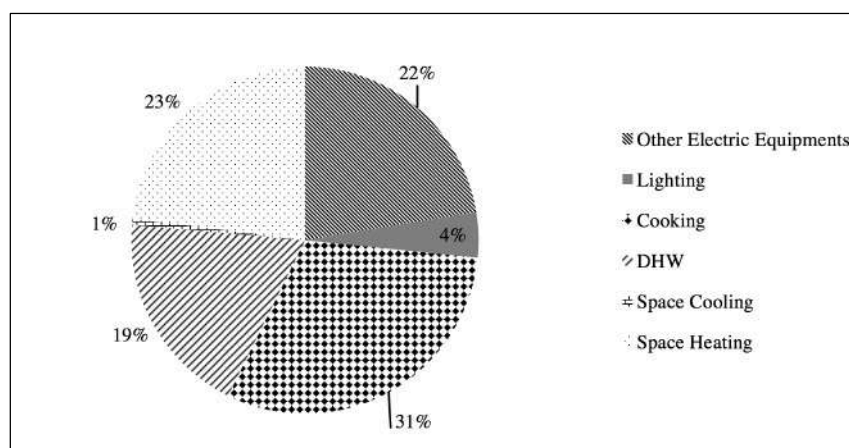


Figure 4.1 – Portuguese residential final energy consumption by end-use in 2005

The methods to estimate the demand for the different end-uses until 2050 are explained, in detail, in the following section.

4.2.1.3 Reference scenario and sensitivity analysis

A Reference (REF) scenario was build intending to be a benchmark for the analysis of ESD projections. REF is consistent with current expectations followed by past recent trends, being a

plausible scenario for Portugal. REF is supported by a storyline previously used for prospective studies in Portugal (Seixas *et al.*, 2012) and is a comprehensive scenario including all end-use sectors (*i.e.* Residential, Industry, Transports, Services and Agriculture).

Projections of ESD can vary substantially according to the uncertainty behind the evolution of the parameters in each end-use. Therefore, a sensitivity analysis was performed taking variations over selected parameters to assess its uncertainties and specific impacts on future energy services estimations (*e.g.* 2050). A range of plausible variations supported on acceptable limits within a logical decision framework for each parameter was adopted, instead of systematic variations over all parameters, once this approach would probably not represent likely futures, not capturing individual end-use specificities. The analysis resulted in more than 140 sensitivity analysis scenarios, allowing the understanding on which parameters have more impact and uncertainty on ESD.

Sensitivity analysis in similar studies, have been done through the assessment of variables that might affect directly final energy consumption, like primary energy prices (Daioglou *et al.* (2012) and Auffhammer and Aroonruengsawat (2011)); discount rates (Simões *et al.*, 2008), climate change induced variations on heating and cooling consumption (Li *et al.* (2012)). Herein, we focus our analysis on the drivers governing energy services demand instead energy consumption. The approach adopted to perform the sensitivity analysis aim to capture the weight of household infrastructure, social, climate and behavioral changes in the energy services demand, including the uncertainty associated with specific parameters.

Heating and cooling needs for REF were estimated following Eq. 3 and 4 for the different household archetypes and the results are described in Table 4.4. Twelve household archetypes were defined based on available information and national expertise on houses construction characteristics. Households constructed “post 2005” are assigned the best building envelope characteristics according to energy standards as defined in the Thermal Regulation for Buildings for Portugal (Decree Law n. ° 80/2006). According to Panão *et al.* (2011), heating energy demand calculations through the described methodology are reliable for a great number of buildings in Portugal, while for the cooling energy needs calculations, the methodology does not reproduce properly the thermal behavior of buildings. Albeit, the results achieved are in line with the expectations of Panão *et al.* (2011), that considers that traditional and passive architecture shows reduced cooling energy needs, under the Portuguese climate conditions.

Table 4.4 - Heating and cooling needs for different household types for Portugal in REF scenario

Heating needs (N _{ic}) (kWh/m ² ·year)			
Household Type	Households pre 1990	Households 1990-2005	Households post 2005
Single House North	267.4	139.5	95.3

Multi-Apartment North	102.4	94.5	91.3
Single House South	94.6	76.7	53.7
Multi-Apartment South	68.7	57.0	51.4
Cooling needs (Nvc) (kWh/m²·year)			
Household Type	Households pre 1990	Households between 1990 and 2005	Households post 2005
Single House North	8.3	9.6	10.3
Multi-Apartment North	6.9	8.3	8.8
Single House and Multi-Apartment South	15.5	1.5	16.9

Table 4.5 describes the assumptions for the parameters of REF scenario for all the end-uses and the variations assessed on the sensitivity analysis.

Table 4.5 – Reference scenario parameters and sensitivity analysis variations

	Reference Scenario		Sensitivity analysis
End-uses	Parameters (2005 and future evolution)	Comment/Sources	(variations to the REF)
Space Heating and Cooling [Eq. 5 and Eq. 6]	Household area as in Table 4.3	-	1. Half of the growth rate 2. Keep constant as in 2010 average areas 3. Double of the growth rate
	Nic and Nvc as in Table 4.4 and constant for the future.	-	1. -30% to +30% (with 5% steps) for heating 2. -10% to +83% for cooling
	Growth of 0.25%/year for both heating and cooling thermal comfort levels.	In 2005, the effective energy consumption (thermal comfort) for heating and cooling represented only 10% of the total energy needs. Projections of increase are duly justified by an increase of thermal comfort levels inside households.	1. Keep constant as in 2005 figure (0%) 2. Increase of 1.5, 2, 2.5 and 3% each 5 year
Water Heating [Eq. 7 and Eq. 8]	$Cr_{dhw} = 40$ liters per person per day, constant until 2050	Decree Law n. ° 80/2006	3. -10% to 50% (between 36 to 60 liters)
	$\Delta T = 45^{\circ}\text{C}$, constant until 2050	Decree Law n. ° 80/2006	4. -10% to +10% (between 40.5°C to 49.5°C)
	$n_d = 183$ days/year, constant until 2050	Expert judgment	5. -5% to +70% figures (between 173 days to 310 days)
	$Odhw_n = 98\%$ in 2005. 100% penetration was assumed	Simões <i>et al.</i> (2008)	Keep constant as in 2010 figure (<i>i.e.</i> 98%)

	from 2010 onwards.		Increase to 99% in 2015 and constant afterwards
	PH_n as described in Table 1	-	Keep constant as in 2010 Double of the growth rate Half of the growth rate
Cooking [Eq. 9]	$O_{cook_n} = 100\%$ in 2005	INE (2008)	-
	$Cook = 1450$ kWh/year-household until 2050	Expert judgment	1. Variations of -30% to +30% (from ≈ 1000 to 1900 kWh/year)
Refrigeration [Eq. 10]	O_{an} for freezers: growing from 68% (2005) to 71% in 2015 and stabilizing afterwards.	The main difficulty regarding the calculation of electric equipment's demand is the availability of data with the necessary desegregation level. It was necessary to review and harmonize several sources of information (e.g. [3]; [40]; [43]; [56]) and to make assumptions regarding penetration rate of electrical equipment's, efficiency classes' breakdown for the base year and annual average consumption.	<u>Freezers ownership rate (O_{an})</u> 1. Keep constant as in 2010 2. 1% to 2% annual increase (reaching saturation in 2050 and 2030 respectively) 3. Specific energy needs (E_{en}) 30% to +30%
Washing/Drying Machines	O_{an} for dish washing machines: 35% in 2005 and increasing until 89% in 2050. Dish washing machines cycles: 4 per week Cloth drying machine cycles: 2 per week		<u>Example for Washing Machines Ownership rate (O_{an}):</u> Keep constant growth rate as in 2010 Higher growth rate (e.g. reaching saturation in 2040) <u>Specific energy needs per year (E_{en})</u> Washing cycles per week – 2, 3, 5, 6 and 7.
Lighting [Eq. 11]	$LB_n = 11.4$ light bulbs per household in 2005 A systematic increase (1.4%/year) in the number of light bulbs is assumed.	MEI (2008)	1. Keep constant as in 2010; 2. 1% to 4% annual increase
	Specific energy needs (E_t) = 35.96 kWh/bulb	As explained in Section 4.2.2.1	-30% to +30%
Other Electrics [Eq. 13]	Growth rate, $te_n = 0.5\%$ /year	Expert judgment	0.75% to 3%/year from 2015 onwards

As described in the above table, there are several parameters influencing the energy services demand for each end-use. Climate change, consumer behavior associated with the use of heating and cooling equipment (*i.e.* thermal comfort) and household characteristics (*e.g.* location, age, type) influencing directly the energy needs, are the drivers behind energy services demand for heating and cooling. For the other end-uses, consumer behavior, ownership of equipment and specific energy needs are also important drivers. A more detailed explanation of the values and variations used in the sensitivity analysis is presented.

Heating/cooling energy demand derived from Eq. 3 and Eq. 4 and presented in Table 4.4, indicates the value of energy needs for a household, considering the hypothesis of a permanent heated/cooled area during the heating/cooling season. These needs are theoretical since in residential buildings, the

actual cooled and heated area represents only a small fraction of a household and the devices that supply this demand are switched-on only part of the time. As mentioned by Asimakopoulos *et al.* (2012), the partial coverage of the energy needs due to social and economic reasons is difficult to predict (*i.e.* evolution of poverty). Therefore, in sensitivity analysis addressing heating and cooling ESD, we explored the uncertainty patterns on thermal comfort levels evolution, with variations aiming to capture an increasing convergence between the energy needs inside households and effective energy consumption to supply these needs.

According to Santos and Miranda (2012), a generalized increase of monthly cooling energy demand and a reduction of monthly heating energy demand, as well as a reduction of the heating season and a consequent extension of the cooling season is likely for Portugal due to expected climate change. Asimakopoulos *et al.* (2012) identifies for Greece an increase in cooling needs around 83% in 2041-2050 and an average reduction of the heating energy needs to about 22.4% for the same period (A1B scenario). The variations considered for the heating and cooling specific energy needs accommodated this range. Households' area projections were also assessed through variations in the growth rate to evaluate possible changes in Portuguese households.

Concerning water heating (DHW) demand, variations on the penetration rate of DHW equipment below saturation was considered, as well as changes of future levels of water consumption, variations on the temperature to warm water and on the number of water consumption days. Since the number of persons per household also influences the DHW energy needs, we changed the future expectations of this parameter to accommodate uncertainty on the number of persons of the Portuguese families in the future.

The evolution of consumption patterns justifies future variations in the energy needed for cooking (*Cook*) (*e.g.* going out for dinner more times) as for washing and drying machines (*e.g.* less washing cycles per week), giving rationale to evaluate the specific useful energy needs (E_{en}).

For lighting and considering that several energy policies are targeting this end-use to promote technology development, as increased LED penetration, the assumption that the useful energy per light bulb will be constant as used in the REF might not hold true. Furthermore, the number of consumption hours can also vary. To take all this in consideration in the sensitivity analysis we varied the value of E_l . The number of light bulbs per household was also changed, increasing past growth trends.

For the OE end-use, a wide range of growth rates was considered to estimate future energy needs aiming to capture plausible future evolutions derived from changes in lifestyles, households' occupant behavior and growing ownership of this equipment.

This methodology neglects the influence of price and income elasticity of demand for energy services as well as a detailed analysis on the role that household occupants' behavior may have on energy

consumption patterns (this can be further assessed by the analysis of information resulting from new experiences with smart metering).

4.2.2. Final energy demand

As previously stated, the demand for future energy services is satisfied by a technology portfolio and the respective final energy consumption profile, and thus technological development, energy efficiency improvements and insulation measures, among others, is accommodated through the TIMES_PT model (Simões *et al.*, 2008). This supports our assumption that projections relying on energy services makes easier to understand and assess the role of each component in the final energy planning and policy.

Once we intended to evaluate the range of the parameters used in ESD sensitivity analysis, only the highest and lowest variations scenarios for each end-use (*i.e.* 20 scenarios selected plus the REF) are presented for further analysis.

TIMES_PT is a peer-reviewed linear programming optimization bottom-up technology model that results from the implementation for Portugal of the TIMES model generator, developed by Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency. The generic model structure can be adapted to simulate a particular energy system at local, national or multi regional levels.

In these types of models, primary and final energy carriers compete with each other and thus the energy demand exogenously fed into the model is the demand for energy services and materials. Depending on the availability and prices of primary energy resources introduced in the model, the quantities of final energy carriers (as electricity or natural gas) are endogenously generated while trying to satisfy the demand for energy services at minimum total system costs. The big advantage with this kind of large energy system models is that they can capture the competition of limited resources and track the energy flows from primary energy all the way to the demand. More information on TIMES development and equations can be found in Loulou *et al.* (2005a, 2005b) and Loulou *et al.* (2007).

The TIMES_PT model represents the energy system of Portugal in 2005 and its possible long-term developments until 2050. The actual system encompasses all the steps from primary resources in place to the supply of the energy services demanded by energy consumers, through the chain of processes, which transform, transport, distribute and convert energy into services. Besides residential buildings, the model also represents the transport, services, industry and agriculture end-use sectors as well as primary energy supply, electricity generation and refining. Possible future developments of the system are driven by reference demands for energy services (*e.g.* commercial lighting, residential space heating, residential lighting and many others), the supply curves of the resources (*e.g.* amount

available at each price level), along with possible environmental constraints, which are provided as exogenous inputs to the model.

The model outputs include installed capacities for electricity production, primary and final energy consumption, energy trade and greenhouse gases emissions in 5-year time steps (*i.e.* 2005, 2010, 2015, etc.) TIMES_PT is supported by an up to date technological database from end-use technologies (*e.g.* boilers, refrigerators, cars) to energy production facilities, characterized by its economic and technological parameters. Specifically, on the residential sector, the database possesses more than 500 heating, cooling, water heating, cooking technologies as well as lighting and electric equipment (*e.g.* refrigerators, washing, drying and dish washing machines) divided per type and/or efficiency classes. The model also considers the improvement of the energy performance of existing buildings through higher thermal insulation levels on the envelope components (*e.g.* roof, floor and internal and external walls) and replacement of windows. TIMES_PT model has been used extensively for different purposes: research (Simões *et al.* 2008) and policy support studies as in Seixas *et al.* (2008), Seixas *et al.* (2010) and Seixas *et al.* (2012), with a close interaction and collaboration with private and public national energy stakeholders.

The model was calibrated for 2005 and validated to 2010 according to final energy consumption statistics (DGEG 2011a), electricity installed capacity and energy trade (Seixas *et al.*, 2012), and includes national energy related policies goals (*e.g.* energy efficiency targets from the National Action Plan for Energy Efficiency (MEI, 2008). Primary energy prices were taken from the Current Policies scenario of the World Energy Outlook 2011 (IEA, 2011) until 2035, and linear growth onwards. Climate policy (*e.g.* Carbon Dioxide (CO₂) cap or price) is not considered once we wanted to analyze the impact of the ESD variations on final energy consumption without the influence of a CO₂ constraint.

4.3 Results

In the next sections, we present and assess the results of energy services demand and final energy for each end-use of the REF scenario and the sensitivity analysis.

4.3.1. Projections of future energy services demand

4.3.1.1 Reference scenario

The estimates of the ESD REF scenario show an increase of almost 80% in 2050 compared to 2005 values, near 1.3%/year. Regardless the end-use considered, it is expected an increasing energy demand, explained by the introduction of new electric equipment, more hours of use of computers and televisions, higher penetration of electric appliances and increasing thermal comfort levels converging

to European figures (Figure 4.2). Added to all these factors, the underlying role of socioeconomic factors and changes in the building stock also has a high effect on these developments.

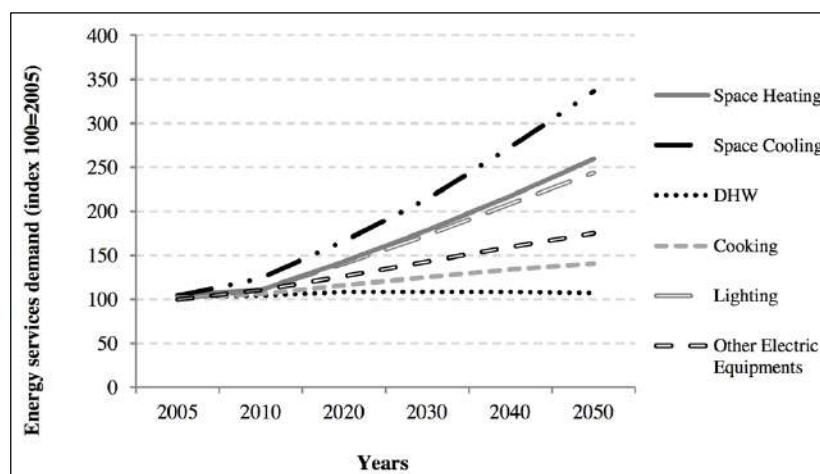


Figure 4.2 – Energy services demand trends for the different end-uses until 2050 (REF scenario)

Space heating is projected to continue growing until 2050 (2% per year), representing near 28% of total ESD, due to increased levels of thermal comfort and ownership (almost all households will have heating systems). Regarding space cooling services demand, the increase is sharper (more than twofold), explained by the combination of: 1) low starting point in 2005 (*i.e.* low penetration) and 2) future increase of thermal comfort levels. These growing trends on thermal comfort inside households are supported by statistical data around Europe. Opposite to the findings of Rosa-Flores and Gálvez (2010) to Mexico, where changes affecting water heating and cooking promise to be more important than those affecting other electricity uses; for Portugal, we found that water heating demand has the lower growth rate from 2005-2050, being almost constant, as a result of fewer inhabitants per household and a decrease of the Portuguese population. All other end-uses demand grows more or less depending on the level of penetration in 2005 and the future ownership expectations. This increasing use is influenced for example by cheaper appliances, increased personal wealth and individualized lifestyles meaning that one household may have multiple versions of the same appliance.

For validation purposes, the computed ESD of the REF was performed for 2010, through the comparison with the final energy consumption in residential households for that year. It was found that our calculated energy services for heating and cooling, supported on the useful energy needs from Table 4.4, surpass final energy consumption. Final energy consumption represented around 10% of the estimated ESD, which is line with the information described in Decree Law n. ° 80/2006. For the other end-uses it is more difficult to make such an assessment but differences on final energy consumption and energy services can be explained by different factors, which are not fully captured by our calculations. Firstly, the useful energy computed for the several end-uses is theoretical and is

influenced by factors such as households' occupant behavior through equipment utilization. Secondly, and even though we considered only households and not all the dwelling stock, households are not constantly occupied; therefore, not heated, cooled and using electrical equipment. Thirdly, when occupied, room conditioning is not applied all the time, for all the household area to the same indoor temperature. Finally, changes in the inter-annual HDD and energy prices may also explain less energy consumption. All this, fallout in lower final energy consumption than estimated ESD, thus we can say that energy services are currently in Portugal not being fully satisfied.

4.3.1.2 Sensitivity analysis

The trends of ESD for REF scenario and sensitivity scenarios, according to variations of the parameters used to compute energy services demand for heating are presented in Figure 4.3. Variations over households' area (scenarios A1 to A3); thermal comfort (T1 to T5) and energy needs (N1-N12) are highlighted. For heating, the T5 and T1 scenarios represent the highest and lowest variation of ESD, all the other variations fall within this range. Therefore, these two scenarios were used as TIMES_PT inputs for assessing the final energy demand to fulfill heating needs. Thermal comfort is the main driver governing the heating ESD.

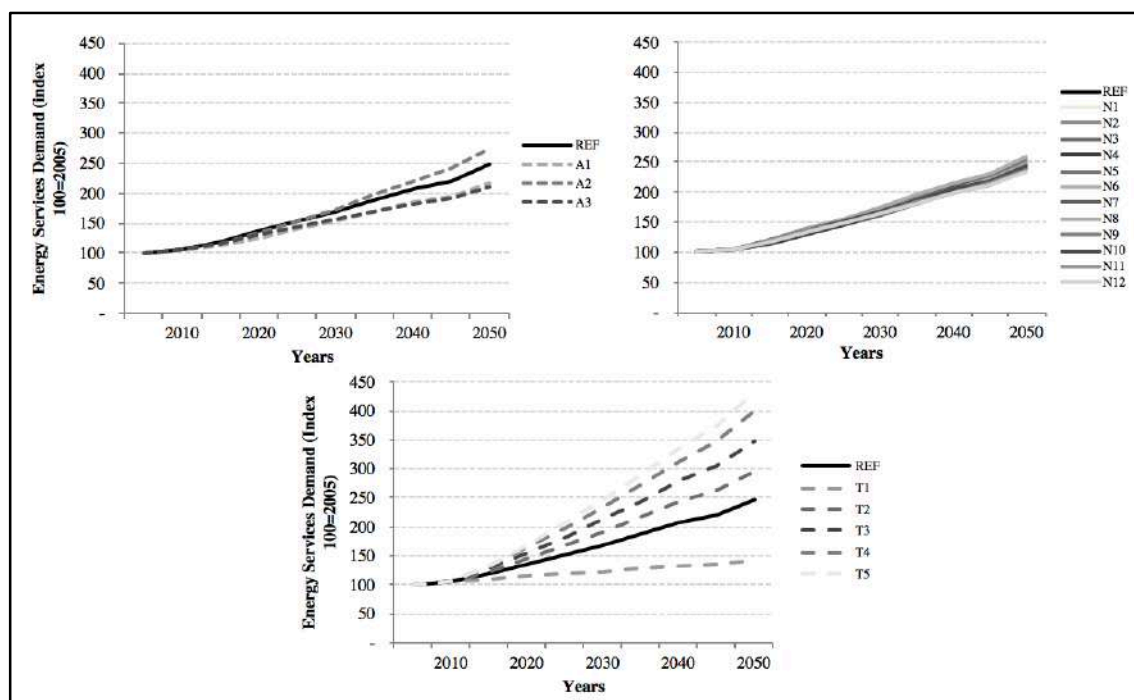


Figure 4.3 – REF and sensitivity analysis scenarios assessed for heating demand

Table 4.6 summarizes the impact of the variations for each end-use on the energy services demand of the REF scenario in 2050, from where were chosen the highest and lowest variations.

Table 4.6 – Impact of the parameters variations on the ESD of the REF scenario in 2050

End-Uses	Parameter	Impact in ESD REF (2050)
Space Heating [Eq. 3 and Eq. 5]	Households Area ($S_{n[NIS, SH/MA, <1990, 1990-2005, >2005]}$)	-15% to +18%
	Specific energy needs of new households ($Nic_{[N/S, SH/MA, >2005]}$)	-6% to +6%
	Thermal Comfort	-47% to +84%
Space Cooling [Eq. 4 and Eq. 6]	Households Area ($S_{n[NIS, SH/MA, <1990, 1990-2005, >2005]}$)	-16% a +19%
	Specific energy needs of new households ($Nvc_{[N/S, SH/MA, >2005]}$)	-10% to +83%
	Thermal Comfort	-47% to +84%
Water Heating [Eq. 7 and Eq. 8]	Ownership rate ($Odhw_n$)	-2.5% to -1%
	Temperature increase (ΔT)	-10% to +10%
	Daily average water consumption (CR_{dhw})	-10% to +50%
	Number of water consumption days (n_d)	-5% to +70%
	Persons per household (PH_n)	-25% to +32%
Cooking [Eq. 9]	Specific energy needs ($Cook$)	-30% to +30%
Refrigeration [Eq. 10]	Freezers Ownership rate (O_{an})	-4% to +16%
	Specific energy needs (E_{en})	-30% to +30%
Dish washing machines [Eq. 10]	Ownership rate (O_{an})	-51% to +21%
	Specific energy needs (E_{en})	-50% a +75%
Cloth drying machines [Eq. 10]	Ownership rate (O_{an})	-52% a +68%
	Specific energy needs (E_{en})	+1% to +7%
Cloth washing machines [Eq. 10]	Specific energy needs (E_{en})	-5% to +21%
Lighting [Eq. 11]	Number of light bulbs per household (LB_n)	-40% to +158%
	Specific energy needs (E_l)	-30% to +30%
Other Electrics [Eq. 13]	Energy needs (OE_n)	+9% to +136%

The results from the sensitivity analysis clearly demonstrate the relevance of supporting energy demand projections on energy services, allowing a clear knowledge of the assumptions behind them and the importance of each parameter:

- For heating and cooling, the results indicate that the uncertainty associated with the increase of thermal comfort overcomes the uncertainty on the expansion in households' size and on thermal behavior of buildings due to *e.g.* climate change. These results are in line with the ones presented by Young and Steemers (2011), where the behavioral patterns of air conditioning equipment use were the most influential elements in household cooling energy consumption. The physical characteristics of buildings appear to be marginal in terms of their effect on cooling energy consumption.

- For water heating, and since both the ownership of equipment and the range of temperature variations is not wide, the highest uncertainty is on the assumptions on social structure (*i.e.* family size) of a household and on the consumer behavior (water use and number of days of consumption), with an impact that could vary from -25% to 70% in the energy service demand of 2050, when compared to REF.

- For the remaining end-uses, there is a pattern, where in general high variations in the specific energy needs related to changes in consumer behavior have a stronger impact in the ESD than the penetration rate of equipment. This holds true especially for the end-uses where the ownership of equipment is already high. Rosa-Flores and Gálvez (2010) also indicates technology penetration and utilization of equipment as very important variables affecting home energy use.

4.3.2. Impact of energy services demand projections on final energy

Final energy consumption to satisfy the projected ESD is an output of the TIMES_PT model, allowing to understand the role of technology and fuel switches on future energy demand. Our goal is to assess how and at what extent variations on thermal comfort, climate conditions and equipment ownership would change the patterns of final energy consumption. For the case of residential sector, TIMES model adds a layer of technology considering energy efficiency improvements and increasing thermal quality of the building envelope through insulation measures.

4.3.2.1 Reference scenario

Notwithstanding the significant growth (1.3%/year) in the demand for energy services, the final energy to satisfy it shows a lower growth (0.1%/year). This is explained in general by an increasing efficiency of the energy system through diversification of the fuel supply: changes from biomass, oil, heat, and liquefied petroleum gas to an increase use of solar collectors (8%/year); natural gas (3%/year) and electricity equipment (1%/year), and insulation measures improving the thermal behavior of existing buildings (4%/year). Previous work by Ruijven *et al.* (2010) projected fuel use in Western Europe to remain quite stable until 2030. The weight of residential sector in the total energy consumption in 2050 (15%) is projected to remain similar to 2005 (17%).

The evolution of the ESD and final energy consumption between 2005 and 2050 for REF by end-use is presented in Figure 4.4. For visualization purposes kitchen appliances (*e.g.* washing machines, refrigeration) demand were all included on the other electric equipment. The decrease of energy consumption in the long run for cooking, lighting and space heating is fully explained by more efficient technologies based on natural gas and electricity in the first case, LEDs and compact fluorescent bulbs in the second and heat pumps and insulation measures in the latter. Our results for cooking are upheld by the results of Daioglou *et al.* (2012) which have also stated that the energy demand for cooking falls in households due to fuel switching. These results indicate that, in these end-

uses, the role of technology may significantly overweight behavioral practices and socio-economic changes.

The decreasing trend results for heating energy consumption until 2050 are consistent with those presented in other studies (*e.g.* Aguiar *et al.* (2002), Olonscheck *et al.* (2011) and Rosenberg *et al.* (2012)). Straightforward comparisons are not possible since timeframes and baseline assumptions are not the same as in Aguiar *et al.* (2002), and diverse geographical and climate conditions are different as in Olonscheck *et al.* (2011) and Rosenberg *et al.* (2012). However, it should be considered that the Portuguese households have historically different characteristics regarding insulation measures that affect the thermal comfort levels. As demonstrated by the current energy *per capita* consumption, comparing to both EU₂₇ average and with countries with similar climate conditions, Portugal still has lower levels of consumption as well as thermal comfort levels inside households. This supports our results that despite future increasing demand for space heating energy services, this might outcome in a small decrease of final energy consumption in 2050 compared to 2005.

We find that energy consumption for cooling will keep increasing despite technological energy efficiency improvements. Young and Steemers (2011) also stated that the domestic cooling likely increase may undermine energy efficiency strategies related to the improvement of building design and fabric, and environmental systems for lighting, heating and cooling. Our findings for air conditioning evolution for Portugal (*i.e.* Mediterranean climate) are similar with the ones presented by others authors for similar climate conditions: Xu *et al.* (2012) for California identified that cooling energy consumption increase and heating energy consumption decrease over the next 100 years; Pilli-Sihvola *et al.* (2010) presented results for Southern Europe, where increases in cooling outweighed decrease in heating.

Concerning final energy demand for DHW, it is expected an increase since the energy services will be guaranteed with the use of less efficient renewable energy sources like boilers running on biomass pellets and solar collectors. Final energy growth rates for Other Electric equipment as refrigeration, kitchen appliances and small electric equipment suffer a consumption reduction due to efficiency improvements (*e.g.* refrigerators Class A or higher). Large appliances targeted by the EU Directives on labeling and the EU mandatory efficiency standards account for a decreasing share of the total consumption. This goes in line with Ruijven *et al.* (2010) findings, where technology improvement correlates negatively with future energy use. Smaller electric equipment (*e.g.* computers) raises their final energy consumption as a result of increasing equipment ownership, offsetting expected energy efficiency improvements. For these latest end-uses, and besides the likely continued improvements on energy efficiency, the policy focus and monitoring should be also devoted for consumers' behavior. Brounen *et al.* (2012) in their results also showed that the variation in residential energy consumption is a function of both technical characteristics of the dwelling and the composition and background of a household.

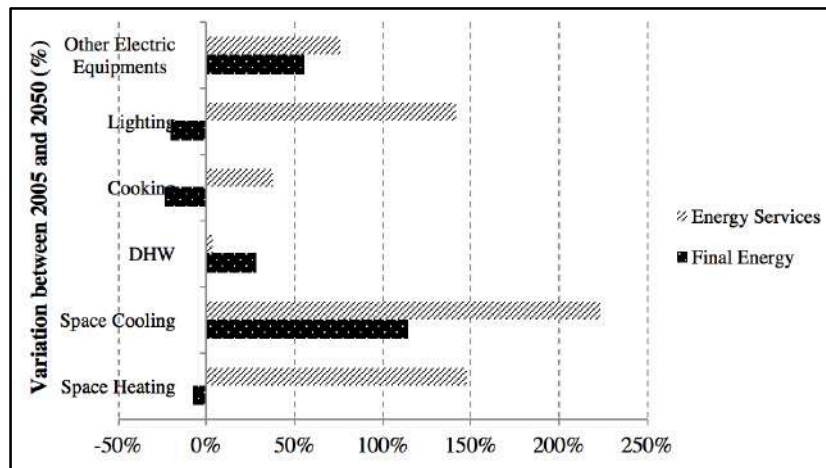


Figure 4.4 – Comparison between the evolution of the demand for energy services and final energy between 2005 and 2050 for REF

4.3.2.2 Sensitivity analysis

Twenty ESD scenarios corresponding to the highest and lowest impact from each parameter for each end-use were considered as input for TIMES_PT model to assess its impact on final energy consumption. The results for each end-use show that the uncertainty on the assumptions behind the parameters is mostly tilted for higher levels of consumption, as illustrated by Figure 4.5. Heating and other electric equipment are the end-uses showing stronger impacts on final energy consumption, due to their high share in the total Portuguese residential consumption, and the high uncertainty range of the parameters (*i.e.* thermal comfort levels and OE growth rates). For DHW the impact is more relevant on lower levels of consumptions, while for lighting is the opposite. In cooking the uncertainty is equally distributed to higher and lower consumption. Finally, despite a strong increase in the final energy consumption for cooling observed for REF, the impact of uncertainty range of parameters is not wide.

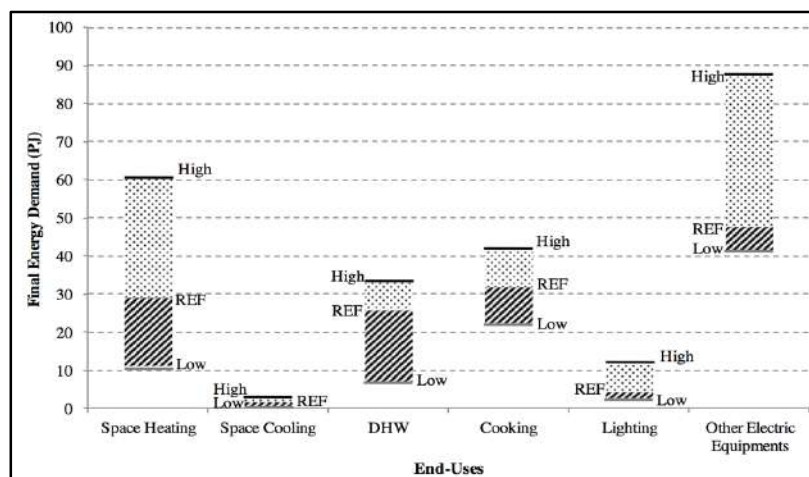


Figure 4.5 – Final energy consumption range between the REF and the Highest and Lowest variation scenario of each end-use in 2050

Sensitivity analysis results also indicate that extreme variations over energy services parameters from the REF could have a strong impact on both energy production and demand supply systems, namely by overestimating the production which leads to unnecessary economic costs or underestimated demand that induce problems regarding security of supply.

For illustration purposes, the energy consumption for heating is expected to decrease -0.2% per annum in the REF, while, for the High space heating demand scenario (T5) (+84%) the growth rate is around 1.5%/year. This trend has an impact on fuel consumption in 2050 compared to the REF: electricity ($\approx +10\%$; 8 PJ); natural gas ($\approx +45\%$; 20 PJ) and oil products ($\approx +100\%$; 4 PJ) explained by increased adoption of heat pumps, electric heaters and natural gas and oil boilers. In the other hand, a Low space heating scenario (T1) (-47%), fallout in a consumption reduction of -2.3% per annum, with decrease use of electricity (-7%; 72 to 67 PJ), natural gas (-23%; 44 to 34 PJ) and oil products (-42%) in 2050 compared to the REF. No disruptive technological and fuel changes are expected to accomplish the ESD uncertainty range.

For lighting, results estimate for a REF scenario a reduction of -0.51% per annum of the final energy consumption. In a Low lighting demand scenario (-40%), the reduction is expected to be sharper (-1.63%/year) with a 3% reduction of electricity consumption in 2050 compared to REF. In a High lighting scenario (+158%), the electricity consumption is expected to increase 10% in 2050 comparatively to REF, with an annual growth rate of 1.6% per annum for the period under analysis. Fouquet and Pearson (2011) also considers that long run trends and the relative stability of the price elasticity estimates for lighting suggest that increased efficiency is likely to be eroded by rising income levels. This idea falls better in our High scenario assumptions where the number of light bulbs per household and the hours of use are higher.

Our results for both energy services and final energy consumption (REF and sensitivity analysis) support our assumption that improved knowledge on ESD drivers help to identify where policies should tackle to foster effective energy reduction - both energy efficiency increase as well as the drivers behind ESD, especially the ones more related to consumer behavior. As stated by Haas *et al.* (2008) it is necessary a shift from historical trend where efficiency improvements are lower than the increase in service demand.

4.4 Conclusion

This paper presents a bottom-up methodology to compute ESD in the residential buildings up to 2050. This research aims to increase the knowledge on households' energy consumption profile in southwestern European region. Moreover, the research carried out in this paper allows for an improved understanding on the data of several parameters that drive the ESD in Portugal, avoiding the use of approximate values as in a study for the European households (*i.e.* Anström *et al.*, 2010).

The use of a combined methodological strategy supported by an energy services bottom-up approach and a technological model gives insights on the complexity between energy services and energy consumption. The use of such a methodology has limitations, mainly due to the need of a substantial number of disaggregated information and the necessity of adapting or simplifying some parameters, which can increase uncertainty. We find that uncertainty on some end-uses energy services can have significant impact on future projections depending on the different parameters range. Nevertheless, the influence of underlying parameters on the projections of ESD, have been identified, discussed and evaluated through a sensitivity analysis. The weight of different parameters was explored and the impacts on ESD showed where monitoring efforts should be devoted in the future to minimize that uncertainty. Our results unfold that increased attention should be given to parameters more related to household occupants' behavior (*e.g.* thermal comfort expectation; electrical equipment use) specially associated with heating and other electric equipment services demand.

Since energy systems investments are made to provide ESD, the work presented herein shows the benefits of estimating final energy projections supported on energy services. This turned out to be a more understandable approach, in the sense that all the parameters governing ESD and final energy can be subject to specific analysis (*i.e.* climate, technology, behavior), depending on the purpose of the study.

The case study results show that the demand for energy services will continue to increase in the long run (mainly cooling and lighting) due to the expected increase of thermal comfort levels and use of equipment. The introduction of buildings climate regulation with insulation rules, the compliance of energy efficiency policies and the substitution of a significant proportion of appliances, implies that the increase of ESD does not induce a similar increase of final energy consumption. Globally, for Portuguese households, the REF scenario shows that energy consumption growth is lower (0.1%/year) comparing to ESD (1.3%/year), although in some cases like lighting, cooking and space heating, a decrease of final energy is observed despite ESD increase. These results indicate that, in these end-uses, the role of technology may significantly overweight behavioral practices and socio-economic changes.

Ultimately, results from the technological model on sensitivity analysis show that the space heating and other electrics are the end-use with higher impact on final energy consumption. However, no disruptive technological and fuel changes are expected to accomplish the ESD uncertainty range.

This paper addresses the heterogeneity of the different end-uses (*e.g.* floor space and appliance ownership) to improve extra options for a detailed analysis, a research gap identified by Ruijven *et al.* (2010) Our results illustrate that energy policies, namely on effective energy consumption reduction, should focus specific drivers behind each end-use on both technological and non-technological factors.

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Authors Contributions

J. P. Gouveia structured and wrote the paper, set the modelling framework and all the calculations, model runs and analysis related to the detailed energy services and final energy demand. P. Fortes defined a first approach to the energy services demand methodology. J. Seixas supported the design of the paper and its in-depth revision.

Nomenclature

Subscripts

- N,S – location in the country (North or South)
- SH,MA – type of household (Single House or Multi apartment)
- $<1990, 1990-2005, >2005$ – year of construction (before 1990 or between 1990-2005 or after 2005)

Variables and Parameters

- CR_{dhw} – daily average water consumption for DHW (liters)
- C_n – energy service demand for cooking (kWh/year)
- $Cook$ – useful energy needed for cooking per household (kWh/year·household)
- Dhw_n – useful energy needed for domestic hot water per household (kWh/year·household)
- $DhwT_n$ – energy service demand for DHW (kWh/year)
- E_{en} – useful energy needed per equipment class (kWh/year)
- E_l – specific useful energy per light bulb in the base year (kWh)
- Eoe_{n0} – final energy for other electrics (kWh)
- $HouT_n$ – number of households
- LB_n – number of bulbs per household (bulbs/household)
- L_n – energy service demand for lighting (kWh/year)
- n_d – number of water consumption days (days)
- Nic – heating needs (kWh/m²·year)
- NiT_n – total heating ESD n (kWh/year)
- NvT_n – total cooling ESD (kWh/year)
- Nvc – cooling needs (kWh/m²·year)
- Qg – total gains (kWh/year)
- QGU – total net gains = internal gains + solar gains (kWh/year)
- Qt – heat lost by the envelope (kWh/year)
- Qv – heat lost by air exchange (kWh/ year)
- ΔT – temperature increase needed to reach the reference temperature in hot water (°C)
- RWM_n – energy service demand for refrigeration and washing machines (kWh/ year)
- S_n – net floor area (m²)
- O_{an} – ownership of each appliance (*i.e.* refrigeration equipment, cloth washing and drying machines and dishwashers) (%)

- O_{cook_n} - ownership rate of cooking equipment (%)
- O_{dhw_n} - ownership rate of DWH equipment (%)
- O_{en} - ownership rate of kitchen appliances per efficiency class (%)
- OE_{n0} - useful energy per household for the base year for OE appliances (kWh/household)
- OE_n - useful energy demand in the year n for OE appliances (kWh)
- PH_n - number of persons per household (inhabitant /household)
- Pop_n - annual population (inhabitant)
- te_n - growth rate of OE energy consumption from year $n-1$ to year n (%)

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Chapter 5 | Integrated Energy Planning

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Analytical Framework to support Integrated City Energy Planning

ABSTRACT

Cities are core energy systems to consider towards promoting sustainability and climate protection. Multiple data sources are increasingly available at different temporal and spatial resolutions, covering the whole city energy system (*i.e.* supply, transport, distribution, and end-use), which facilitates an integrated energy planning towards sustainable energy policies and measures at the city level. This paper presents a structured analytical framework integrating multiple and complex data sources, models and tools over the city, required to feed an integrated energy planning process to deliver future sustainable energy paths, including untapped energy saving potential. The framework deals with the data pipeline gathering and analysis tools for a city energy system, and focuses on: 1) residential buildings, 2) transport and mobility, 3) other energy demand sectors (*i.e.* waste, water and sewage systems; industries, public lighting, public buildings, services and agriculture), and 4) energy supply system, including local renewables. Energy indicators are published in a geographic information system platform acting as the communication platform with local stakeholders (*e.g.* citizens, investors, city planners, decision makers) towards a co-design process, to feed an integrated energy-planning tool. This tool includes a technology based energy system model developed until 2030, which generates cost-effective sustainable measures and a multi-criteria assessment, which helps prioritizing those measures by considering also social criteria. Selected results for Évora, in Portugal, illustrate how the proposed analytical framework integrates different data sources, tools and multi scale data granularity, advancing on integrated city energy planning.

KEYWORDS

Integrated Energy Planning; Geographic Information Systems; Building Stock; Transports and Mobility; Smart meters; Sustainable Cities

5.1 Introduction

The deployment of low carbon technologies for sustainable energy production and use requires the active engagement of local and regional communities. Several programmes and plans (*e.g.* IDB (2011); CoM (2012)) have involved cities working towards sustainable development, decarbonisation and improving quality of life for their citizens. Cities' activities affect the environment in both negative and positive ways (Dodman *et al.* (2013)), which leads to the need of cities to address climate change, reduce energy consumption and increase the use of renewable energy through the development of holistic plans rooted in environment, society and economy aspects. Though, city authorities will not be able to address increasing energy demands, changing demographics and ageing infrastructure, without the support of appropriate methods, and data analysis throughout the urban development value chain (WEF, 2016).

At the same time, it has been recognized that there is a need for an improved comprehensiveness of the city planning process towards sustainable energy use driven by integrated approaches (WEF (2016); Keirstead *et al.* (2012); Zanon and Verones (2013)) supported by ex-ante cost-benefit evaluation, information and communication technologies and energy systems models. Russo *et al.* (2016) corroborates this need, underlining that planning and management processes are desired to support decision making processes in order to design and operate cities infrastructures and services.

Consequently, innovative tools and models with extensive data gathering and analysis to evaluate and perform in-depth analysis of alternative measures, will help pave the way towards long term energy planning, fully capturing the economic, technical and social potential of each city in the most efficient way. Several authors have presented different perspectives and models for simulating future cities, regarding its energy use and planning (*e.g.* Kostevšek *et al.* (2013); Yamagata and Seya (2013); Yeo *et al.* (2013); Chen and Chen (2015); Fonseca and Schlueter (2015)).

Keirstead *et al.* (2012) reviewed 219 papers concluding that, despite the diversity of modelling practices of urban energy systems, the studies usually compartmentalize the assessments focusing on specific aspects of energy use and mostly use exogenous input data. A few examples; Falke and Schnettler (2016) cover only residential buildings for the design of energy supply systems and Aste *et al.* (2016) only evaluates the energy retrofit in public and zero emissions buildings. This split tends to miss synergies of technical solutions and of common policy instruments, conducting to serious inefficiencies. We argue that the integration of the different energy demand sectors of the city is crucial for proper decisions on investments, comparing the cost effectiveness of measures, for a short, medium and long term city energy planning.

Integrated city energy systems have been approached by several authors: Mirakyan and Guio (2013) suggested a four phase-scheme for energy planning presenting methods and tools for each phase; Zhou *et al.* (2014) used a fractile-based interval mixed-integer programming to deliver solutions for

energy supply, electricity generation, air pollutants mitigation, and carbon dioxide control, among others; Neves *et al.* (2015) identified the need for a holistic perspective to local energy systems while using a local energy planning model focused on energy services demand; Cosmi *et al.* (2015) presented a methodology to characterize the whole energy system from policy background, energy uses and infrastructures as well as market behavior and community attitude for sustainable development; Mirakyan and Guio (2015) discussed the different types of uncertainties related to integrated energy planning.

Although the growing availability of advanced computing and sensing capabilities facilitates the access to big data repositories with city information at several levels (Sanz *et al.*, 2015), it still requires decision-makers to trust and understand the indicators and tools behind them. In this paper, we go beyond the identification and calculation of indicators, instead we depict the collection of different data sources and its analysis, and portray the interoperability of diverse types of data (with different temporal and spatial dimensions), to provide useful and comprehensive information and knowledge to an integrated energy-planning tool while considering all city demand sectors and its spatial patterns.

The novelty of this paper lies in a structured analytical framework to integrate multiple data sources and methods, with different temporal and spatial resolution (e.g. door to door surveys, smart meters, stakeholders' engagement, energy statistics), models (transport and mobility, buildings simulation, energy system optimization) and analysis tools (statistical, geographic information systems (GIS)), able to support an Integrated City Energy Planning (ICEP). In this sense, the paper is more methodological than result oriented, showing how comprehensive data gathering and processing steps are key to deliver future sustainable energy pathways while considering the interactions of energy use and production in the city. Compared to the above-mentioned studies, the focus given to all the data pipeline and planning process; from extensive data capture and modelling processes to results validation with stakeholders.

This work has been developed under the FP7 European funded project InSMART – Integrated Smart City Planning, for four European cities: Évora (Portugal), Cesena (Italy), Nottingham (United Kingdom) and Trikala (Greece), with the support of scientific and technical organizations of the same countries.

The paper is organized in four sections. The analytical framework and the data, tools and methods used are portrayed per energy demand sector in Section 5.2. The methodology is operationalized and discussed with selected results for the case study in Section 5.3. The conclusions are summarized in Section 5.4.

5.2 Analytical framework

Integrated energy planning involves the economic, social and environmental dimensions of a city while characterizing all the energy demand sectors. It requires the combination of multiple data sources, tools and methods dealing with the different planning phases (Mirakyan and Guio (2013)). In this section, the overall analytical framework is presented. It provides a structured process combining diverse spatiotemporal datasets and employing a suite of tools for each energy sector component. The process culminates with the integration of all the information within a GIS common platform to deliver a coherent dataset that can be used by integrated models and stakeholders. We argue that a coherent database of city indicators such as the one described enables city decision-makers to efficiently achieve their sustainable energy and climate targets. Brandoni and Polonara (2012) also disclose that the most definitive aspect in energy planning and effective policy execution is the availability of adequate data combined with detailed modelling and simulation to improve the knowledge of existing systems, namely on energy flows among different consumers and city districts and on alternative energy measures.

The analytical framework bridges the gap between data needs and availability through collection from the ground up and analysis for all city energy sectors (*i.e.* residential buildings; transport and mobility; other energy demand sectors and supply side). It provides a description of the demand centers; namely the quantification of the stocks of processes and technologies (e.g. buildings, space heating technologies ownership, number of vehicles) and characterization of energy services required in the selected geographical units of a city (*i.e.* spatial districts). The framework makes use of multi-scale data of diverse type and granularity including a) 15 minutes' electricity consumption data from smart meters, b) monthly/annual statistical energy production and consumption data, c) detailed energy modelling of buildings archetypes, d) city transport characteristics and mobility flows, and e) door-to-door surveys. All this analysis and data allow for the representation of the municipality in a base year and supports the projections until 2030 of the energy system in the integrated City Energy Planning Tool.

City energy' indicators for the projected time horizon are mapped into a web based GIS platform allowing for geospatial analysis, bringing forward the awareness and participation of different levels of city stakeholders (*e.g.* municipality technicians, planners and decision-makers, utilities, transport companies, citizen groups, and market associations). The stakeholders' participation at different stages of the framework is essential in assembling an acceptable, realistic and mostly beneficial city action plan. Energy indicators regarding the different city sectors will feed the ICEP tool that includes the city energy technological model linked with a multi-criteria assessment tool, as illustrated in Figure 5.1.

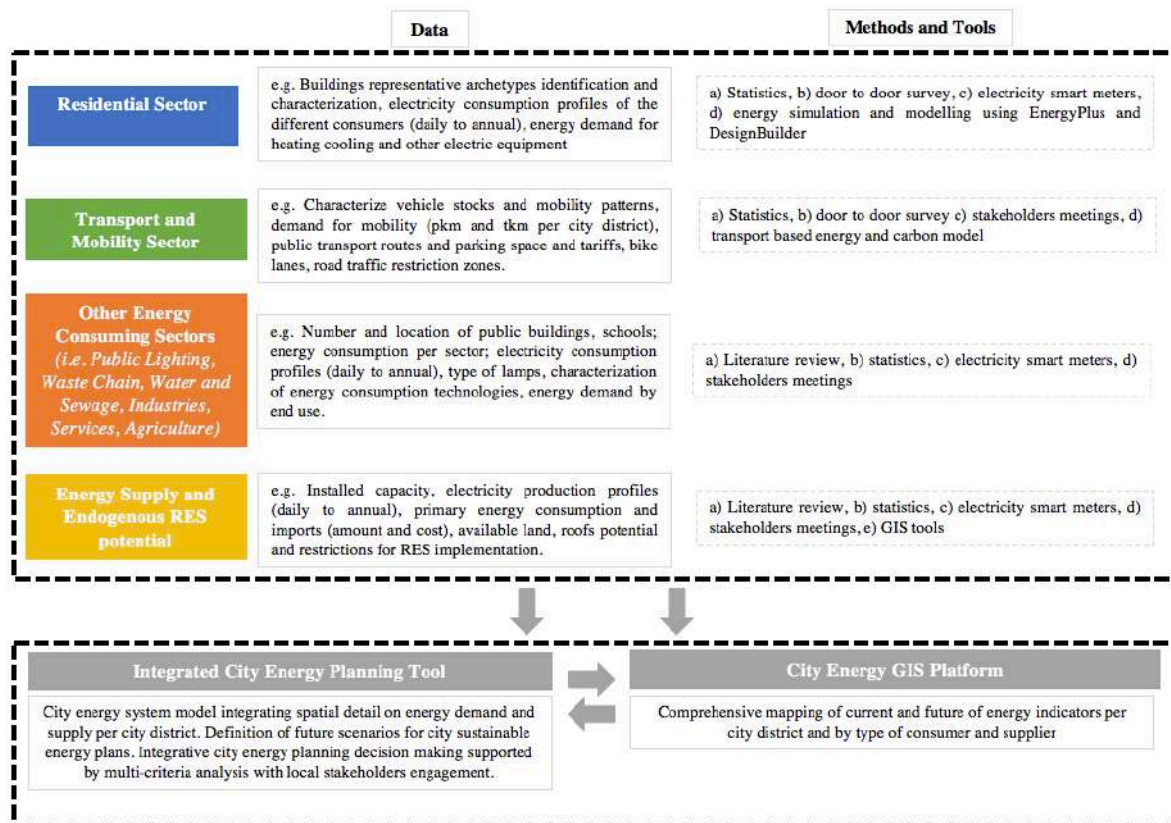


Figure 5.1 – General framework concept for an Integrated City Energy Planning

The concept and operability of the analytical framework regarding data gathering and processing will be illustrated by the case conducted in the municipality of Évora, including the city and the surrounding rural areas (Section 5.3). An explanation of the data, tools and methods used for each component of the framework is portrayed in the next sections.

5.2.1 Residential buildings

Energy use from buildings represents a significant element of a city's overall energy use (around 25-30% (UN-Habitat, 2008)). Accurate representation and modelling of buildings energy demand allows for the support of policies towards the improvement of buildings energy performance and energy infrastructure planning (Ma and Cheng, 2016). In this section, we detail the multiple data sources available to provide a comprehensive range of indicators to characterize the residential sector within the ICEP.

5.2.1.1 Housing statistics

The residential sector is highly heterogeneous, due to building characteristics, householders' behavior and occupant's energy literacy; representing a major challenge in applying systematic energy planning methodologies. Therefore, relevant residential building archetypes should be considered, characterized by indicators usually available from national statistics (e.g. Census data), like the

building form (e.g. detached, semi-detached and terraced houses, multi-apartment buildings), the period of construction (e.g. until 1945, 1946-1990, 1991-2000, after 2000), the number of floors (e.g. 1, 2, 5 or higher) and the roof types (e.g. sloped, flat). These indicators should be addressed at the mostly detailed spatial unit available for a city, in order to get a relevant spatial pattern of the buildings archetypes. A materiality criterion for the settlement of spatial representativeness of the archetypes to be used could be the frequency of the indicators higher than 5% in each administrative division (e.g. civil parish).

Definition of the building archetypes provide the guidelines for the type of buildings to address in the surveys, the energy simulation modelling (Section 5.2.1.4) and the structure for the residential sector in the ICEP tool, while accommodating spatial heterogeneity of energy flows.

5.2.1.2. Door-to-door surveys on energy use at households

Surveys of households' energy use and characterization are a conventional method for detailed data collection, increasingly common in many developed countries (e.g. INE and ICESD (2011), NRC (2011)). However, few studies focus on the city spatial detail, missing the opportunity to characterize the determinants of energy consumption at the different spatial zones in the city. A robust characterization of the residential sector at district level requires a door-to-door survey to cover information about the physical characteristics of dwellings (e.g. load bearing structure, type of windows, insulation of external walls and roofs), socio-economic details and behavior of the occupants (e.g. number of persons, income, age, hours of use of equipment), appliances characteristics, use and ownership (see annex I). Reliable and significant results require the data to be spatially resolved and statistically significant. Therefore, the city building stock surveys should comply with city district minimum quotas based on the preponderance of each archetype in each city district. The survey results provide a highly-detailed snapshot of the city housing stock compiling information not usually available in such spatial detail. In our framework, this data will be used as inputs to the energy services demand models (Figure 5.1) (Section 5.2.1.4) and to provide the level of detail required to feed the integrated energy planning (Section 5.2.6).

5.2.1.3. Electricity smart meters

The increasing availability of smart meters, information and communication technologies included in home appliances and real-time home energy-monitoring services, provides data that allows for an exhaustive characterization of electricity consumption. Usually, consumers' segmentation is based on electricity consumption profiles, however, the socio-economic characteristics of the households matched with detailed characterization of electricity consumption patterns by building archetype provide in-depth knowledge on consumers' segmentation (Gouveia and Seixas, 2016). Smart meters' data analysis provides the identification of differentiated daily to annual electricity consumption profiles into the ICEP tool where different energy policies and instruments can be evaluated for

specific groups of consumers (*e.g.* vulnerable consumers under fuel poverty) located in different city districts. Moreover, it is also valuable for the validation of the buildings simulation modelling work.

5.2.1.4. Energy services demand modelling

Energy services demand is key for integrated energy planning and usually is accomplished through building simulation. The objective of this component is to simulate the energy services demand in each household archetype, in current conditions, as well as under a range of energy retrofit measures to assess its impact and cost on energy consumption. The energy services demand on space heating and cooling and on electric appliances, differentiated by building archetypes throughout the year, are of outmost importance to the ICEP tool, as explained in Section 5.2.6. The simulation builds upon data collected from the surveys (*e.g.* wall, roof and insulation type). The following steps suggest how to gather a full perspective of the residential energy demand in each spatial unit within a city:

1. Quantify, from the surveys, the likelihood of relevant features for energy consumption in households, like a shading device, bearing structure type, insulation or cooling system.
2. Identify meaningful sub-archetypes from the pre-defined archetypes of the building stock, if significant architectural differences in each archetype (*e.g.* different roof designs, number of floors in the building) exist. They provide an approximation of the characteristics of the real city building stock.
3. Construct energy models, using *e.g.* Design Builder (DB, 2015) for each of the sub-archetypes identified in step 2 and simulate them in an energy simulation model like EnergyPlus (DOE and NREL, 2015), to obtain the energy needs (heating, cooling and specific electricity) per building or per square meter.
4. Perform sensitivity analysis on each sub-archetype model to identify the set of significant variables affecting energy use. For example, cooling set point, wall thickness, orientation and glazing ratio.
5. With the final sub-archetypes defined, a synthetic building stock can be generated using probability density functions associated with each building parameter. This data should be supplemented by any local knowledge of the stock not identified in the surveys).
6. If needed, use surface area (m^2) per archetype to sum up energy usage (kWh/m^2) value for the whole city (kWh).

An extended description of the energy simulation methodology of residential buildings can be found in Long *et al.* (2015). Our approach provides an approximation of the characteristics of the city building stock and the distribution of the different archetypes across the city districts, delivering spatial energy services demand to feed the ICEP tool. Simulated energy services demand indicators also input the city GIS energy platform, taking the location of each archetype in each district, to identify consumption hotspots or regions of special interest (*e.g.* district heating network expansion;

city districts and archetypes where energy efficiency and renovation measures should be prioritized), and to visualize the potential of energy savings in a comprehensive way. Table 5.1 summarizes the key outcomes of the residential sector and Figure 5.2 depicts the data workflow towards the ICEP tool.

Table 5.1 – Residential buildings key data per spatial unit

Housing and energy statistics	Door to door surveys	Electricity smart meters	Energy simulation modelling
<ul style="list-style-type: none"> • Demographics (households, buildings and resident population) [A1] • Monthly final energy consumption by fuel [A2] • Local environment and infrastructure (e.g. degree days) [A3] • Building Archetypes [A4] • Demolition and new building construction rates [A5] • Heating and cooling set point from legislation [A6] • Energy consumption per fuel and end use [A7] 	<ul style="list-style-type: none"> • Building dimension (e.g. height, footprint area, number of floors), period of construction, bearing structure, type of insulation, windows framing and glass type, roof type [A8] • Number of household members, age, gender [A9] • Household average monthly income, tenure type [A10] • Ownership, technical characteristics' and use of equipment (space heating and cooling, water heating, refrigerators and coolers, televisions and computers, lamps, microwaves) [A11] • Smart meter number [A12] 	<ul style="list-style-type: none"> • Daily to annual electricity consumption profiles per building archetype and consumer type (based on 15minutes temporal resolution of electricity consumption data (kWh) [A13] 	<ul style="list-style-type: none"> • Building energy performance (kWh/m²/year) per archetype and use (e.g. heating and cooling) and potential impact of energy efficiency measures (e.g. insulation, windows change) [A14]

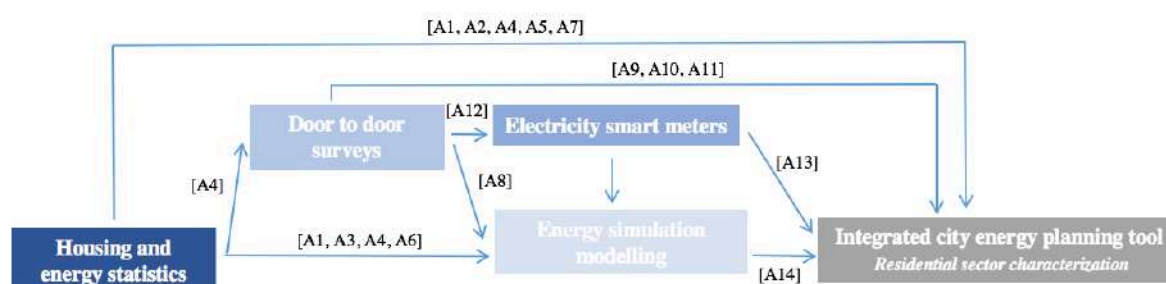


Figure 5.2– Data workflow of residential buildings targeted to the ICEP tool

5.2.2. Transports and mobility

Transportation, including public, private, passenger and freight, plays a major role in all cities. In EU28, transport represents roughly a third of the total energy usage, the largest contribution of any sector and about a fifth of greenhouse gas emissions (GHG) (Eurostat, 2016). Within our framework, transport and mobility is tackled by the mobility flows among the different city zones and assessed through a transport-based energy use and emissions model to represent current and future situations. Usually, the majority of the spatially explicit data needed to support this type of models is not available. Therefore, door-to-door surveys with travel diaries beyond national statistics are good options, as well as relevant stakeholders' involvement in the data collection process (*i.e.* municipality transport department, public transport companies). The key outcomes to feed the ICEP tool include the demand for passenger and freight mobility (pkm and tkm, respectively) by city zone and the vehicle stock characterization.

To address the city mobility patterns with representative spatial detail, there is the need to split it into detailed zones, producing a map to be used as a show card during the surveys. Sufficient detail is necessary in order to get the respondents to identify the places they travel to and from on the map. These zones can be split considering natural or human made boundaries (e.g. creeks, rivers, railways), and different areas services (as municipal equipment as pools and gyms, residential, industrial and services). Aggregation of existing administrative zones may also be a possibility, if they include small populations and mobility flows while using the same roads. Since each city has its own spatial dynamics, experts and municipal authorities with local knowledge should work jointly to implement this approach.

5.2.2.1. Door-to-door surveys for transportation and mobility

Some European countries carry out travel surveys, either regularly or irregularly (*e.g.* Netherland, Germany, France, Sweden) (Pasaoglu *et al.*, 2014), although they are rare for most of the EU countries at a national, regional or local level. If no consistent baseline information is available for mobility patterns and stock of vehicles characterization per detailed spatial units, a survey should be conducted. Dedicated transport and mobility surveys can also provide important data on households' socio-economic characteristics, number and type of vehicles and on patterns of private transportation (locations and purposes) through travel diaries. Moreover, they can provide the characterization of mobility demand per vehicle, per person, journey purpose and distances covered on commuting, either within each zone or across the city zones.

Minimum quotas of surveys collected at each city zone should be set to ensure the representativeness of residents within a city. Four variables are typically selected to capture the city mobility patterns: weekday and weekend; age of the interviewed (*e.g.* 18-34, 35-49, 50-64, 65+); working status (full

time, part time, student, retired, not working) and geographic location (*e.g.* by city minimum spatial statistical district).

5.2.2.2. *Transportation statistics and stakeholders' involvement*

Data acquisition for transport and mobility should involve relevant city stakeholders (*e.g.* municipality transport department; public transport companies) as main contributors on existing city's infrastructure, *e.g.* parking lots, speed limits definition, land use occupation, public transportation routes and schedules, and on the definition of future scenarios and expectations regarding city expansion, new roads or bike lanes, new major attractions or workplaces hubs. Other relevant information from national statistics include the number of households and car ownership, retail floor-space and jobs per city zone; and characterization of the cities vehicle fleet by fuel type (*e.g.* petrol, diesel, electric) and emissions standards (*i.e.* Euro 1- Euro 6).

5.2.2.3 *Mobility and energy demand modelling*

Whilst energy efficiency in transport has been increased, there is still much improvement to achieve the EU targets (reduce transport emissions by 60% by 2050 (EEA, 2016)). Therefore, a tool to test city mobility flows scenarios, covering transport as well as land use and behavioral change, is of high importance. A transport-based energy and carbon model covering the geographic scope of the city and the relevant surrounding areas, and parameterized for each city zone should be used to estimate the demand of mobility (*i.e.* passengers-kilometer (pkm) and tone-kilometer (tkm)) in each city zone and between different zones of the city. General inputs to the transport model include: a) specific city characteristics as zoning, distances, public transport services, land use; b) trip purposes, speeds, fares, vehicle types and modes; and c) energy and emissions parameters for the various transport choices (mode, destination, route). The outputs include mobility demand per vehicle type per zone-zone movement, trips per person, number of vehicles and related energy consumption and emissions.

The spatial based mobility demand of the city is of utmost importance to feed the ICEP tool to drive the selection of measures towards the city sustainable mobility, taking a joint optimization of the overall city energy system while respecting the mobility conditions at the zone level. Table 5.2 lists the key data to compile per city district regarding the transport and mobility component, while Figure 5.3 presents the data workflow.

Table 5.2 – Transport and mobility key data per spatial unit

Door to door surveys	Transportation statistics and stakeholders' involvement	Mobility demand modelling
<ul style="list-style-type: none"> • Mobility patterns from travel diaries between city sectors [B1] • Number and type of private vehicles <i>per capita</i> [B2] 	<ul style="list-style-type: none"> • Demographics [B5] • Number of parking spaces (paid and free) [B6] • Number of private and public vehicles 	<ul style="list-style-type: none"> • Annual demand (people and vehicles) and distance traveled (pkm and tkm) per vehicle type [B13] • Annual number of public transport trips

<ul style="list-style-type: none"> • Mode share and average trip length information [B3] • Journey purpose splits [B4] 	<ul style="list-style-type: none"> (light and heavy for passengers and freight) [B7] • Public transports infrastructure (routes, tariffs, number of passengers) [B8] • Length and use of bicycle paths and lanes [B9] • Land use maps [B10] • Average speed maps [B11] • Fuel consumption [B12] 	<ul style="list-style-type: none"> <i>per capita</i> [B14] • Demand movements between city sectors, by vehicle type [B15]
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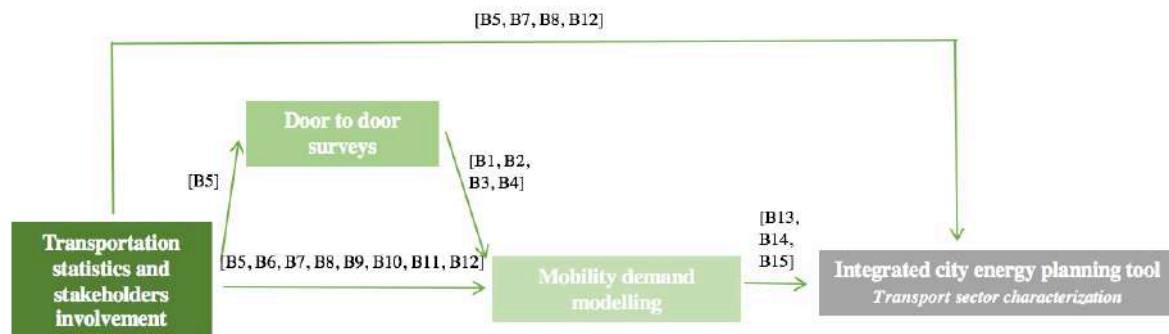


Figure 5.3 – Data workflow of transport and mobility sector towards ICEP tool

5.2.3. Other energy demand sectors

Our framework includes also other city energy demand sectors, namely: a) Public utilities (*i.e.* water/sewage infrastructures, waste chain and public lighting), b) Services buildings (*i.e.* hospitals, retails centers, schools, public administration buildings), c) Industry and d) Agriculture. Detailed public information on the characteristics and operation of the facilities of public utilities and industries is scarce, mostly if they are managed by private entities with confidentiality restrictions. Regarding the services and commercial buildings, there is usually a lack of consolidated knowledge of the buildings characterization and energy consumption for the different city districts, either through regular national/municipal statistics or sporadic surveys or studies. To overcome these barriers, multiple data sources, and procedures are combined to gather detailed, updated and harmonized information, including literature review of existing reports; electricity smart meters' data per facility or aggregated by subsector; total energy demand and intensities per units of output (mainly for industries and agriculture); relevant stakeholders' inputs concerning water and sewage facilities and services sectors.

An exhaustive identification of indicators and variables to characterize the energy consumption can be compiled for each subsector to be sent to relevant stakeholders for data acquisition. Taking the public lighting as an example, relevant data include the type and number of luminaires and lamps in place by spatial unit, the respective electricity consumption and working hours. Street lighting is one of the most essential services provided by municipal authorities, and; therefore, the measures that reduce

energy consumption should not include turning off lamps, but its substitution through technological improvement or better use. The introduction of new technologies to be tested in the ICEP tool, like light emitting diodes or smart controls, will deliver high improvements in energy usage and lower costs. For other city utilities, services building and industries, when no detailed information per facility/building is available or collected, intensity indicators (*e.g.* energy use per square meter or per materials produced) can be used.

Collecting information for services, industries and public utilities is a hard task due to many and differentiated stakeholders to contact, data selection and harmonization needed to support the ICEP tool for future city energy scenarios assessment. It should be underlined that the engagement of the municipality technical departments and private stakeholders during all the data collection process is paramount to get adequate and accurate information and knowledge. Table 5.3 outlines the key indicators from the data collection and Figure 5.4 presents the data workflow for the ‘Other sectors’ component of our framework.

Table 5.3 – Key data for other sectors per spatial unit

Literature review, statistics and stakeholders’ involvement	Electricity smart meters
Public Utilities	
<ul style="list-style-type: none"> • Final energy consumption by sub sector [C1] <p><u>Street Lighting and Public Spaces</u> [C2]</p> <ul style="list-style-type: none"> • Urban green areas and fountains (location, size and associated electricity consumption) • Number and type of light operation control systems (<i>e.g.</i> photocell, astronomical time clock, tele parameterized, remote control, flow regulator) • Number and type of Luminaire (<i>e.g.</i> urban, rural, garden, decorative) and lamps (<i>e.g.</i> mercury, high and low pressure sodium, metal iodates, fluorescent and LED) <p><u>Sewage and Water System</u> [C3]</p> <ul style="list-style-type: none"> • Percentage of population served by sewage collection per type (<i>e.g.</i> public sewage system, septic tanks) • Total domestic water consumption <i>per capita</i> • Number, characteristics and energy consumption of water and sewage treatment facilities and distribution systems (<i>e.g.</i> pumping stations) <p><u>Waste Chain</u> [C4]</p> <ul style="list-style-type: none"> • Number and energy consumption of municipal solid wastes facilities (<i>e.g.</i> sorting centers, landfill) • Total monthly collected municipal solid wastes <i>per capita</i> per type (<i>e.g.</i> plastic, glass, paper, undifferentiated) • Number and energy consumption of waste collection vehicle fleet 	<ul style="list-style-type: none"> • 15 minutes’ temporal resolution of electricity consumption data (kWh) allows building daily to monthly electricity consumption load curves per type of utility or facility [C7]

Services Buildings [C5]	
<ul style="list-style-type: none"> • Number of services buildings (<i>i.e.</i> retail, hospitals, banks, schools, offices) • Square meters of services buildings per type Energy consumption of services buildings per type • Activity hours of services buildings per type 	<ul style="list-style-type: none"> • 15 minutes' temporal resolution of electricity consumption data (kWh) allows building daily to monthly electricity consumption load curves per type of service [C8]
Industries and Agriculture [C6]	
<ul style="list-style-type: none"> • Location of the main industrial sites and agriculture activities • Energy consumption per industry sub sector and agriculture 	<ul style="list-style-type: none"> • 15 minutes' temporal resolution of electricity consumption data (kWh) allows building daily to monthly electricity consumption load curves per industry subsector and agriculture activities [C9]

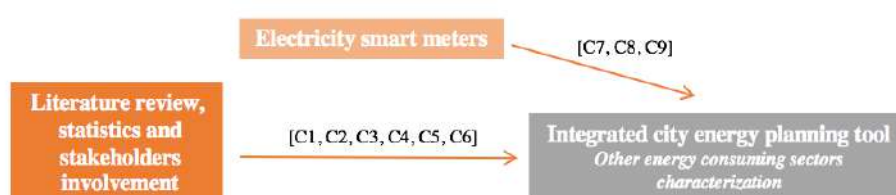


Figure 5.4– Data workflow of the other city energy demand sectors targeted to ICEP tool

5.2.4. Energy supply and endogenous renewables potential

The city energy system must also acknowledge the energy supply such as natural gas, district heating, electricity networks, oil products distribution, and local renewables. Therefore, the characterization of the city supply sources is essential to assess the current and future low-carbon energy supply alternatives, to comply with ambitious energy and environmental targets. An overview of the supply infrastructure of the city can be gathered from literature review of existing reports and maps, and energy statistics. The involvement of stakeholders (*e.g.* distribution system operators (DSO), energy companies, municipality technical departments) is very important due to the private and confidential nature of some of the needed information. If available, electricity smart meters' data should be taken to characterize the city supply system, as of solar PV producers. Information on the current decentralized facilities (*e.g.* rooftop PV and solar thermal), the utility scale units (*e.g.* solar PV power plants, cogeneration plants) and on the coverage of existing supply networks should be acquired, taking its spatial location.

For a city's robust energy planning covering the next 10 to 20 years, the estimation of the spatial-explicit technical potential of local renewables is of outmost importance to offer cost-effective options for the sustainable city energy system. Whenever appropriate, the endogenous technical potential of different renewable options, and creation/expansion of district heating and other energy supply networks, should also be assessed. Table 5.4 depicts the main data collected to be taken into account in the ICEP tool and Figure 5.5 portrays the data framework.

Table 5.4 – Energy supply and endogenous renewables potential key data per spatial unit

Literature review, energy statistics and stakeholders' involvement	Electricity smart meters	GIS and statistical analysis
<ul style="list-style-type: none"> • Monthly energy production per type of technology (wind, biogas, biomass, geothermal) [D1] • Municipality land use restrictions (e.g. legal and infrastructures) [D2] • Altimetry maps [D3] • Irradiation Maps [D4] • Average Wind Speed and Number of Equivalent Full Load Hours [D5] • Heated water needs per person [D6] • District heating network [D7] • Natural gas consumption and distribution network [D8] • Annual biomass consumption [D9] 	<ul style="list-style-type: none"> • 15 minutes' electricity production data (kWh) per facility (e.g. utility scale PV plant and rooftop) [D10] 	<ul style="list-style-type: none"> • Total suitable land for each renewable technology [D11] • Maps with optimal solar exposure [D12] • Total rooftop area available for PV or solar thermal technologies [D13] • Total building's façade suitable for PV [D14] • Electricity capacity/production potential per technology [D15] • Total hot water needs per building archetype [D16]

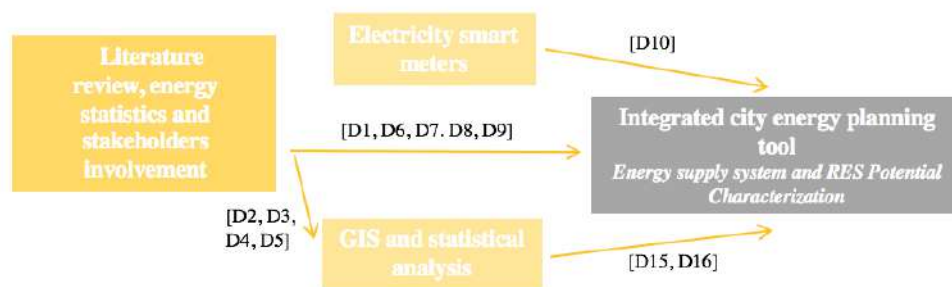


Figure 5.5 – Data workflow from the city supply and endogenous RES potential targeted to ICEP tool

5.2.5. City energy GIS platform

The mapping of the several energy data layers produced for the different city sectors (Tables 5.1 to 5.4) is useful to provide a comprehensive visualization of the city's energy services demand and energy consumption patterns, to fully understand where the energy hotspots are currently located and where key future transitions will mostly occur. The city energy GIS platform holds all 'spatial' and 'spatial enabled' energy related data for the city energy sectors and is the first tool for data integration, connecting spatially the different energy system components. The GIS platform may display the energy indicators for future scenarios from the assessment of specific policy impacts obtained from the ICEP tool, acting as a powerful visualization tool to support stakeholders' participation towards the design of energy policies and measures respecting their spatial features and effectiveness. The city GIS platform offer the significant features for energy planning, like: a) Display the energy production and consumption at the city spatial unit, depicting where energy is produced, distributed and consumed inside the city. Examples include the distribution of energy consumption indicators of the building stock, the mobility maps between city zones, the geographical distribution

of heat demand, energy savings potential, possible location of PV plants size/roof top. b) Monitor changes of energy production and consumption patterns in the city over time; d) Communicate the city' energy system information to citizens, the public sector and the market (Kilias and Rigopoulos, 2015), leveraging public and market awareness on energy efficiency and carbon emissions reduction.

5.2.6. Integrated City Energy Planning (ICEP) tool

This paper aims to present a comprehensive framework to deal with the multitude and complexity of data sources to characterize the different sectors settled in a city energy system, to feed the ICEP tool rather than to go in much detail on this tool. However, an explanation on how to use the wide range of datasets, with multiple spatial and temporal resolutions, towards its combination to deliver detailed future sustainable energy scenarios for the city is needed for clarity.

The ultimate objective of the ICEP tool is the conclusion for the cost-effective and social-relevant optimum mix of measures and technologies to pave the way towards the achievement of cities' sustainable targets, such as those stated in the Covenant of Mayors, or others, requiring high contributions of renewables and/or aggressive emissions reductions. Integrated energy system models are good candidates to be used to assess policy and technological strategies (IEA, 2016) while providing a consistent structure for its analysis. Nakata *et al.* (2011) provides an extensive revision of the application of energy system models for assessing different sectors. We use the technological-based TIMES (The Integrated Markal-EFOM System) energy system model (Loulou *et al.*, 2005) detailed for the different city's energy sectors and spatially explicit for each city district, refined with the city stakeholders' validation through a multi-criteria decision making tool.

The TIMES model generator was developed as part of the IEA-ETSAP collaboration, using long term energy scenarios at different spatial scales to conduct in-depth energy and environmental analyses (*e.g.* Loulou *et al.* (2004); Gouveia *et al.* (2013); Sarbassov *et al.* (2013)). TIMES is a technology-rich, bottom-up optimization model integrating the entire energy/emission system of the city, including the procurement, transformation, trade, and consumption of a large number of energy forms. For a detailed city planning, this kind of models should operate over the reference energy system at each city pre-defined spatial unit, *i.e.* the connected energy flows from supply to distribution to consumption delivering the multiple energy services (*e.g.* space cooling and heating, passenger and freight mobility) at the different end users (*e.g.* residential and services buildings, transport, industries, water and waste utilities) in each spatial unit. The reference energy system should be designed and validated according to statistics of a base year (*e.g.* 2013/2014). The TIMES_city model represents the municipality from the base year till 2035 in five-year time steps. Each year is subdivided into 32 time slices representing day, night and peak periods of the day for both week days (257 days) and weekends (remaining 108 days) and differentiated for each season

(Summer, Winter and Inter-seasonal). This allows for a proper integration of the different levels of granularity of the data collected.

The TIMES model is supported by an extensive database of technological options from which the cost-effective mix of technologies will be derived to supply the city energy services demand along the modelling time horizon. Therefore, a TIMES model at city level departs from the current energy system and generates future scenarios of cost-effective energy technologies, taking into consideration city planning goals and policies (*e.g.* expansion of a services hotspot in a specific city district, reducing the city overall GHG emissions, complying with a renewable target) while fulfilling the exogenous demand for energy services of the various city districts. Model outputs are: energy flows, energy commodity prices, GHG and air quality emissions; new supply infrastructures and demand device purchases, total installed capacity of technologies and energy expenditures.

Under our methodological proposal, a shortlist of the most interesting alternative scenarios of measures from the modelling work should be cross-compared and ranked using of a comprehensive non-compensatory multi decision making method (MCDM). This process is typically conducted through workshops with the city stakeholders to consider non-technological factors in the selection of the measures to apply in the city. The application of multi-criteria decision making in energy planning problems have gained considerable ground between research communities (*e.g.* Haralambopoulos and Polatidis (2003); Pohekar and Ramachandran (2004); Løken (2007)). City stakeholders working in synergy to address city challenges has been recognized as a good practice, and its involvement in weighting the different sustainability concerns of the city, and in evaluating the ICEP tool results to address economic, environmental and social issues through MCDM procedures is a good opportunity to leverage stakeholders' contributions to cities sustainable future. Selected measures after the MCDM can be subject to a detailed economic analysis to identify relevant investment needs and other costs indicators. Finally, a detailed and realistic implementation plan can be developed to describe the necessary steps, required resources and monitoring procedures for each city.

The integrated framework presented in this sub-section underlines the need for detailed, spatial resolved and high-quality energy data to feed all the process up to the two integration tools – energy system model coupled with MCDM acting as an integrated energy-planning tool and the city energy GIS platform. However, for many cases, city energy datasets are just not available, and the efforts for its availability are a top priority for the local governance. Figure 5.6 shows how the multiple data sets, detailed in the previous sections, feed the reference energy system of a city TIMES model, and how selected outcomes, from a wide range of results, can be used for energy city planning.

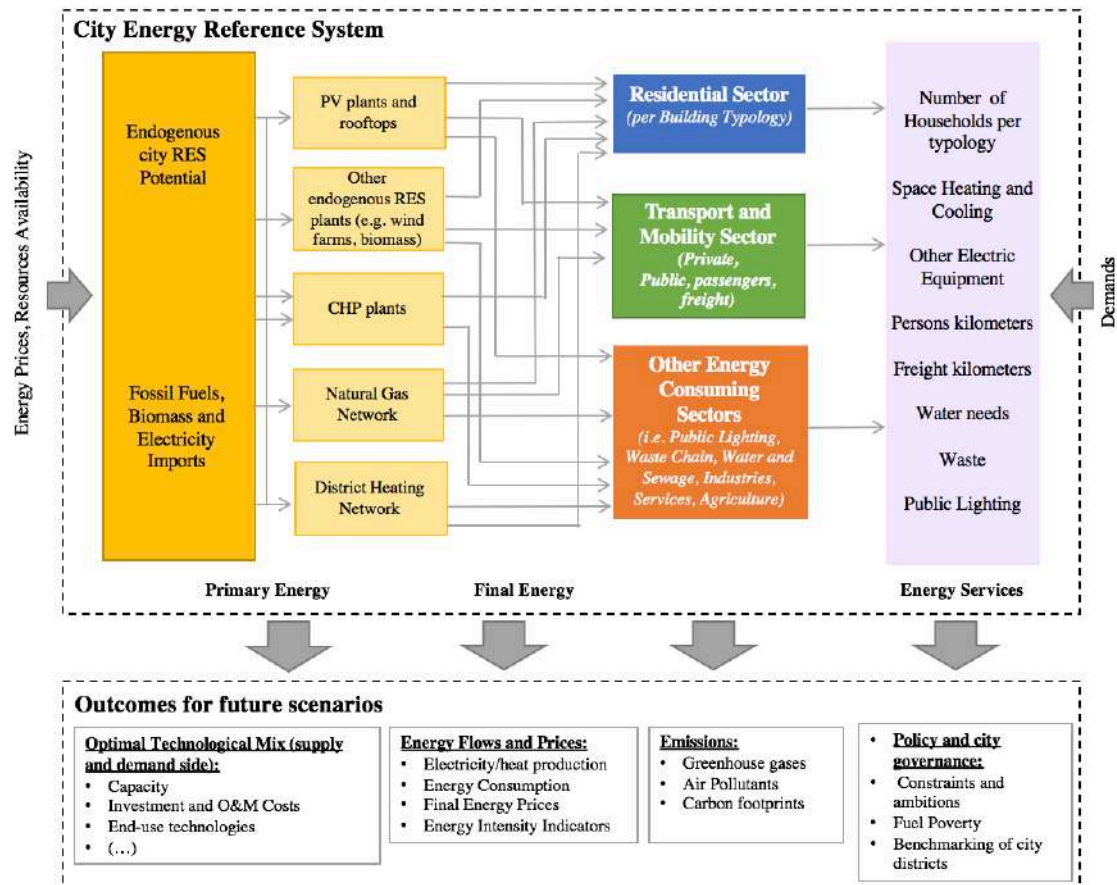


Figure 5.6 – Integrated city energy planning structure and outcomes

5.3. Results

In this section, we unfold the diversity of datasets that fully describe in detail the city energy system for the case of Évora in Portugal to illustrate the operationalization of the proposed data pipeline and framework. Therefore, it is out of the scope of this paper to present in detail results from the city energy planning tool, as this would make the paper extremely lengthy. Nonetheless, we include a couple of questions at the end of each of the sub-sections that we consider should be addressed by the integrated tool, and we present very brief examples of the results we have obtained, aiming to illustrate the full set of final achievements for the city planning.

Évora city is awarded a United Nations patrimonial and cultural world heritage; it is a major international tourist attraction city; it was the first city in Portugal equipped with a massive electricity smart metering system (EDP, 2016). It is located in the Alentejo region of Portugal covering 1307 km², with about 57 000 inhabitants (INE, 2011). The demographic and economic potential, the concentration of industrial and logistics make the municipality of Évora a strong and dynamic regional hub. Évora economy is mainly based on the services sector, including decentralized services of the central government. Industry includes electronics and electromechanical components and civil construction. The municipality of Évora has a *per capita* annual final energy consumption of around

48 GJ, which compares with 61 GJ for the average country (DGEG, 2016). The Sankey diagram of Figure 5.7 provides a comprehensive view of the current energy consumption profile of the different economic sectors and fuels used.

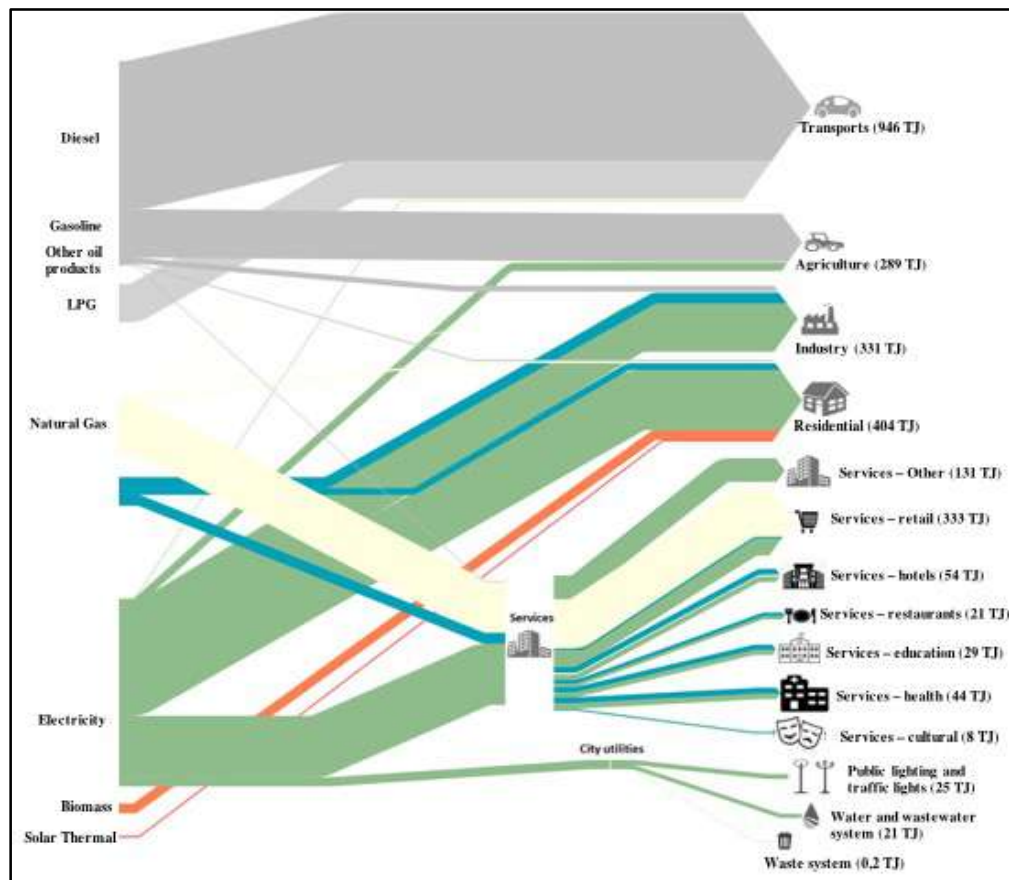


Figure 5.7 – Sankey diagram of Évora energy system (2013) (data source: (DGEG, 2016).

Évora is divided into 12 parishes: three urban (one in the historical center) and nine rural parishes. The population is concentrated in urban areas, with 80% living in urban areas and 8% living inside the city walls (PORDATA, 2016). We consider the area outside of the urban limits to the surrounding rural areas of the city to properly address the sustainability underlying the interplay of mobility and housing decisions, as presented by Science for Environment Policy (2015) and because there is no specific governance body at the city level but only at municipal level. For this reason, we take the whole municipality of Évora instead of only the city.

GIS representation of energy indicators and the ICEP tool is implemented over four spatially explicit zones, that take distinctive features on energy use. All the nine rural parishes were combined in one single zone (1 - Rural), due to the very similar characteristics of the residential buildings, while the three urban parishes were considered individually (2 - Malagueira e Horta das Figueiras; 3 - S. Mamede, Sé e S. Pedro e St. Antão, 4 - Bacelo e Sra da Saúde), as shown in Figure 5.8 (left).

For the case of mobility patterns, we acknowledge, jointly with the municipality experts, the need for 21 zones, taken the following guidelines: A – the zones never include areas from two parishes; B - aggregation of rural parishes (small populations and flows) that use the same roads to the city; C - disaggregation of urban parishes into units following barrier, like parishes bounded by creeks, railroads or other barriers to flow; and divided by different classes of land use (*i.e.* industrial, residential, retail). Following this methodology, the rural parishes were grouped into five zones and the urban parishes were disaggregated into 16 zones (Gouveia *et al.*, 2015), as shown in Figure 5.8 (right). The 21 zones were combined afterwards in the four districts for the integrated energy planning analysis.

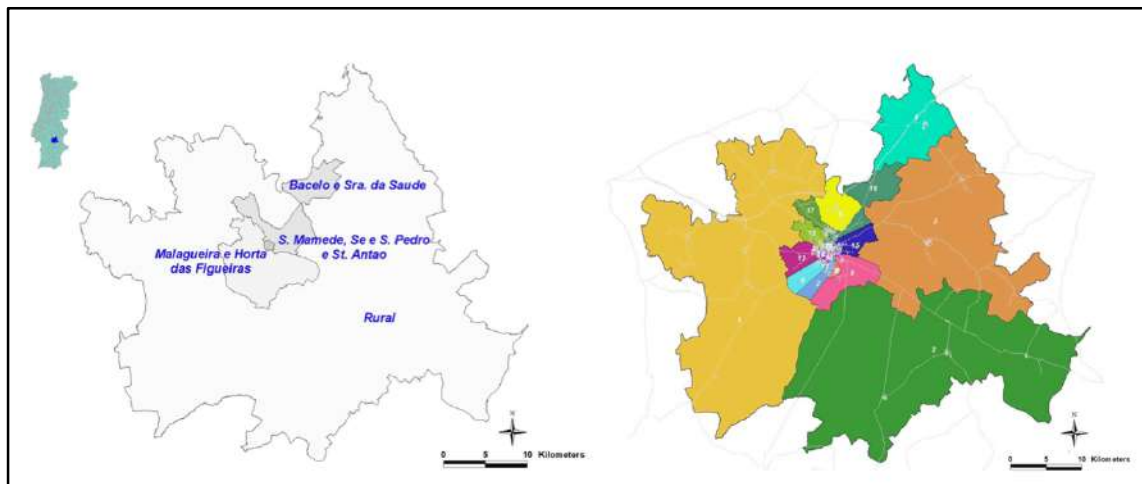


Figure 5.8 - Location of the city of Évora in Portugal and the four districts selected for integrated energy system spatial analysis (left) and the 21 city zones used for in-depth mobility analysis

5.3.1 Residential buildings data collection

5.3.1.1 Housing statistics

Ten archetypes were taken based on a building stock characterization (INE, 2011), which account for around 80% of all the buildings. The remaining 20% represent very diverse set of distinct archetypes, difficult to characterize individually. Data analysis indicates that 92% of the residential buildings are associated with single-family houses (mainly terraced houses) and only 8% with apartments (INE, 2011) which is quite different from the average EU countries with 64% and 36%, respectively (Economidou *et al.*, 2011). A substantial share of the buildings stock in Évora, as in other European cities, is older than 50 years. Around 20% of buildings have been built before 1940 when energy-building regulations were very few. A large increase in construction in 1946-1990 is also evident, representing around 56% of the current city stock (INE, 2011). Figure 5.9 displays how the buildings archetypes are distributed along the four city districts.

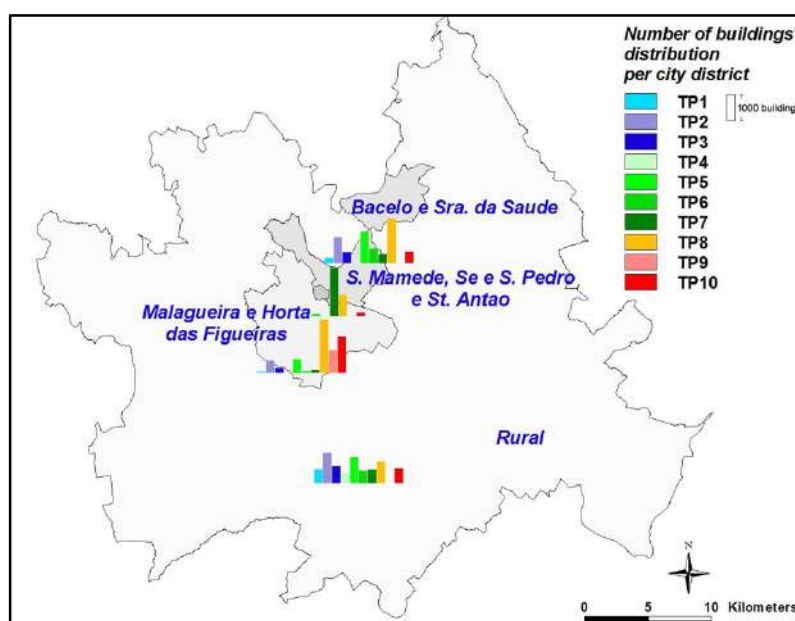








Figure 5.9 – Buildings archetypes representativeness in each city district

5.3.1.2 Door-to-door surveys on energy use at households

A minimum of 400 surveys was settled to provide a confidence interval of 95% +/- 5% for the total residential buildings in the municipality. To reduce the difficulties of the interviewers in defining where and which houses (*i.e.* archetypes) should be interviewed a pre-analysis of potential locations (*i.e.* where they are highly frequent) was done using the geographic database at neighborhood level. An extensive 110-question survey was performed between June and September 2014 across the municipality (37% of the surveys in rural area, and the remaining from urban areas) to collect information of a diverse but representative set of households from the ten archetypes. The survey included three groups of questions on: (1) general buildings features (age, height, type, location) and householders' socio-economic profile (occupancy, income, households' members age, gender), (2) dwellings construction characteristics, such as type of insulation, type of walls, and characteristics of the roof, (3) individual equipment usage and technical details. We experienced different levels of awareness: the first set of questions were generally well answered, the second got increased difficulty and; therefore, lower rates of valid answers, and the third set was poorly answered due to the extensive detail needed. We could collect 97% of the total expected surveys. Table 5.5 presents a sample of the data collected through the surveys, for two buildings archetypes.

Table 5.5 – Examples of buildings' data gathered from door-to-door surveys for two archetypes of Évora

Archetype		TP2	TP8
Sub-Archetype		21_1	81_1
External view of Design Builder model			
Photo of an example property			
Internal Zoning			
Parameters/Assumptions			
General Information	Location	Rural, Baccelo e Sra da Saude, Malagueira e Horta das Figueiras	Rural, Baccelo e Sra da Saude, Malagueira e Horta das Figueiras
	Type of dwelling	Detached	Terraced
	Age of construction	Between 1946 and 1990	Between 1946 and 1990
	Total floor area (m2)	176	141
	Conditioned floor area (m2)	84	67
	Set point temperature heating (°C)	20	20
Geometry	Set point temperature cooling (°C)	25	25
	Number of floors	1	1
	Room in the roof	No	No
	Glazing ration of the south façade of the build	13%	16%
	Glazing ration of the north façade of the build	12%	8%
	Infiltration rate	0,7	0,7
Construction	Exterior walls type	Brickwork Single Layer (82%)	Brickwork Single Layer (67%)
	Exterior wall thickness (cm)	25	28
	Wall insulation type	None (90%)	None (100%)
	Roof type	Sloped	Sloped
	Roof insulated	No	No
	Window framing type	Wood (58%)	Aluminum (54%) Wood (46%)
Household Members	Glass type	Single Glazed (81%)	Single Glazed (88%)
	Occupation contract	Owner (86%)	Owner (63%)
	Average number of occupants	2,7	2,7
	Relationship of occupants	Family (86%)	Family (92%)
	Working status of the chad of the family	Retired (54%), Working Full Time (23%)	Retired (50%), Working Full Time (38%)
	Average monthly income (€)	Between 751-1500€ (50%), Less than 750€ (27%)	Between 751-1500€ (56%)
Electrical Equipments Ownership	Refrigerators (%)	100%	100%
	Freezers (%)	69%	65%
	Cloth Washing Machines (%)	88%	100%
	Dish Washing Machines (%)	42%	39%
Heating Equipments Ownership	Air Conditioning (%)	7%	17%
	Electric Heaters (%)	57%	46%
	Fireplaces (%)	10%	4%
	FirePlaces with heat recovery (%)	17%	4%
	Solar thermal (%)	0%	0%
Cooling Equipments Ownership	Air Conditioning (%)	13%	38%
	Fan Coils (%)	53%	36%

5.3.1.3 Electricity smart meters

The electricity DSO has in Évora around 31 000 smart meters with electricity registries available since 2011 (EDP, 2016). Matching the surveyed households and smart meters' data availability resulted in 68% of the surveyed households with detailed electricity consumption data. The reasons for this gap are twofold: 1) the interviewers were not able to identify the number of the meter so we were not able to link the household survey to the meters' database (25%) and 2) no smart meter was installed in that household (3%). We got a sample of 265 households with four complete years (2011 to 2014) of high-resolution (15 min) electricity data. Figure 5.10 presents the annual profile of electricity consumption for three distinct building archetypes, corresponding to very distinct consumption profiles, which illustrates the diversity of analysis that can be delivered useful for different city stakeholders.

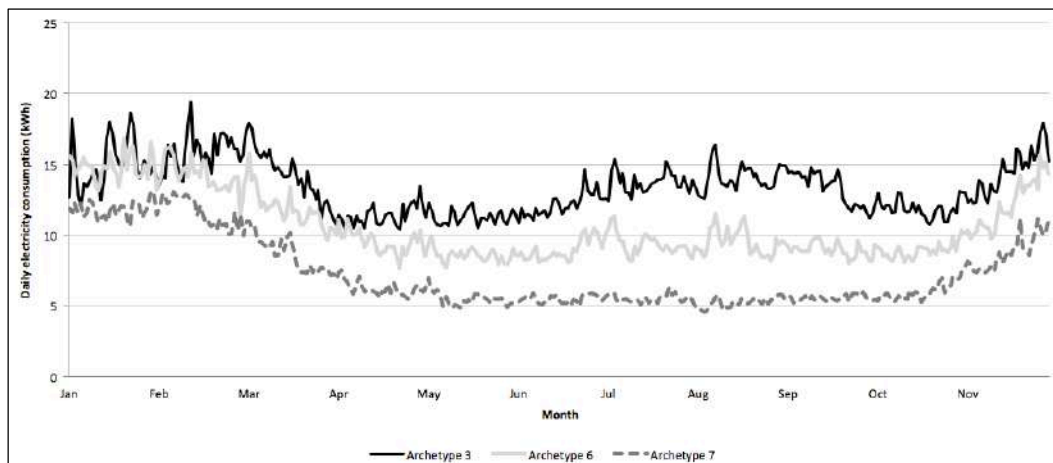


Figure 5.10 - Daily average electricity consumption (2011-2014 average) per building archetype

5.3.1.4 Energy services demand modelling

A crucial step of the analytical framework is to assess the residential buildings energy demand for heating, cooling and other end uses. The initial ten archetypes supported on the statistical analysis were expanded into 26 sub-archetypes using the methodology described in Section 5.2.1.4 while considering relevant differences, for example in number of floors, geometry and occupation of the roof, wall construction types. The construction materials and structures were defined for the 26 sub-archetypes based on the statistical analysis of the survey data. The results of the EnergyPlus simulations, showing differences in annual total energy use across the archetypes, taking the energy use by demand for heating, cooling and electricity, are shown in Figure 5.11. The households with high-energy use (TP2.2_1, TP2.2_12 and TP5.2_51) are much large properties (*i.e.* average area $>180\text{m}^2$), while the smallest properties (less than 100m^2) (TP5.1_1, TP7.1_1 and TP8.1_1) show very low annual energy use.

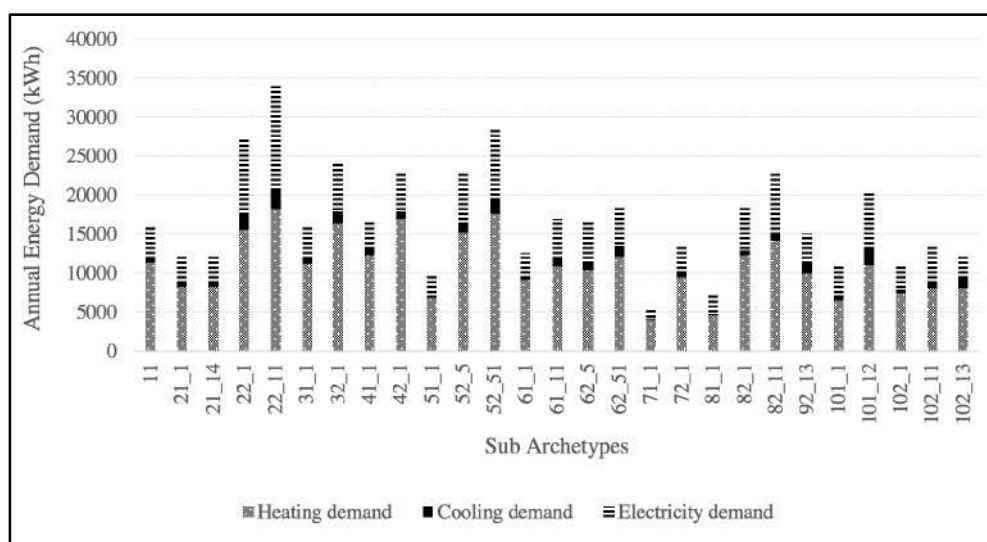


Figure 5.11 – Annual energy demand (kWh/year) for the residential building sub archetypes

As mentioned in Section 5.2.1.4, a sensitivity analysis was performed for all archetypes. The sensitivity analysis revealed a uniform impact for all the parameters tested across the archetypes (Long *et al.*, 2015). Heating and cooling set points were the dominant factors affecting energy use in all archetypes. Lowering heating and raising cooling indoor temperature settings is the most effective way to reduce the household energy use. Improved heating/cooling control systems (*e.g.* thermostatic radiator valves, room thermostats) may also assist in enabling residents to better control the heating and cooling set points.

Air change ratio (*i.e.* infiltration rate) was also revealed as a significant parameter affecting building energy use. However, it is a difficult parameter to measure accurately and large reductions in infiltration rate can be difficult to achieve. Small reductions could; however, be made through replacement of leaky doors and windows and installation of draught proofing measures. The thickness and insulation of external walls are also significant parameters, making clear that the installation of insulation would reduce heating energy demand (Long *et al.*, 2015).

This detailed assessment from modelling simulating of archetypes, as representatives of the residential buildings stock, and extrapolating for the entire city, illustrates the importance to feed, in a reliable and consistent manner, the energy services demand of the 27 sub-archetypes for the ICEP tool. By using ICEP tool we could deliver answers for this sort of questions:

- (i) What are the cost effective technological options to provide thermal comfort per archetype at each city district? (We should expect different solutions for the historical city center district and for the rural district).

By applying the ICEP tool for Évora we identified that insulation options were more cost effective in the rural district where there is a higher proportion of archetype 5 dwellings. In that zone, where a natural gas infrastructure is not available for dwellings, insulating walls and roofs is proportionally slightly more cost-effective than in the other city districts.

- (ii) What is the cost-effective reduction in energy consumption per dwelling till 2030?

By applying the ICEP tool for Évora we estimated cost-effective reductions in energy consumption in residential buildings of 4% in 2030 vis-à-vis 2013 values (from 16.73 GJ/dwelling in 2013 to 16.12 GJ/dwelling in 2030) in a Baseline scenario (*i.e.* without any imposed CO₂ reduction target or a specific building retrofit measure). In this case, the energy savings are mostly due to the expected increase in deployment of building insulation options and more effective appliances.

- (iii) What is the impact of installing solar thermal hot water panels in 40% of dwellings by 2030?

With the ICEP tool, we have assessed that for the case Évora this would lead to lowering the energy consumption per dwelling in 7% in 2030 compared to 2013 values and leading to a reduction in the

residential sector CO₂ emissions *per capita* from 0.60 tCO₂/inhabitant in 2013 to 0.48 tCO₂/inhabitant in 2030, due to the lower consumption of gas and electricity for water heating. With the ICEP tool we estimate that this would require a total investment of approximately 30 400 euros until 2030, which is mainly done in archetypes 5 and 8 located in city zone 2.

5.3.2. Transports and mobility

5.3.2.1 Door-to-door surveys for transportation and mobility

As for the case of households, a minimum of 400 surveys was considered as necessary to provide a confidence interval of 95% +/- 5%, (*i.e.* if 50% of our samples state that they travel by car, we can be 95% certain that the true proportion of car drivers in the city lies between 45% and 55%). However, for randomness sake, the households surveyed for the mobility survey were different from those for the residential survey.

A total of 460 transport surveys in the municipality of Évora were carried out from June to August 2014. Nearly 50% of the households had at least two light passenger vehicles with an average of 1.4 vehicles per household in the whole municipality. When assessing differences from rural and urban households, we conclude that the motorization rate is lower in rural houses (38% had at least two vehicles against urban households with 50%). Only 12% of the surveyed households had motorbikes.

The survey results also disclose for Évora municipality that the people working full time or part time, the majority (89%) travels to just one location: 82% commuting by car, 5% by bus and 12% on foot. Looking at travel for all purposes, we get 46% of trips by car, only 2% by bus and 53% by walking or cycling. Regarding the spatial dynamics of mobility, 93% of the total trips registered started and ended within the municipality boundary. On average, people take just over 15 minutes doing one-way journey to their working place. Figure 5.12 shows the variation in travel purpose splits by modelled zone. Through the travel diaries, an important share of the working population (34%) from all zones goes to the historical city center zone, while only 10% of the surveyed population goes to work to the rural areas.

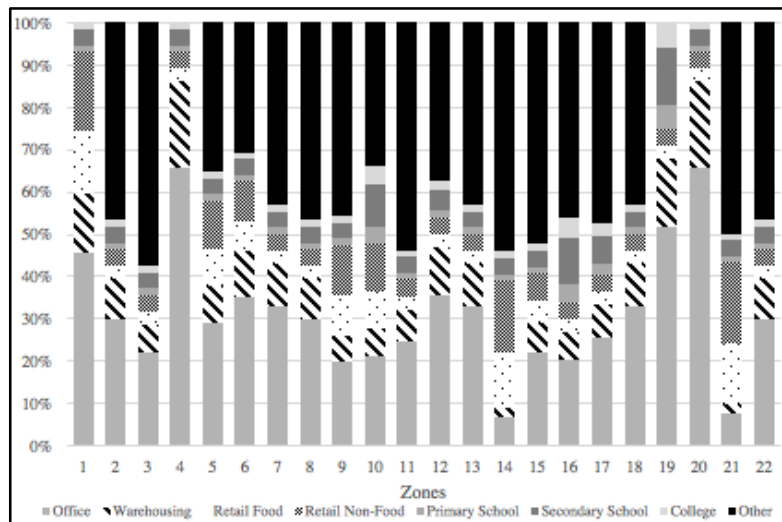


Figure 5.12 – Residential travel purpose split by modelled zones from the surveys

5.3.2.2. Transportation statistics and stakeholders' involvement

The door-to-door survey only collects information on private mobility patterns. Public available reports, national and local statistics and municipal stakeholders were key to get information on the characterization of public transportation (*i.e.* buses, trains), parking (*e.g.* costs, size), and speed limits in specific zones of the municipality, as well as detailed information on routes, occupancy, schedules and tariffs/fares.

5.3.2.3. Mobility and energy demand modelling

An energy and carbon transport model was used for the mobility and energy demand assessment, supported by data collected through surveys. The model represents a typical day, with no attempt to model different days of the week or 'peak' and 'off-peak' travel conditions (Irons *et al.*, 2014). Previous versions of the transport model were used for: improvements to bus priority and development of bus corridors, introduction of smartcard ticketing, measures to encourage shifts to public transport, walking or cycling, and low emission zones (*e.g.* MVA (2013a) and MVA (2013b)). The emissions model is based on a model developed from the United Kingdom Department for Transport and UK's Transport Research Laboratory study (TRL, 2009), which makes use of data from the National Atmospheric Emissions Inventory (NAEI, 2015) and COPERT emissions coefficients (Emisia, 2012).

The model is split in the 21 city zones plus a 22nd zone covering the area outside the municipality, allowing to assess traveling to and from the municipality. It was calibrated with the transport survey data by looking at mode shares and average trip lengths. The model provides for each of the years under study (in this case 2014, 2020 and 2030) (i) the mobility demand by zones (origin and destination), vehicle type and a comparison to current vehicle stocks, (ii) energy consumption, such as energy per fuel type, per person, per trip and split by vehicle type; (iii) and emissions outputs. Figure

5.13 illustrates the energy consumption per origin zone for the base year (2014). The origins mirror the distribution of buildings, since all the trips are modelled as two directional home-based journeys. The zones furthest away from the center have a high-energy usage due to large travel distances. The zones at southern of the historic center contain large amounts of retail and industrial land use being attractors to trips, although show low energy consumption, compared to the northern zones due to short distances to travel to reach these destinations (Pollard and Irons, 2015). The information created in this framework component to input in the GIS and in the ICEP tool generally consists of a coherent picture of the distribution of trips (from origin to destination sectors) and associated transport modes and the estimations of the respective total number of pkm and tkm travelled.

Such data allowed the ICEP tool to answer question as:

- (i) Considering the future growth in transport demand, driven by any large land use development or regeneration projects, new residential areas, or new vehicles restrictions areas, what will be the optimal mobility choices, in terms of technology (e.g. private passenger cars vs. public transport) and routes?

We have assessed that the optimal mobility strategic choices in the case of Évora are ensuring a shift of 15% from private cars mobility to public transportation from 2020 onwards, promoting the use of biofuels in the whole public transport fleet by 2030, and interdiction for all type of vehicles and concerning all purposes to the Évora Acropolis (a minor are within the city historic centre) from 2020 onwards.

- (ii) What will be the impact on energy consumption and emissions, from different transport modes delivering future needs of passenger mobility?

By applying the ICEP tool for Évora we estimated cost-effective reductions in CO₂ emissions in the transport sector of 35% in 2030 vis-à-vis 2013 values in a Baseline scenario (*i.e.* without any imposed CO₂ reduction target or a specific transport related measures). This is mainly due to the combination of two factors: a) reduction of travelled km due to the expected decrease in the population, coupled with b) a very significant cost-effective replacement of passenger cars with more efficient new vehicles. The energy consumption associated to passenger cars in Évora will vary from 2.57 GJ/1000 vehicle.km in 2013 to 1.36 GJ/1000 vehicle.km in 2030). The car stock travelling in Évora in 2013 is already old, with an average age of 15 or more years.

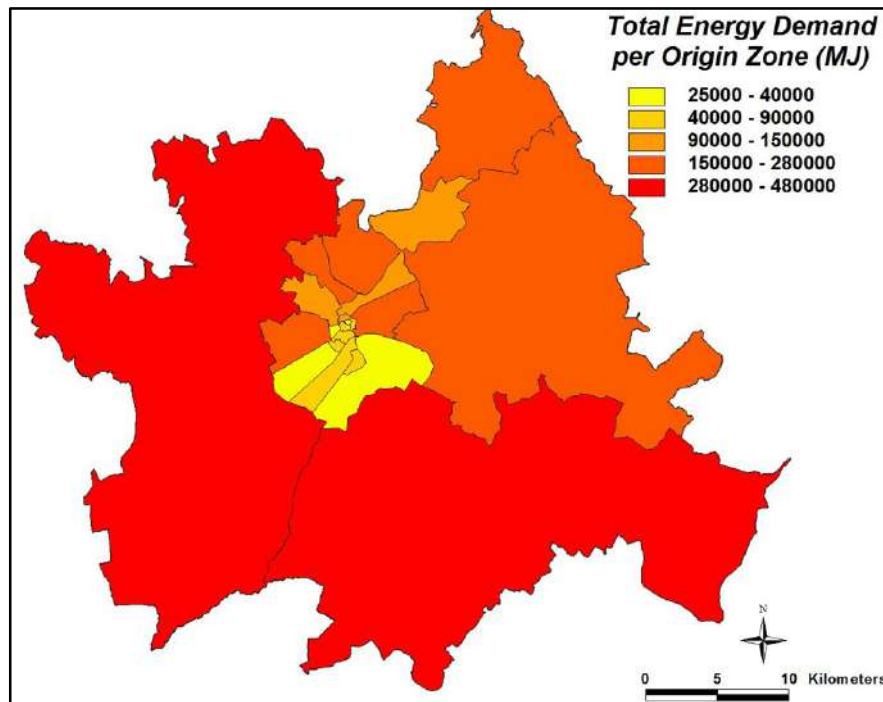


Figure 5.13 –Total final energy demand (MJ) per origin zone (2014)

5.3.3. Other energy demand sectors

The scope of the analysis of the city utilities, industries, agriculture and services focus on the energy consumption for the four-city city districts, although relying on individual facilities data when available. Examples of results range from electricity consumption load curves (daily, seasonal, annual) differentiated by public lighting, water management facilities, industries, retail, agriculture and different services, to the energy consumption, number, size (when applicable), location of public lighting, schools, public buildings and waste/water facilities.

To look at how the sectoral demand varies over the course of a typical day and year to input in the ICEP tool, we performed a set of data analysis over 15 minutes' electricity consumption registries (Gouveia *et al.*, 2016b). A sample data of more than 800 electricity smart meters was retrieved for three types of consumers: normal low voltage (*i.e.* less or equal to 13.8 kVA), special low voltage (*i.e.* from 13.8 kVA to 100 kVA) and special medium voltage (*i.e.* higher than 100 kVA) encompassing all the different energy demand sectors (EDP, 2016).

A selected example of an output of this step is presented in Figure 5.14 referring on public lighting. Similar data for water and wastewater systems, waste chain, industries, agriculture and for the services buildings was also collected as depicted in Table 5.4.

The electricity consumption for public lighting (including traffic lights) was 25 TJ in 2014 (DGEG, 2016) corresponding to 5% of total electricity consumption in the municipality of Évora. This consumption varies through the year as a function of the daylight hours across seasons/days, which is

extracted from the analysis of the smart meters' data and used as input as one of the characteristics of the public lighting sector in the ICEP tool. Information on the type of lamps and power per city district was retrieved from the DSO database (EDP, 2015a) which depicts the detailed consumption and type of lamps per city district.

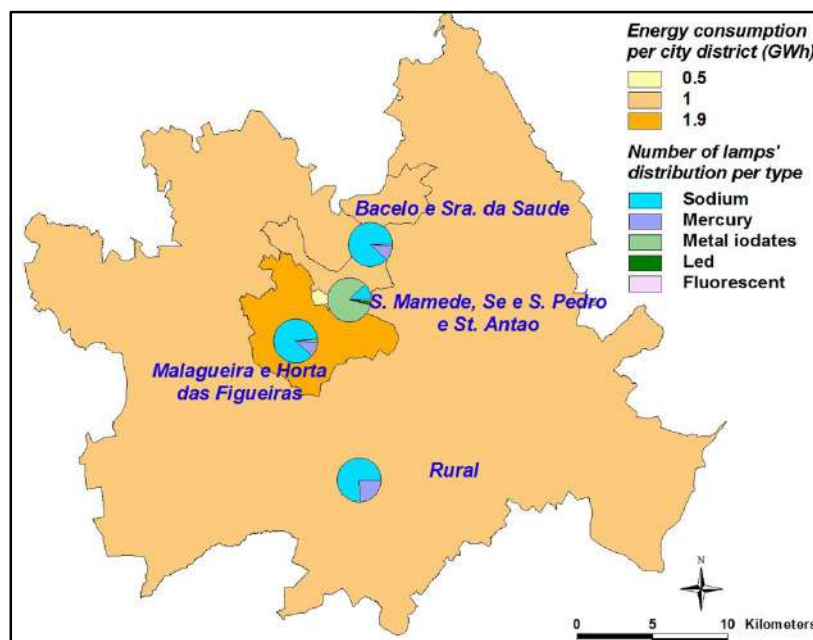


Figure 5.14 - Public lighting electricity consumption and number of lamps per type of technology by city district (2014)

Data collected regarding the other energy demand sectors was used to support the ICEP tool to answer questions like:

- (i) What is the impact in terms of emission and energy consumption of decreasing the municipal solid waste production *per capita* in 20% from 2013 values?

For the case of Évora this was found to lead to a reduction of CO₂ emissions of 89.66 ktCO₂ in 2030 compared to a Baseline scenario, due to an energy saving of 950.87 GJ. These are relatively modest impacts compared to the total emissions and energy consumption in the city (*i.e.* they represent less than 1% emission and energy reductions) but; nonetheless, indicate a measure of the contribution for this sector.

5.3.4 Energy supply and endogenous renewables potential

This section shows selected results on the energy supply system and on the endogenous renewable potential estimations. The municipality of Évora is fully covered by the electricity grid, while the natural gas network only covers the urban districts. There are some infrastructures selling biomass, mostly informal, for residential heating and widespread fuel stations selling oil products for the transports.

Engaging the electricity utility in data gathering allows obtaining detailed information on the current electricity production (15 minute registries) from utility scale PV systems and roof top facilities, which is crucial for the characterization of different profiles: a) annual and seasonal electricity production, b) hourly electricity production and c) capacity factor (EDP, 2015b).

Regarding city endogenous renewable potential, biogas, wind and geothermal were assessed with no significant potential while the solar photovoltaic (PV) technology was selected as the most important RES due to high solar incoming radiation (5040 Wh/m²/day) (PVGIS, 2016). Its potential was estimated at two levels:

(a) Utility scale (PV track and concentrated photovoltaic systems with 1 MW, 10 MW, 20 MW and 30 MW) through the spatial assessment of the characteristics of the available and suitable area for solar farms in the rural areas by using Solar GIS (GeoModel Solar, 2016) and ArcGIS/Arctoolbox – (Solar Analyst), while taking into consideration spatial planning regulations in place and scenarios of land use restrictions (Lourenço, 2014);

(b) Building integrated PV (rooftop and façade) considering local specific buildings characteristics (*e.g.* optimal conditions in terms of orientation, and slopes between 25° and 35°) that determine the PV panels suitable area, following Byrne *et al.* (2015), and their performance, considering specific PV technologies (Hwang *et al.*, 2012). The rooftops in each city district were analyzed through GIS tools and complemented with the households' survey information, while the façade area was associated with the floor area as in IEA (2002). The results are presented at the district level (*i.e.* PV plant size), although, when appropriate, the estimations were made at building archetype level (*i.e.* for PV rooftop).

Detailed information on both methodologies and results can be found in Dias *et al.* (2015). Figure 5.15 depicts an example of results showing the location of current PV plants and the suitable locations for potential PV plants under different project size and land use restrictions scenarios. The utility scale PV potential in Évora rural areas can reach up to 1.5 GW, being the PV project sizes between 1 MW and 10 MW the most appropriate due to higher efficiency in terms of area occupancy.

Data obtained at this step was fed into the ICEP to answer issues as:

- (i) At what extent, solar PV could supply the future city energy needs?

We have studied different scenarios assessing the possible contribution of plant size and roof size PV options for Évora using the ICEP tool. We have found that the electricity generated within the municipality can vary from the 0.84 GWh in 2013 up to 9.19/41.54 GWh generated from PV in 2030. The range of the 2030 variation is due to the design of the two tested scenarios. In this first we estimated the impact of having roof size PV panels installed in dwellings corresponding to 10% of maximum feasible potential by 2020. In the latter, we studied the role of new plant size PV power

plants deployed in the municipality rural zone practically up to the maximum technical potential. These amounts of generated electricity from PV (both roof and plant size) lead to circa less 30% electricity imports from outside Évora.

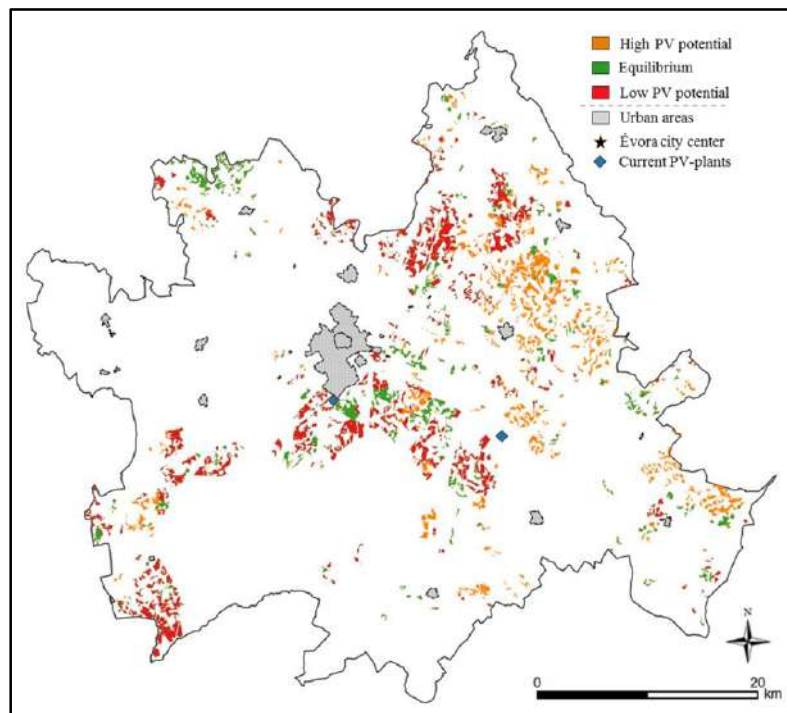


Figure 5.15 – Current PV plants and suitable locations of potential PV plants of 1 MW according to land use restrictions scenarios (Low, Equilibrium and High)

5.3.5. Integrated City Energy Planning (ICEP) tool

We argue that effective sustainable energy planning in cities requires detailed and spatially explicit datasets, driving the design and implementation of policies and measures targeted to local socio-economic profiles and specific infrastructures characteristics. Otherwise, the implementation of policies and measures equally across all city districts or with no integration with other sectors is potentially ineffective and resource wasted.

City managers and other stakeholders need to work together to address the needs of the citizens. The World Economic Forum (2016) identified several challenges (*e.g.* governance, budget constraints, demographics) city managers will face on their road towards a sustainable energy future. Smart regulation and robust planning is required to overcome those issues.

Energy systems engineering provides a methodological scientific framework to arrive at realistic integrated solutions to complex energy problems, by adopting a holistic, systems-based approach, especially at decision making and planning stage (Zanon and Verones, 2013). The analytical framework proposed herein, including data collection pipeline and intermediate specific modeling

activities, intends to feed an integrated energy system model (*e.g.* TIMES_Évora) coupled with a MCDM used as the ICEP tool to the municipality of Évora.

We recognize that the data and methods used have different uncertainty sources comprised in different temporal and spatial levels of detail. For integrated planning purposes, a common spatial organization needed to be adopted and then a coarser scale was taken, *i.e.*, the four districts, to allow for a fully integrated assessment. However, the 10 archetypes are taken individually in each district. Moreover, the ICEP tool follows a kind of an agent-based approach supporting the idea that each archetype represents a typical family with specific socio-economic profile and then a willingness to pay for new technologies, including vehicles. In this sense, the 10 archetypes-in-the-four zones fully accomplishes either the high spatial detail gathered in data collection as the city spatial dynamics to generate pathways for sustainable energy futures.

The proposed framework advances on a fully harmonized and coherent energy system analysis and planning supported by systematic and detailed data collection and integrating detailed city sectors modeling tools. This information sets the basis for proper development and comparison of alternative scenario. Alternative scenarios are built considering different pathways for the city regarding demographics evolution, economic sectors development, city districts evolution, enabling informed discussion of the different options and decision-making. Each scenarios' outputs are expressed at each city district and mapped into the city GIS depicting the spatial distribution of the impact of energy related policies and measures assessed at the city district level.

The capability of an energy system optimization model as TIMES serving the main purpose of a core planning tool (*i.e.* ICEP tool), while including inputs from relevant city stakeholders (*e.g.*, municipality) along the data cascade collection, methodology, design of policy scenarios and validation of results, gives policy relevance. At the last stage, the alternative scenarios of measures were assessed with respect to non-technical criteria through a collaborative multi-criteria decision making method to address economic, environmental and social issues (*e.g.* using PROMETHEE - Preference Ranking Organization Method for the Enrichment of Evaluations) (VPSolutions, 2013), which in some cases changing the ranking of priority of some cost-effective solutions when social criteria were considered

In all the process the city energy GIS platform is used as a core tool to communicate with the stakeholders allowing the visualization of the spatial distribution of energy demand and the comparison among the city sectors (*e.g.* transport vs buildings vs public lighting).

The data framework towards the ICEP tool, as exposed in this paper, offers the opportunity to design new and innovative solutions bringing forward the value of multiple data to effective decisions, both at the citizen level and at the policy decision level. The analytical framework is highly supported on technical and specialized tools, though we consider that a strong stakeholder engagement and

participation during all the process will help city managers and urban planners to largely benefit from the outcomes of the ICEP. Furthermore, it is worth noting that the analytical framework, data collection process and multi model use was tested in four significantly different cities, showing operational proof of the capabilities of our methodology. Nevertheless, specific national contexts and interests of each city were taken into account along the process, and particularly in the details of representation of the system and in the scenarios definition.

5.4. Conclusions

Cities are core energy systems pointing to sustainability and climate protection. Detailed and multiple data sources are increasingly available at different temporal and spatial resolutions, and this paper contributes to demonstrate how these datasets can be combined and jointly assessed with specific sector models to feed an integrated energy planning tool coupling an energy system model, to a MCDM to deliver science-based and social-accepted future sustainable pathways for the city.

We present an analytical framework with an integrated vision of the territory intending to address incomplete interpretations and dispersed data of the energy system in cities, which usually generate multiple inefficiencies. Integrated city planning through data analytics, taking the city energy system from the supply to the demand components, driven by optimal cost-efficient assessment will allow to deliver policies and measures towards higher energy use efficiency towards sustainable energy future targets.

The proposed analytical framework has been developed within EU InSMART project and applied to four cities. The main novelty of this approach is the process of data pipeline, highlighting data gathering procedures and data processing tools and models, depicting the whole process of analysis and showing typical results. The analytical framework can be used as a template for the planning of integrated energy systems at the city level supported by in-depth spatial detailed characterization of the different city energy demand sectors. A vast set of indicators are presented covering all the city energy sectors, as well as selected modeling tools and analysis, that can be adopted as guidelines to implement an integrated energy planning approach in cities.

The paper demonstrate how to collect and assess the data to fully characterize the city energy system in different spatial units (*e.g.* district level): 1) residential buildings sector through the use of door-to-door surveys, 15 minutes electricity consumption data from smart meters, statistical data and detailed energy simulation of representative buildings archetypes; 2) transport and mobility through door-to-door surveys, information from stakeholders and transport model portraying energy and mobility flows within the city; 3) other sectors focusing on the characterization of public utilities infrastructures of waste, water and sewage, public lighting, industries and services, through high resolution smart meters data, national to regional statistics and stakeholders consultation; 4) energy

supply options through the assessments of RES potential taking the local level spatial planning constraints.

The integration of the vast datasets into a GIS platform for visualization purposes allows the valuable participation of different city stakeholders, bringing forward a key advantage of this methodology. The stakeholders' participation at different stages of the methodology is essential in assembling an acceptable, realistic and mostly beneficial city action plan.

ICEP tool results show that for the case study city (Évora), the measures that have biggest impact in sustainable energy consumption of the municipality are not the ones under its direct influence (namely measures regarding residential buildings) which represents a challenge for a new generation of local energy policies.

A fully optimized smart city planning requires heavy city analytics, namely through the collection and combination of a plethora of information from energy statistics by city district or blocks; sensors and metering within households, services buildings, public spaces and city utilities; smart technologies for transport management and roads; and stakeholders' inputs through comprehensive procedures. This paper showed how to deal and manage such data complexity in an organized framework with the purpose to pave the way for a comprehensive and robust city planning, leverage the city role in assuring sustainable energy provision and climate protection.

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Authors Contributions

J. P. Gouveia structured and wrote the majority of the paper, and has helped to carry out the data collection and analysis for all the steps of the framework. J. Seixas supported the design of the overall study, contributed for the manuscript draft and its in-depth revision. M. Andrade and V. Nunes provided the data from the electricity smart meters. N. Bilo and A. Valentim were involved in the data collection for all the components of the framework and particularly on the conduction of the door-to-door surveys at Évora. L. Dias contributed to the data collection, analysis of the other energy demand sectors and integrated modelling. S. Simoes worked on the integrated tool modelling and analysis of the associated results. M. Gargiulo contributed to the design of the research. G. Giannakidis coordinated the study. D. Irons and M. Pollard conducted the transport data collection design and the

transport and mobility modelling work. G. Long and D. Robinson contributed to the residential buildings data collection design and performed the buildings simulation modelling work. C. Nychtis, provided help for the data preparation, mainly for data related to building typologies. A. Rigopoulos developed the GIS platform and made the maps. All authors gave final approval for publication.

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Chapter 6 | General Discussion and Conclusions

“The value of an idea lies in the using of it” - Thomas A. Edison

6.1 General discussion

The research carried out in this dissertation brought to the spotlight the needs and benefits of looking deeper into residential sector energy consumption in a southern European country. Residential sector consumption is a moving target prone to increase the complexity of policies and instruments that have to address this challenge, which calls for different levels of knowledge to feed multiscale policies. The motivation for this dissertation was to expand the understanding of energy consumption patterns, consumers' role on energy consumption, indoor thermal comfort, and the levels of satisfaction of energy services demand. In a country potentially highly impacted by climate change, with low levels of income and significant lower energy consumption *per capita* compared to EU28 average, looking into these issues gains even more importance. The research work combined detailed analysis at different spatial (national, city, and consumers level) and time scales (hour to annual).

While assessing the whole chain of the residential energy consumption, the electricity consumption and its determinants deserved a special focus. Current electricity consumption patterns and specific consumer groups using smart meters were evaluated. A look to the future and to the inclusion of the residential sector in an integrated perspective of an energy system was also carried out, assessing the uncertainty and impacts of variables changes in energy services demand and final energy consumption.

Using Portugal and in particular the municipality of Évora as case studies, it is possible to present how the results and methodologies are relevant for a region where a balance between effective energy consumption reduction and increase thermal comfort levels is needed. The use of Évora also enabled to take advantage of the extensive and detailed smart meters data. Due to regional specificities and recognizing the need for detailed analysis and dedicated policies and measures the results may not be scaled up.

The novel contributions of this research comprise both methodological and results advancements. The methodological advances give input to the research arena, while the obtained results can support policy development and bring societal and market value. Table 6.1 summarizes the main achievements of this research, pointing out some of the key insights for policy. Chapters 2 and 3 are positioned to deliver insights for policies tailored for local and consumer groups, while chapters 4 and 5 convey results to be integrated in multi-level and multi-sectoral policies. The results are intended to support the design and creation of more suitable instruments since they can integrate well-known energy consumer understanding.

The outcomes described in Chapter 2, from the assessment of consumer groups and load profiles characterization, can support the design of new business models for ESCO's, DSO'S or energy suppliers (value for market). The topics and results from Chapter 3 highlight the fuel poverty problem and current thermal comfort vulnerability of the region (value for society). From the abovementioned chapters and under a smart grid environment with big data available, the ability of effectively segment

and characterize groups of consumers and understand consumption patterns gain an add value. The focus on the consumers is paramount since it is needed to understand who they are, what, why and how they consume energy. For example, in the same city and neighborhood, we came up with 10 clusters of electricity consumers, and the knowledge on the determinants governing such households. This is crucial to support, develop and roll out tailored, applicable and innovative engagement actions/policies to effectively combine steering changes in consumer behavior, energy services demand drivers, thermal comfort levels, energy technologies deployment and energy savings.

The work carried out herein, transforming data to knowledge at different levels, is also valuable to energy suppliers, to tariff design or demand side management schemes and to assess the impacts and purpose of personalized services (*e.g.* integration of PV, energy efficiency measures, inter-sectoral electricity consumption/generation complementarities). All the chapters' results contribute to deliver insights to support decision and policy-making, for local stakeholders as municipalities, regarding the determinants of consumption and assessment consumers and behaviors; for energy agencies to support measures targeting specific groups of consumers (*e.g.* vulnerable); and for national and regional long term energy planning.

6.2 Answering research questions

This section presents more detailed conclusions, summarizing the answers to the research questions addressed in the different chapters of this dissertation.

RQ#1 - What are the main determinants governing electricity consumption for different types of household consumers?

The first research question sets the ground for this work, while better understanding electricity consumption groups and drivers of electricity consumption. The process of identifying and characterizing consumer groups and electricity consumption patterns within a southwestern European region allowed to: i) extract and understand significant differences of consumers within the same region and with very different consumption patterns compared to other EU countries with different socio-economic and climate backgrounds.

From the clustering analysis, it was identified 10 groups of distinct electricity consumers for the sample used within a city of around 56 000 inhabitants. The assessment for Évora shows that three major groups of determinants characterize the electricity consumption segmentation, explaining the differences between consumers: 1) physical characteristics of a dwelling, especially the year of construction and floor area; 2) HVAC equipment and fireplaces ownership and use; and 3) occupants' profiles (mainly number of persons per household and average monthly income).

The clustering approach and analysis from smart meters' data also allowed to differentiate types of annual electricity consumption profiles, delivering significant knowledge on types of consumers in the region.; a U shaped (sharp and soft), a W shaped and a Flat annual profile. U shape pattern was the

most common one, covering 77% of the sampled households which could be also considered as majority in the whole country. U profiles present a visual difference of consumption on winter and the remaining seasons portraying the inexistence or low use of cooling equipment in the summer compared to a use of electricity-based technologies for space heating in the colder months of winter. These results are clearly aligned with the national statistics and general knowledge of the low space cooling equipment ownership and use in the country (i.e. 0.5% of households' energy consumption (INE and DGEG, 2011)). W annual profile depicts clear distinctions of electricity consumption between summer and winter and the inter-seasons period. These consumer groups with high values of daily consumption present a strong hump-shaped consumption in summer. The profiles suggest that the respective households might have high ownership rates and use of HVAC systems for cooling and low use of electrical equipment for heating in the winter or both high use of electrical systems for cooling and heating. The knowledge extracted from these differentiated profiles backed up by the socio-economic and building structure details feed the definition of major policies and instruments especially targeted to each group of consumers with expected distinct impacts.

The current results show the importance of regional and consumer group strategies on equipment substitution, insulation measures and the role of renewable energy integration in buildings, as also proposed in the Ljubljana declaration, within a European region that faces specific barriers for promoting EE and RES, as climatic conditions leading to a traditional low emphasis on insulation and ageing building stock (ELIH Med, MARIE and Proforbiomed, 2013).

From the work developed in Chapter 2, we conclude that the knowledge on the drivers behind household energy consumption and typical consumption profiles is crucial to design energy policies and instruments that effectively assure the transition to low carbon and reliable energy systems. Crossing the consumption registries of electricity delivered by the smart meters with the main determinants of energy consumption in each household retrieved from qualitative door-to-door survey-based data, proves to be a powerful method to distinguish groups of electricity consumers, allowing to derive insights for an individually feedback evaluation tailored to effective energy savings.

RQ#2 – Why to identify specific consumer groups and behaviors?

The work carried out in Chapter 3 suggests new uses for smart meters' datasets as to recognize and better understand fuel poverty issues and consumers' behavior on space heating and cooling. Howell *et al.* (2005) underlined that energy use in the residential sector can be best understood by focusing on specific end use functions and their drivers. The relevance of each end-use in the overall energy consumption is highly dependent on climate, physical dwelling characteristics, appliances and system characteristics, ownership, and occupancy behavior, as concluded previously when answering to RQ#1. In the work developed in the third Chapter, the importance of looking to vulnerable consumers and major end uses as climatization is acknowledged. These topics are particularly important in the

case study region, under the scope of a wider European energy policy focused on energy consumption reduction.

In this chapter, and for answering the second research question, we evaluate both daily and annual electricity consumption profiles for two purposes: 1) look for very distinct consumer groups and characterize them, while estimating the satisfaction of thermal comfort levels from confronting electricity consumption with energy services demand modeling calculations for climatization, and 2) assess consumers' behavior regarding electricity consumption when outside temperatures change.

The research results advance on the state of the art since they enable a better understanding of consumers typification and daily routines; support the identification of specific consumer groups definition supported on their use of climatization equipment and allow for a closer look to the fuel poverty topic in Portugal.

On the first part of the chapter, a new concept “fuel obesity” is brought to the table, to understand if a very high daily electricity consumption compared to, both the average and low consumption level consumer groups, is a consequence of overconsumption, unsustainable and inefficient energy use. Throughout the steps of the research, it was recognizable that while the assessment of electricity consumption levels and profiles might support the concept; when combining those results with the demand for energy services for the respective building typologies, the results still portray the lack of fulfilment of thermal comfort levels inside households both in heating and cooling season. This way it can be said that, combining smart meters and energy simulations allow for closing the circuit of analysis, making a clearer appraisal of energy services demand and energy consumption while supporting the assessment of equity issues on energy use that could serve to define targeted policy measures and incentives. This research lifts the veil on the concept of fuel obesity, that despite not being confirmed, future research in other regions and samples should pursue to better understand if it can be conveyed.

Hence, from the second part of the chapter, it is concluded that high resolution hourly electricity consumption data at the household level could be used as a proxy of active consumer behavior regarding space heating. We consider that this would also apply for space cooling, nevertheless from our data and sample, this was not the case. The daily routines and behavior of distinct consumer groups on such an important end use as climatization needs to be correctly understood to have a better planning and targeted policies, programs and incentives. The assessment of temperature-driven load variations as proxies for active behavior is supported by the socio-economic details of the households (*e.g.* ownership of heating and cooling equipment, income level) in order to highlight factors that could confirm or mask (*e.g.* due to the ownership of other heating equipment based on gas or biomass) that relationship. This kind of analysis and findings have a high value for a wide range of applications within a smart grid environment. As also discussed in Rhodes *et al.* (2014) they could also serve as a starting point for utilities looking to reduce electricity use during peak times and to the advantages of policies such as time-of-use or real-time electricity structures that might affect consumers differently.

ESCO's and consumer associations would benefit from this knowledge on the temporal shape of residential energy use and its determinants to better engage consumers and target the most significantly impacted houses on *e.g.* efficiency upgrades, group insulation improvement scheme and customized communication strategies.

Ellegård and Palm (2011) states that policies aimed at promoting energy savings in the household sector must relate to and rely on individuals' daily choices and household routines – what they do in their everyday lives. Energy efficiency policy instruments are mostly designed based on a normative perspective of market behavior of economic actors, which are assumed to receive the market signals and act on the grounds of their own rationality. Still, the economic rationality in energy use and energy saving behaviors is an often-entangled topic depending on various parameters (Oikonomou *et al.*, 2009).

Energy conservation and energy efficiency are presently the most powerful tools in the transition to a clean energy future. However, the results from Chapter 2 and 3 also shed the light on the importance of the integration of PV and solar thermal systems in a high solar radiance region as Évora when detailed registries on consumption are available. This knowledge on the patterns of use and daily peaks could be used to feed new business models investment and micro grids definition; to better take advantage of RES investments, optimize PV self-production, minimize grid investments and address complementarity of consumption/production within different household groups or even with other energy consuming sectors. All this knowledge can further support decision makers and other energy stakeholders in developing *e.g.* demand side management actions, alternative tariff design, specific energy efficiency measures and peak shaving assessments.

RQ#3 – How, and in what extent, the uncertainty associated with the determinants of energy consumption will impact energy services demand and final energy consumption in the long term?

The answer to this research question is carried out in chapter four, where a bottom-up methodology to project detailed energy end uses demand in the Portuguese residential buildings until 2050 is proposed. Space heating and cooling, water heating, lighting, cooking, refrigeration and electric appliances (*e.g.* dish washing, cloth washing, among others) were considered, followed by *ceteris paribus* assessment of the energy consumption determinants.

It is argued in this chapter of the dissertation that the planning of future energy systems, especially in the residential sector, should be supported by energy services demand instead of final energy consumption, allowing future options of energy resources and technologies available to satisfy energy needs, as well as encompassing the expected changes on the determinants of energy consumption (*e.g.* socio-economic; changes on climate, on private consumption, thermal comfort and on lifestyle).

A range of plausible variations of the parameters defining a Reference scenario end-use services demand was assessed, resulting in around 140 ESD sensitivity analysis scenarios. And a selection was made of a set of 21 scenarios corresponding to the highest and lowest variation of each parameter for each end-use plus the REF, serving as input for the technological optimization model TIMES_PT. The model estimated final energy demand and technology portfolio allowing to conclude on the impact of uncertainty of energy services demand in final energy. The use of a combined methodological strategy supported by an energy services bottom-up approach and a technological model gives insights on the complexity between energy services and energy consumption.

This chapter recognizes energy consumption in the residential sector as a moving target stressing the importance of understanding the current determinants of energy consumption that distinguish energy consumers disclosed in the previous chapters, but also to recognize how they could change for the future under long term energy planning.

The results underpinned that for some end uses, technology (and energy efficiency improvements) might outweigh behavioral practices and lifestyle changes as in space heating and lighting. Nonetheless, it is recommended to give focus to uncertain parameters related with consumer behavior, especially those on space heating and other electric end uses, as thermal comfort and equipment use.

For space heating and cooling, the results indicate that the uncertainty associated with the increase of thermal comfort overcomes the uncertainty on the expansion in households' size and on thermal behavior of buildings due to *e.g.*, climate change. These results are in line with the ones presented by Young and Steemers (2011), where the behavioral patterns of air conditioning equipment use were the most influential elements in household cooling energy consumption; and are also supported by the research findings from the previous chapters.

The research carried out in this chapter allows for an improved understanding on the data of several parameters that drive energy services demand in Portugal, avoiding the use of approximate values as in other studies for the European households (*i.e.* Anström *et al.*, 2010). Furthermore, it considers the heterogeneity of the different end-uses (*e.g.*, floor space and appliance ownership) to improve extra options for a detailed analysis, a research gap identified by Ruijven *et al.* (2010); results illustrating once again that energy policies, namely for effective energy consumption reduction, should focus specific determinants behind each end-use on both technological and non-technological factors.

RQ#4 - How multiple data and tools can be integrated to inform sustainable city planning and policy?

The last research question is addressed in Chapter 5 showing how the work carried out in the previous chapters can be considered in the big picture, under city level energy planning. There is a critical need for improved comprehensive city planning driven by integrated approaches, supported by ex-ante cost-benefit evaluation and using energy systems models towards cities sustainable energy use. Hence, innovative tools and models to assess and perform in-depth analysis of various alternative measures

will help to pave the way towards more efficient energy use, to fully capture the potential of each city in the most efficient (economical, technical) way.

In the fifth chapter, we propose an analytical framework to integrate multiple data sources, from smart meters and surveys, models on different city's energy components, and analysis tools over the city, required to feed an energy planning integrative tool to deliver future sustainable energy paths. The integrative tool takes the city energy system and focuses on the data gathering and analysis tools on: 1) residential buildings, 2) transport and mobility, 3) other energy consuming sectors (waste, water and sewage systems; public lighting and gardens, public buildings, services), and 4) energy supply system, including local renewables. Selected results for Évora city illustrate how the proposed analytical framework advances on integrative city planning and show how energy services demand projections and the knowledge of different groups of consumers and determinants could be included within a wider framework of analysis.

It is shown that an improved understanding of the energy flows between city districts and at the building level/consumer level is necessary for the identification and evaluation of possible energy related measures to be considered for each energy consuming sector, and for the advance of urban sustainability governance.

It is recognized that the availability of data for the characterization of EU buildings is far from ideal. Hence, in this chapter we delve into the collection of data needed for the residential sector as input for the integrative planning tool provided by multiple sources and a combination of statistical data analysis, dedicated household surveys, electricity smart meters' data analysis, where available, and buildings simulation models.

The measures with highest impact in sustainable energy consumption of the municipality are not the ones under the municipality direct influence (*e.g.* measures regarding residential buildings), which is a challenge for a new generation of local energy policies; and also stress the importance of our previous results for other type of stakeholders as ESCO's, energy utilities, consumer groups.

6.3 Final remarks

This dissertation has covered the residential energy sector for Portugal, from the determinants and energy services demand, zooming in on targeted consumers and climatization behaviors to current and long term assessments. While transforming data to knowledge, the work delivers insights for different stakeholders, policy and acting levels. Table 6.1 synthetizes the work from problem design to the advancing of knowledge and societal insights.

Table 6.1 – Dissertation overview: from problem design to advanced knowledge and societal insights

Problem Identification	Research Questions	Advancing methods and knowledge	Insights to policy and stakeholders
<p>Stabilization or reduction of households' electricity consumption while fulfilling electricity service needs has been pointed out as a major goal in developed countries to prevent harmful environmental impacts and fossil fuel imports. The specificities of Residential sector and regional/country differences need to be identified in order to better understand energy consumption patterns, the determinants of energy consumption and the dichotomy of energy consumption reduction vs indoor thermal comfort increase. This requires a detailed knowledge on consumers and electricity consumption patterns.</p>	<p>RQ#1 - What are the main determinants governing electricity consumption for different types of household consumers?</p>	<p>The successful design and implementation of residential sector instruments and measures can be achieved through the integration and better understanding of households' electricity consumption patterns using high resolution data from smart metering coupled with the knowledge on socio-economic details. In this work, a consumer segmentation, identifying and characterizing different types of consumers was applied. Main contribution: screening tool to compare energy consumption patterns and consumer groups of households for a southwest European city.</p>	<p>Set the ground for the definition of tailor-made policy recommendations for targeted consumer groups (<i>e.g.</i> vulnerable consumer groups, inefficient consumers) and behavior/practices to peak demand management, social support policies, EE measures and instruments and RES integration. The methodologies could be used to diagnose houses that are the highest fluctuating energy consumers and trigger energy audits or the low energy consumers where support measures should be applied.</p>
<p>Single evaluation of countries where space heating might not be the main problem as in EU northern countries (<i>e.g.</i> Portugal), have been recurrently dismissed. Several facts point Portugal as severely endangered by fuel poverty with low indoor thermal comfort. Ranking in the top of EU countries with the poorest housing status; 30% of people at risk of poverty, 28% of people enabled to keep home adequately warm, 36% living in a dwelling not comfortably cool during summer time; income distribution is more unequal compared to EU28; 30% of the population receives social tariff support for the payment electricity and natural gas bills; energy prices are significantly higher than EU28 average. Heating and cooling thermal performance gaps identified at local level to be around 90% (Palma, 2017). All these indicators have continuously been increasing in recent years stressing the need for an in-depth and dedicated studies on fuel poverty for Portugal.</p> <p>On the other end, it is also important to understand the patterns of consumption and behavior of high electricity consumption users for identify other types of policy and measures interventions.</p>	<p>RQ#2 - Why to identify specific consumer groups and behaviors?</p>	<p>A new methodology and new datasets to assess the fuel poverty thematic was applied; and a new approach was present to better understand consumers' behavior for space heating and cooling. This knowledge may be used either by policy makers targeting fuel poverty, thermal comfort levels and energy efficiency measures; and by ESCO's and energy providers for direct consumer feedback and tailor-made initiatives of tariff design, energy efficiency recommendations and equipment substitution.</p>	<p>Three major groups of determinants characterize the distinctions in electricity consumption segmentation: physical characteristics of a dwelling, especially year of construction and floor area; HVAC equipment and fireplaces ownership and use; and occupants' profiles (mainly number and monthly income). Looking deeper to specific consumer groups, occupants' behavior is the most significant determinant of electricity consumption, especially regarding space heating and cooling.</p>

Problem Identification	Research Questions	Advancing methods and knowledge	Insights to policy and stakeholders
<p>Projections of energy demand are important for energy security supply and low carbon futures, and usually rely on final energy consumption trends methods, limiting the opportunity for future options. Methods supported by final energy are very limitative because future options are locked in. Projections of energy demand require approaches based on energy services, implying a deeper knowledge between energy services and technology options</p>	<p>RQ#3 - How and in what extent, the uncertainty associated with the determinants of energy consumption will impact energy services demand and final energy consumption in the long term?</p>	<p>Methods supported by energy services are much preferred to estimate future energy demand, since they are better suited to accomplish end-users needs understanding the role of each energy consumption determinant.</p> <p>A bottom-up methodology was developed to project detailed energy end-uses demand in the Portuguese residential buildings until 2050, aiming to identify the parameters governing energy services demand uncertainty, through a sensitivity analysis. The partial equilibrium TIMES (The Integrated MARKAL-EFOM System) model was used to assess technology options and final energy needs for the range of parameters variations for each end-use. The impact of uncertainty of energy services demand in final energy was highlighted. Technology can overweight behavioral practices and lifestyle changes for some end-uses, as space heating and lighting. Nevertheless, important focus should be given to uncertain parameters related with consumer behavior, especially those on heating and other electric end-uses, as thermal comfort and equipment's use.</p>	<p>Main results show that technology can overweight behavioral practices and lifestyle changes for some end-uses as in space heating and lighting. Nevertheless, important focus should be given to uncertain parameters related with consumer behavior, especially those on heating and other electric end-uses, as thermal comfort and equipment's use.</p>
<p>City authorities will likely not be able to address the increasing energy demand, changing demographics and ageing infrastructure, without the support of appropriate methods, and data analysis throughout the urban development value chain (WEF, 2016). There is a need for an improved comprehensiveness of the city planning process towards sustainable energy use driven by integrated approaches. Current studies usually compartmentalize the assessments on urban energy systems focusing on specific aspects of energy use and mostly use exogenous input data.</p>	<p>RQ#4 - How multiple data and tools can be integrated to inform sustainable city planning and policy?</p>	<p>Integrated city planning through data analytics, taking the city energy system from the supply to the demand components, driven by optimal cost-efficient assessment allow to deliver policies and measures towards higher energy use efficiency towards sustainable energy future targets.</p> <p>It is designed a structured process of data pipeline, highlighting data gathering procedures and data processing tools and models, depicting the whole process of analysis and showing typical results, required to feed an integrated energy planning process to deliver future sustainable energy paths.</p>	<p>The analytical framework can be used as a template for the planning of integrated energy systems at the city level supported by in-depth spatial detailed characterization of the different city energy demand sectors.</p> <p>Data availability and accessibility increases the awareness of all stakeholders to new and innovative sustainable energy options. The results for Évora for the residential sector showed: 1) that the city can provide meaningful amounts of RES at affordable costs; 2) the need to review existing municipal programs for private buildings renovation in the historic center and provide access to credit schemes for residential owners towards passive energy efficiency measures in the building envelope.</p>

Future work should comprise similar assessments and cluster analysis to the ones depicted in chapter 2 at national level for other country regions to validate the results achieved herein and understand if they can be used for country level analysis. Another line of work, would be to integrate this knowledge for the residential sector consumption profiles with analysis of consumption profiles from other sectors under the scope of large RES integration, micro grids implementation, energy storage units at both utilities and individual scale, electric vehicles charging patterns, among others.

Future research on the topics of Chapters 2 and 3 should consider the design and testing of the impact of targeted policies on overall energy consumption. Incentives and subsidies could be important factor for the penetration of more efficient equipment and improved thermal quality of buildings, increased use of a specific fuel and adoption of renewable energy technologies. The body of literature on the determinants of energy consumption and energy savings do not give a strong focus on this factor, showing that it should be better studied. As mentioned by Egger *et al.* (2012) in the residential sector, experts observed the removal of the financial incentives for energy efficiency in Portugal.

One of the limitations of Chapters 2 and 3 refers to the analysis supported only on electricity consumption data. Further work should; therefore, include smart meter data from natural gas and knowledge on the biomass consumption to fully grasp energy consumption patterns, consumer groups typification and indoor thermal comfort understanding in the region.

One have to bear in mind that, since the objectives and timelines of the project (*i.e.* INSMART) that supported the development of the work carried out for Chapter 5, were slightly different from the ones taken in this work, the energy services demand methodology (Chapter 4) and defined consumer groups (Chapters 2 and 3) were not directly used within the framework for the city energy planning. Future research on city/national energy planning level should take into account detailed inputs on consumer groups, assessing policies and instruments within a broader framework.

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Annexes

Annexes Contents

For the development of this research different support tools were used such as smart meters' data and surveys. The surveys presented herein were designed and carried out in the city within the EU InSMART project. This chapter only includes the questions made to the citizens in both surveys and do not include the overall design and recommendations to the interviewers.

The annexes of this dissertation are the following:

- Annex I – Residential Sector Survey
- Annex II – Transport and Mobility Survey

The residential sector survey results were used within the research and papers described in Chapter 2 and Chapter 3. Both surveys were used to feed in the dedicated models (transportation and buildings energy simulation models) and the integrated city energy planning tool presented in Chapter 5.

Annex I – Residential Sector Survey

1. General Data		
Building form	Terraced house Detached Semi-detached Multi-family / apartment building	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
Building Use	Residential <input type="checkbox"/> Mixed <input type="checkbox"/> If mixed use, please provide information of specific uses by floor	
Address		
Total area (sq.m)		
Building height		
Number of Floors		
Area per floor (sq.m)	Basement Ground Floor 1 st 2 nd 3 rd	
Construction Year		
No of apartments		
Apartment number which is surveyed		
Floor at which apartment is located		
Apartment total area (sq.m)		
Refurbishment Year		
Type of Refurbishment	<div> Replacement of windows: <input type="checkbox"/> Year: </div> <div> Roof Insulation: <input type="checkbox"/> Year: </div> <div> Wall insulation: <input type="checkbox"/> Year: </div> <div> Boiler replacement: <input type="checkbox"/> </div>	

	<p style="text-align: right;">Year:</p> <p>Other:</p>
Number of residents:	Apartment	Whole building
Energy Certificate	Yes <input type="checkbox"/> No <input type="checkbox"/>	If yes what is the class:

2. Occupant / Contact person data	
<i>Type of Household Occupation Contract</i>	Owner-occupier <input type="checkbox"/> Tenant (private rented) <input type="checkbox"/> Tenant (public rented) <input type="checkbox"/> Leasehold <input type="checkbox"/> Shared ownership <input type="checkbox"/> Building manager <input type="checkbox"/>
<i>Family name / First name</i>	
<i>Age of primary resident</i>	
<i>Vocation / Working status</i>	Professional Full Time <input type="checkbox"/> Professional Part Time <input type="checkbox"/> Retired <input type="checkbox"/> Student <input type="checkbox"/> Other
<i>Number of household members</i>	
<i>Age of each household member</i>	
<i>Gender of each household member</i>	
<i>Relation of household members</i>	Family <input type="checkbox"/> Another Couple <input type="checkbox"/> Room mates <input type="checkbox"/> Other
<i>Degree of Scholarship</i>	None <input type="checkbox"/> 4th Grade <input type="checkbox"/> 6 th Grade <input type="checkbox"/> 9th Grade <input type="checkbox"/> 12th Grade <input type="checkbox"/> Graduation, MsC, PhD <input type="checkbox"/>
<i>Monthly Average Income</i>	Less than 750€ <input type="checkbox"/> Between 751 and 1500€ <input type="checkbox"/> Between 1501 and 2500€ <input type="checkbox"/> More than 2501€ <input type="checkbox"/>
<i>Tel/ Fax</i>	
<i>e-mail</i>	

3. Building Use data (for Non-residential building/Non-residential part of building)	
<i>Operation hours:</i>	Monday – Friday: from - to.....

	Saturday – Sunday: from.....- to.....
Average number of occupants during:	
Working days (Mon – Fri)	
Saturday	
Sunday and Public holidays	

4. Building Envelope data	
Load bearing structure	Concrete <input type="checkbox"/> Masonry walls with plate <input type="checkbox"/> Masonry walls without plate <input type="checkbox"/> Masonry walls with loose stone <input type="checkbox"/> Other / do not know
External walls Construction Type	Single layer <input type="checkbox"/> Double layer <input type="checkbox"/> If Single Layer then choose: <input type="checkbox"/> Brickwork unplastered on one or two sides <input type="checkbox"/> Brickwork plastered on both sides, <input type="checkbox"/> Brickwork with brick finishing, <input type="checkbox"/> Brickwork with stone finishing, <input type="checkbox"/> Stone wall unplastered on one or both sides, <input type="checkbox"/> Stone wall plastered on both sides <input type="checkbox"/> Stone wall with brick finishing, <input type="checkbox"/> Other If Double Layer then choose: <input type="checkbox"/> : Double brickwork unplastered on one or both sides, <input type="checkbox"/> : Double brickwork plastered on both sides, <input type="checkbox"/> : Double brickwork with brick finishing, <input type="checkbox"/> : Double brickwork with stone finishing, <input type="checkbox"/> : Double brickwork with slightly ventilated air layer, <input type="checkbox"/> : Stone wall with brick finishing, <input type="checkbox"/> : Concrete panels plastered on both sides, <input type="checkbox"/> Other
External wall thickness (cm)	
Type of insulation	Expanded Polystyrene <input type="checkbox"/> Extruded Polystyrene <input type="checkbox"/> Polyurethane <input type="checkbox"/> Glass wool <input type="checkbox"/> Stone wool <input type="checkbox"/> Cork <input type="checkbox"/> Does no know/ Other
Insulation layer thickness (cm)	
Position of Insulation	Internal <input type="checkbox"/> External <input type="checkbox"/> Core <input type="checkbox"/>
Roof:	Horizontal concrete roof <input type="checkbox"/> thickness: (cm) Sloped concrete roof <input type="checkbox"/>

<p>Roof space under the sloped roof occupied and heated?</p> <p>Roof insulation layer thickness (cm)</p> <p><i>Type of insulation</i></p>	<p>Sloped Concrete roof with tiles <input type="checkbox"/></p> <p>Horizontal concrete roof on which a sloped wooden frame covered with tiles is constructed <input type="checkbox"/></p> <p>Sloped wooden roof with tiles <input type="checkbox"/></p> <p>If sloped roof, please provide angle of slope ($^{\circ}$):</p> <p>Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>Expanded Polystyrene <input type="checkbox"/></p> <p>Extruded Polystyrene <input type="checkbox"/></p> <p>Polyurethane <input type="checkbox"/></p> <p>Glass wool <input type="checkbox"/></p> <p>Stone wool <input type="checkbox"/></p> <p>Does not know/ Other</p>							
<p><i>Type of windows:</i></p> <p>Framing material</p> <p>Glazing type</p>	<p>Wood <input type="checkbox"/></p> <p>Aluminum <input type="checkbox"/></p> <p>Plastic <input type="checkbox"/></p> <p>Single <input type="checkbox"/></p> <p>Double <input type="checkbox"/></p> <p>Triple <input type="checkbox"/></p> <p>Special <input type="checkbox"/></p>							
<p><i>Ratio of window / wall area by orientation (%)</i>:</p>	<p>South.....</p> <p>East.....</p> <p>West.....</p> <p>North.....</p>							
<p><i>Type of shading system:</i></p> <p><i>Shading type by orientation:</i></p> <p>South façade</p> <p>East façade</p> <p>West façade</p>	<p>Balcony / Overhang <input type="checkbox"/> (1)</p> <p>Shutters <input type="checkbox"/> (2)</p> <p>External Blinds <input type="checkbox"/> (3)</p> <p>Awning <input type="checkbox"/> (4)</p> <p>Side fins <input type="checkbox"/> (5)</p> <p>Other (6)</p> <table border="1" data-bbox="671 1496 1377 1854"> <tr> <td data-bbox="671 1496 1134 1619"> <p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p> </td> <td data-bbox="1134 1496 1377 1619"> <p>Please write depth and width (m), if overhang or fin</p> </td> </tr> <tr> <td data-bbox="671 1619 1134 1753"> <p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p> </td> <td data-bbox="1134 1619 1377 1753"> <p>d</p> </td> </tr> <tr> <td data-bbox="671 1753 1134 1854"> <p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p> </td> <td data-bbox="1134 1753 1377 1854"> <p>w</p> </td> </tr> </table>		<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>Please write depth and width (m), if overhang or fin</p>	<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>d</p>	<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>w</p>
<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>Please write depth and width (m), if overhang or fin</p>							
<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>d</p>							
<p><input type="checkbox"/> (1) <input type="checkbox"/> (2) <input type="checkbox"/> (3) <input type="checkbox"/> (4) <input type="checkbox"/> (5) <input type="checkbox"/> (6)</p>	<p>w</p>							
<p><i>Flooring:</i></p>	<p>Ceramic tiles <input type="checkbox"/></p> <p>Wood <input type="checkbox"/></p> <p>Mosaic <input type="checkbox"/></p> <p>Concrete <input type="checkbox"/></p> <p>Other</p>							

<p>Basement</p> <p>Gr. Floor</p> <p>1st</p> <p>2nd</p> <p>3rd</p> <p>.....</p> <p>Basement occupied and heated?</p> <p>Floor insulation layer thickness (cm)</p> <p>Type of insulation</p>	<p>If flooring material varies, please provide information by floor:</p> <p>.....</p> <p>.....</p> <p>.....</p> <p>.....</p> <p>.....</p> <p>.....</p> <p>Yes <input type="checkbox"/> No <input type="checkbox"/></p> <p>.....</p> <p>Expanded Polystyrene <input type="checkbox"/></p> <p>Extruded Polystyrene <input type="checkbox"/></p> <p>Polyurethane <input type="checkbox"/></p> <p>Glass wool <input type="checkbox"/></p> <p>Stone wool <input type="checkbox"/></p> <p>Other</p>
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4a. Conservatory	
Is there a conservatory attached?	Yes <input type="checkbox"/> No <input type="checkbox"/>
If Yes, please complete separately (especially for the conservatory), boxes (4), (6), (8), (9)	

5. Building layout

Please, provide a draft layout of the building, with spatial dimensions, orientation, street width height of adjacent and opposite buildings.

Please, provide photos of each façade and of the surrounding area.

6. Space Heating system	
Type of heating system	<p>Diesel boiler <input type="checkbox"/></p> <p>Gas boiler <input type="checkbox"/></p> <p>Heat pump <input type="checkbox"/></p> <p>Micro - CHP <input type="checkbox"/></p> <p>A/C <input type="checkbox"/></p> <p>Electric heater <input type="checkbox"/></p> <p>Fireplace <input type="checkbox"/></p> <p>Fireplace with heat recovery <input type="checkbox"/></p> <p>Solar thermal <input type="checkbox"/></p> <p>Solid fuel burner on pellets <input type="checkbox"/></p> <p>Solid fuel burner on biomass <input type="checkbox"/></p> <p>Other</p>
If multiple systems, estimate % of heating needs covered by each system	

Capacity (kW)	
Efficiency	
Type/Model	
Number of systems (if there are multiple systems of the same type e.g. two or more heat pumps)	
Installation year	
Operating hours per day	Winter Period: from- to.....
Operating hours per day	Spring/Autumn Period: from- to..... to get operation profile
Type of heating control	Thermostat <input type="checkbox"/> timer <input type="checkbox"/> thermostatic valve <input type="checkbox"/> other.....

7. Domestic Hot Water system		
Winter season	please describe:	Type: electric resistance <input type="checkbox"/> solar thermal <input type="checkbox"/> gas <input type="checkbox"/> diesel <input type="checkbox"/> biomass <input type="checkbox"/> heat pump <input type="checkbox"/> Other Capacity kW): Operating hours/day:
Summer season	please describe:	Type: electric resistance <input type="checkbox"/> solar <input type="checkbox"/> gas <input type="checkbox"/> diesel <input type="checkbox"/> biomass <input type="checkbox"/> heat pump <input type="checkbox"/> Other Capacity kW): Operating hours/day: For solar systems: Surface of solar panels ... m ²
Is there a hot water storage vessel?	Yes <input type="checkbox"/>	No <input type="checkbox"/>
If yes, what is the volume (lt)		

8. Space Cooling system	
Type	A/C Central <input type="checkbox"/> A/C split units <input type="checkbox"/> Fan coil <input type="checkbox"/> Other
Installation year	
Number of units	
Electric capacity per unit (kW)	
Cooling capacity per unit (kW)	
Operating hours per day	
Is it used for space heating as well?	Yes <input type="checkbox"/> No <input type="checkbox"/>
If yes, please give %%
Roof fans	
Number
Power per fan

9. Lighting system of individual apartments/households
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Type of light bulbs:	Number	Power (W)	Operating hours per day
Incandescent			
Fluorescent			
Fluorescent compact (CFL)			
Halogen			
Light Emitting Diode (LED)			

10. Lighting system in common use areas of the building

Type of light bulbs:	Number	Power (kW)	Operating hours per day
Incandescent			
Fluorescent			
Fluorescent compact (CFL)			
Halogen			
Light Emitting Diode (LED)			
Is there an automation system? What type?	Time scheduling control <input type="checkbox"/> Occupancy sensors <input type="checkbox"/> Other		

10.a Lighting system of non-residential part of building

Type of light bulbs:	Number	Power (W)	Operating hours per day
Incandescent			
Fluorescent			
Fluorescent compact (CFL)			
Halogen			
Light Emitting Diode (LED)			
Type of luminaires	ceiling mounted direct <input type="checkbox"/> ceiling mounted with diffuser <input type="checkbox"/> recessed down lighter <input type="checkbox"/> pendant direct <input type="checkbox"/> pendant indirect <input type="checkbox"/> chandelier <input type="checkbox"/> free standing <input type="checkbox"/> wall-washer <input type="checkbox"/>		
Is there an automation system; What type;	Time scheduling control <input type="checkbox"/> Occupancy sensors <input type="checkbox"/> Other		

11. Other Electric equipment

	Number	Power (kW)	Operating hours per day
Computers - Desktop			
Laptops			
Copiers/Printers			
Refrigerator			
Fridges			
Electric stove			

Gas Stove			
Microwave			
Cloth Washing machine			
Cloth Drying machine			
Cloth Washing and Drying machine			
Dish Washing machine			
Televisions			

12. Energy consumption data of the last three years

Year	Electricity (kWh)	Diesel (lt)	Natural Gas (Nm ³)	Other fuel
2011				
2012				
2013				
Number of the electricity meter:				

13. Energy cost data of the last three years

Year	Electricity (€) incl. tax	Diesel (€) incl. tax	Natural Gas (€) incl. tax	Other fuel (€) incl. tax
2011				
2012				
2013				

14. Onsite energy generation

Is there a PV system on the building? If Yes please provide:	Installed Capacity KWp
Is there another micro-generation system? If yes please describe:	Type of system Fuel Used..... Installed Capacity kW

15. Choices about Renewable energy sources

All energy consumed in the city should be provided by renewable energy sources	Totally Agree <input type="checkbox"/> Agree <input type="checkbox"/> Neutral <input type="checkbox"/> Disagree <input type="checkbox"/> Total Disagree <input type="checkbox"/>
Electricity generation and distribution should be made at a utility scale level	Totally Agree <input type="checkbox"/> Agree <input type="checkbox"/> Neutral <input type="checkbox"/> Disagree <input type="checkbox"/> Total Disagree <input type="checkbox"/>
Electricity generation and distribution should be made at a decentralized level	Totally Agree <input type="checkbox"/> Agree <input type="checkbox"/> Neutral <input type="checkbox"/> Disagree <input type="checkbox"/> Total Disagree <input type="checkbox"/>
On the Renewable energy sources	I would like to be directly consulted and participate in the development of

development which option is preferred:	<p>renewable energy sources <input type="checkbox"/></p> <p>I would like that associations and NGO's took part in the development of renewable energy sources.<input type="checkbox"/></p> <p>I would like that the Municipality departments would ne consulted and participate in the development of renewable energy sources <input type="checkbox"/></p> <p>I would prefer that the responsible authorities make the decisions <input type="checkbox"/></p> <p>Do not know <input type="checkbox"/></p>
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Annex II - Transport and Mobility Survey

Screening Section

- S1. Interviewer's name: _____
- S2. City Sector Number: _____
- S3. Day of week: _____ Date: _____ Month: _____ Year: _____
- S4. Time (24hr clock): _____
- S5. Gender Male ☐ Female ☐
- S6. Please can you tell me which of the following age categories you are in?
- 18-34 ☐
- 35-49 ☐
- 50-64 ☐
- 65+ ☐
- S7. Which of the following best describes your working status?
- Working full time (35+ hours per week) ☐
- Working part time (<35 hours per week) ☐
- Student ☐
- Retired ☐
- Not working ☐
- Full-time Home Duties/Caring for Others ☐
- Other (Please specify)

Main Section

[Read out] I'd like to start by asking you about the journeys you made yesterday, including those which you made for yourself and those in which you were accompanying others. This will help us understand the type of journeys which you make. For each journey, I'll ask where it started and ended, what time you set off and how long the journey lasted, what the main reason for the journey was, how you travelled, and who, if anyone, you were travelling with.

One journey is defined by a single trip for a single purpose, for example if you travelled to work, but stopped off at the shops on your way, then the first journey will be your trip to the shops, your second journey will be from the shop to work, etc. Note that a trip from home to work and back again should be classified as two separate journeys.

[Read out] Please think back to what you were doing yesterday. What was the first journey you made?

[Prompt if necessary:] Did you get up and go to [work/college/ the shops]?

[Interviewer: Please ask the respondent to complete a travel diary description for all journeys made on the preceding day, prompting, 'and then what was the next thing you did that day?'. Note that it does not matter whether the previous day's travel was 'typical' or not]

ONE DAY TRAVEL DIARY FOR THE PREVIOUS DAY

Date diary refers to (i.e. yesterday's date): _____ Day of week diary refers to (i.e. what day was it yesterday?): Mon / Tues / Weds / Thurs / Fri / Sat / Sun

Journey number	In which sector did your journey start?	In which sector did your journey end?	What time did your journey begin?	Journey purpose (to or from....)	How long did your journey take? (in minutes)	Main mode of transport	If main mode is car, how many <u>adults</u> were in the car?	If main mode is car, how many <u>children</u> were in the car?
	<u>Enter sector number</u> from map. If outside sectors on map, enter name of nearest town/city	<u>Enter sector number</u> from map. If outside sectors on map, enter name of nearest town/city	Estimate, using 24-hour clock, e.g. 20:15	<u>Enter number 1-11</u> 1: Normal place of work 2: Education (including escorting others) 3: Other work trip 4: Shopping 5: Personal business (e.g. doctor/bank etc.) 6: Visiting friends/ family 7: Leisure 8: Other (please specify)	Estimate, in minutes, the length of time the journey took e.g. 20 minutes	If more than one mode, enter mode which is used for the greatest distance <u>Enter number 1-9</u> 1: Car/van (driver) 2: Car/van (passenger) 3: Bus 4: Train 5: Motorbike/scooter 6: Bicycle 7 Walk 8 other (specify)	<u>Enter the number</u> of people in the car aged 18+, including yourself e.g. if it was you plus one other adult, enter '2'	<u>Enter the number</u> of people in the car aged 0-17
1								
2								
3								
4								
5								

Q1. Which of the following best describes the type of property you live in?

Detached property ☐

Semi-detached property ☐

Terrace property ☐

Flat/ maisonette ☐

Other (specify)

Q2. How many bedrooms are there in your property?

1 bedroom ☐

2 bedrooms ☐

3 bedrooms ☐

4+ bedrooms ☐

Q3. How many people, including yourself and any children, live in your household?

1 ☐

2 ☐

3 ☐

4 ☐

5 ☐

6 ☐

More than 6 (Please specify ____)

Q4. For each person living in your household, please can you tell me which age category they are in and whether they are male or female? [Interviewer: please tick correct age and gender for each person living in the household]

Person	0-4	5-10	11-17	18-34	35-49	50-64	65+	Male	Female
1									
2									
3									
4									
5									
6									

Q5. How many cars/vans are available for use by members of your household?

0 ☐

1 ☐

2 ☐

3 ☐

More than 3 (*please specify* _____)

IF Answer to Q5 = 0, GOTO Q7

Q6. For each car in your household, please can you tell me it's approximate age and the fuel it uses? [Interviewer: please tick correct age and fuel type for each car]

Car	Less Than 2 Years Old	At Least 2 Years Old and Less Than 5	At Least 5 Years Old and Less Than 10	10 Years or Older	Petrol	Diesel	Cng	Hybrid	Electric
1									
2									
3									
4									
5									

Q7. How many motorbikes/scooters are available for use by members of your household?

0 ☐

1 ☐

2 ☐

3 ☐

More than 3 (*please specify* _____)

Q8. [If S7='working full time' or 'working part time', ask:] Earlier you said that you [work full time/ work part time]. Do you usually...?

Work from home [GOTO END]

Travel to a single workplace [Continue]

Travel to different locations [GOTO END]

Q9. [If Q8=b 'Travel to a single workplace, ask:] **How many times per week do you usually travel to that location?**

1 ☐

2 ☐

3 ☐

4 ☐

5 ☐

More than 5 (*please specify* _____)

Q10. **Which mode do you normally use to travel to your normal place of work** (please tick one only, choosing the mode which covers the longest part of the journey)

1 Car/van (driver) ☐

2: Car/van (passenger) ☐

3: Bus ☐

4: Train ☐

5: Motorbike/scooter ☐

7: Bicycle ☐

8: Walk Other (Please specify _____)

Q11. [If Q8=b 'Travel to a single workplace', ask:] **Which sector number from the map is your work place located. If outside sectors on map, enter name of nearest town/city**

City Sector Number _____

Q12. [If Q8=b 'Travel to a single workplace', ask:] **Approximately how long does it take you to travel to that location?** (Please enter in minutes)

_____ minutes