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Aner Martinez-Soto, María Ignacia Sáez-Lagos, Rokia Raslan & Anna Mavrogianni

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Risk identification of residential energy demand: the case studies of Australia, Chile, the United Kingdom and the United States

Aner Martinez-Soto [a], María Ignacia Sáez-Lagos[a], Rokia Raslan[b] and Anna Mavrogianni[b]

[a]Department of Civil Engineering, Faculty of Engineering and Science, Universidad de La Frontera, Temuco, Chile; [b]UCL Institute for Environmental Design and Engineering, University College London, London, UK

ABSTRACT

A wide range of residential sector energy models have been developed in recent years to determine energy demand and CO_2 emissions and to evaluate energy saving policies. However, modelling outputs are subject to significant variations due to multiple sources of uncertainty, primarily stemming from input parameters and assumptions. This study aims to assess the transferability of the Transferable Energy Model (TREM) and quantify the prediction uncertainty of residential sector energy demand until 2030 in four case study countries (Australia, Chile, United Kingdom and the United States). TREM is able to determine the future annual energy demand in the residential sector according to the area of energy use (space heating, hot water provision, cooking, electrical appliances, lighting), whilst quantifying uncertainties in the results. Significant variations (between −12% and +63%) in residential energy demand in the year 2030 with respect to 2010 were found among the case study countries, suggesting that single total energy demand estimates are associated with considerable uncertainties. This paper also presents a comprehensive database of the range of possible variations in residential energy demand related to a wide range of energy saving measures in each case study country.

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Prognosis energy demand; energy models; residential sector; building stock; risk management; energy consumption

1. Introduction

In the last two decades, global energy consumption in the residential sector has grown steadily at an average annual rate of more than 2% (Price et al., 1998). It is estimated that the residential sector accounts for 29% of global energy consumption. Residential energy demand consists of space heating (53%), appliances (21%), water heating (16%), lighting (5%) and cooking (5%) (IEA, 2008). This increase is associated with negative environmental impacts and energy resource depletion (Nejat et al., 2015). Increasing concerns about such consequences have led to the development of energy saving policies in

CONTACT Anna Mavrogianni a.mavrogianni@ucl.ac.uk Institute for Environmental Design and Engineering, 416, 4th floor, Central House, 14 Upper Woburn Place, London, UK

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recent years worldwide, aiming to increase the energy efficiency of the sector, reduce residential energy demand and associated carbon dioxide emissions (Pablo-Romero et al., 2017). To support these efforts, a plethora of engineering-based building stock energy models have recently been developed able to predict the effects of energy saving policies on energy consumption and carbon dioxide emissions (Snäkin, 2000).

Building stock energy models are an effective tool for predicting energy demand in the residential sector; however, certain challenges need to be addressed in order to facilitate their use and increase the credibility of their results (Kavgic et al., 2010; Swan & Ugursal, 2009). The first challenge is associated with the requirement of highly detailed input parameters (e.g. window sizes, floor space per person, building fabric air tightness, U-values, infiltration rate, interior layouts etc.), for which data sources may not always be available, thus increasing uncertainty of input assumptions and hindering modelling potential (Swan & Ugursal, 2009). Several authors (Cheng & Steemers, 2011; Firth et al., 2010; Hughes, Palmer, Cheng, et al., 2013, 2015; McKenna et al., 2013) have performed sensitivity analyses to determine which input parameters have the greatest impact on the models' output(s). In the most common sensitivity analysis technique (one-at-a-time), the input parameters of the model are modified individually while the other input parameters remain constant. The model is run for every individual variation of the input parameters, following which the variation in the output variable(s) is quantified and the sensitivity coefficient is calculated. Based on existing studies that have carried out one-at-a-time sensitivity analyses (Cheng & Steemers, 2011; Firth et al., 2010; Hughes, Palmer, Cheng, et al., 2013; McKenna et al., 2013), it was shown that a model should not necessarily be based on highly disaggregated input parameters to generate robust and accurate results; this is due to the fact that a limited number of input parameters can potentially have a great impact on overall energy consumption. It is recommended that a balance between aggregation and detail should be achieved (Martinez-Soto & Jentsch, 2020).

Another important aspect in building stock energy modelling is transferability potential. The majority of existing models were developed with the aim to determine the residential energy demand of a specific country. In such cases, the validation process usually entails a comparison of the modelling outputs and statistical data of energy consumption in the case study country (Firth et al., 2010). Therefore, existing models are rarely used beyond their realm of validity; transferring existing models into a different geographic context may result in uncertainties (Bhattacharyya & Timilsina, 2010).

Modelling approaches used to quantify the energy demand in the residential sector can be classified into *top-down* and *bottom-up* approaches. Whilst bottom-up approaches evaluate the impact of parameters with a high level of detail, they are generally unable to capture global energy market interactions. Top-down approaches, on the other hand, cannot assess the impact of individual input parameters on the overall output, but can factor in global scale variables (energy prices, economic growth, population growth) (Kavgic et al., 2010; Swan & Ugursal, 2009). Regardless of modelling approach, it is common to use different scenarios in order to quantify the impact of a particular energy saving measure (Canale et al., 2018; Delmastro et al., 2015; Kialashaki & Reisel, 2013; Mondal et al., 2018). However, when the results of the modelled energy demand predictions were compared against actual energy consumption data, substantial differences often emerge. These differences can be attributed to the fact that existing models do not quantify the impact of multiple sources of uncertainty, which are mainly related, to the inherent limitations of the modelling algorithms, user error or, according to Hughes, Palmer, Cheng, et al. (2013), possible variations in the input parameters.

Figure 1 illustrates a comparison between the results of energy demand predictions for the UK using the domestic stock energy model BREHOMES (Shorrock et al., 2005) (based on three scenarios: A, B and C) and the statistical data on energy consumption published by the UK Department for Business, Energy & Industrial Strategy (DBEIS, 2017). For scenario A, a continuation of the energy consumption trend was assumed between 1990 and 2000. For scenario B, the moderate influence of energy saving measures related to the increase in housing with thermal insulation in the envelope was considered (Shorrock et al., 2005). Last, scenario C considers a reality similar to that of scenario B, but measures were added to conserve energy and reduce carbon emissions, focusing on the uptake and use of central heating systems; based on a heat pump and wood (Shorrock et al., 2005). Figure 1 illustrates the difference between scenario A and B predictions for the year 2030, which is up to 23%. This occurs because greater energy saving measures were considered for scenario B than scenario A, and the effect of these measures further accentuates the difference for the year 2030. It is worth noting that the difference between the results of the energy demand of the extreme scenarios (A and C) in the year 2030 reaches 40%. This offers an indication of the level of uncertainty obtained by the application of different energy saving measures in each scenario.

The actual final energy consumption data in Figure 1 shows that in the period between 1990 and 2005 there was an increasing trend in energy consumption at an average rate of

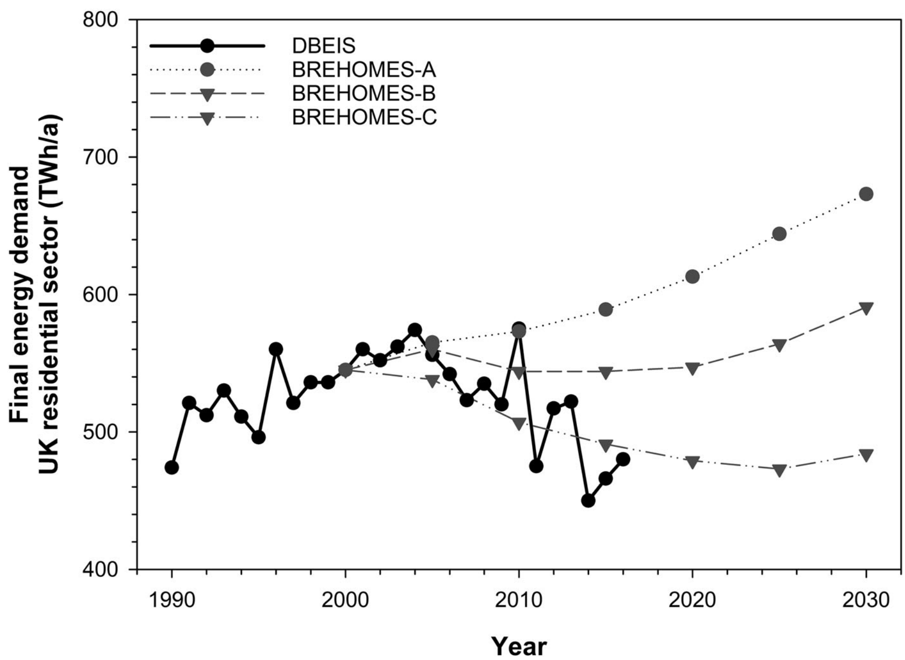

Figure 1. The comparison between the actual energy consumption according to DBEIS and the results of the predictions of energy demand made with the BREHOMES model (scenarios A, B and C) for the UK residential sector. Data for actual energy consumption: (DBEIS, 2017). Data on the results of the predictions made with BREHOMES for scenarios A, B and C (Shorrock et al., 2005).

1%. However, as of 2006, there has been a decrease in energy consumption with a decrease rate of 0.8% (DECC, 2015; Ray et al., 2008). It is believed that this was due to the implementation of energy saving measures in the residential sector that were carried out in previous years (labelling of energy efficiency of household appliances, improvement of thermal insulation of existing and new dwellings) (Ray et al., 2008), added to the increase in outdoor temperatures which has led to a reduction in gas consumption for heating (DECC, 2015), and partly the result of the 2008 financial crisis which limited the spending on fuel.

In the first decade of predictions (year 2010), the results of scenarios A and C differ between −2% and 12%, respectively, compared to the values of the actual final energy consumption. During the second decade of predictions (year 2018), it is observed that the accuracy of the results of scenarios A and C is contrariwise to the previous decade, i.e. the difference between the results of scenarios A are higher (23%) than the results for the scenario C (2%) compared to the values of the actual final energy consumption.

In general, it is observed that even though the three predictions are different, none of them manages to accurately reflect the annual variation of the actual energy consumption. This suggests that the scenarios are a good technique to represent answers to the question 'What would happen if certain energy saving measures are applied?'. Additionally, scenarios offer the possibility to have a spectrum of futures where energy consumption could fluctuate. Nevertheless, they do not necessarily represent an accurate prediction of energy demand and are highly dependent on modelling input assumptions. The principal limitation of deterministic approaches is that each scenario produces individual values of annual energy demand and does not consider the impact of possible variations in the input parameters. This raises the need to develop new approaches that consider the possibility of interaction and variation of the input parameters and of which the results generate a band of probable results.

1.1. The transferable residential energy model (TREM)

TREM is a hybrid residential energy model based on bottom-up statistical modelling. Monte-Carlo simulations are used to generate its input data, thus allowing the analysis and determination of energy demand (Martinez-Soto & Jentsch, 2020). This model facilitates the transferability and simultaneously allows the prediction of domestic energy demand under conditions of uncertainty associated with the interactions between the input parameters. TREM predictions of energy consumption in the residential sector for Germany, Chile and the United Kingdom for the period between 2001 and 2010 (Martinez-Soto & Jentsch, 2020) demonstrated that the model can reliably predict domestic energy consumption for this period (average percentage of error less than 5%). However, a major limitation of this work was that it did not assess the applicability and reliability of TREM energy demand predictions for future years, which are of key importance to future decision making and policy formulation. In addition, further work analysing new cases are needed to verify the degree of transferability of the model to different contexts.

As such, the aim of this study is to assess the transferability of the Transferable Energy Model (TREM) and quantify the future prediction uncertainty of residential sector energy demand for 2020–2030 in four case study countries with distinct contexts; Australia, Chile, United Kingdom (UK) and the United States of America (USA).

To achieve the aims of the study, the selection of case study countries employed two main criteria: (i) Distinctiveness of contexts: The climatic characteristics, number of dwellings and energy demand in each use had to be very different in the selected countries and (ii) Data availability: the countries considered had to have statistical data related to the energy demand and building stock of more than a decade. Following an extensive analysis, the abovementioned countries were deemed to fulfil both criteria and were hence selected.

Outcomes of this work will help enhance the understanding of the quantitative relationship of the variations of modelling input parameters in residential energy demand prediction. In addition, they present an important database that can help quantify the range of possible variations of the impact the application of energy saving measures may have on residential energy consumption in different countries.

2. Methods

The methodological approach adopted is based on the calculation procedure proposed for modelling with TREM. As such, this section presents the calculation procedure and data collection processes reflecting the order followed during the TREM modelling process (Figure 2).

TREM is composed of two modules:

Building stock module: In this module, the total number of domestic buildings of a specific country is grouped into representative dwelling archetypes. In TREM, dwellings can be classified according to building type, construction age group and/or climate region, and each dwelling archetype represents a certain number of buildings that

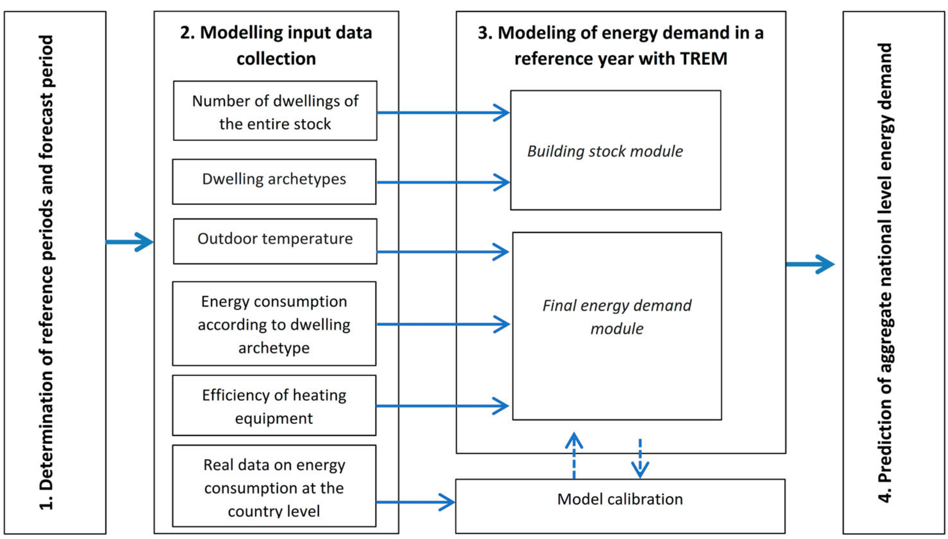

Figure 2. Workflow to determine the future energy demand in the residencial sector for the four case study countries (Australia, Chile, UK and the USA).

combine specific characteristics. In TREM the building stock of a country is determined for the future years by using Equation (1).

$$\begin{aligned} BS_{tot,s,k}(t) = \sum_{a} (GB_{a,s,k,t_R} - A_{wrc,a,s,k}(t) - A_{worc,a,s,k}(t)) \\ + \sum_{2010}^{z} NB_{df,s,k}(t) + \sum_{2010}^{z} NB_{r,s,k}(t) + RB_{a,s,k}(t) \end{aligned} \tag{1}$$

where $BS_{tot,s,k}(t)$ = the total number of buildings in the year t;
GB_{a,s,k,t_R} = Number of buildings in the reference year t_R;
$A_{wrc,a,s,k}(t)$ = Demolition with construction replacement in the year t;
$A_{worc,a,s,k}(t)$ = Demolition without construction replacement in the year t;
$NB_{df,s,k}(t)$ = New buildings based on demographic factors;
$NB_{r,s,k}(t)$ = New buildings as construction replacement;
$RB_{a,s,k}(t)$ = Renovated buildings in year t according to the year of construction,
house archetype and climatic region, a = Contruction year; s = House archetype; k = Climatic region; z = Last year of forecast ***Final energy demand module:*** In this module, average 'measured' final energy consumption data are assigned to each dwelling archetype according to energy use (space heating, hot water provision, cooking, electrical appliances and lighting). The measured final energy consumption values are either already available (using studies based on energy consumption surveys in housing) or need to be separately collated. Additionally, probability factors are used to determine the most probable variations in the final energy consumption of each dwelling archetype. The probability factors are based on the influence of the indoor and outdoor temperature, building fabric thermal insulation and the efficiency of appliances.

The aggregate national level energy demand for each case study country for a reference year (t_R) is calculated by multiplying the number of dwellings of each archetype in the stock with the modelled energy consumption for each archetype. To predict energy demand in the forecast period with TREM, Monte-Carlo simulations were used to determine the possible variations of the results. The results obtained after a simulation are, therefore, not single values of energy forecast, but bands of probability. In the case of the development of the equipment efficiency, these are determined in TREM by using the 'saturation curve' (Equation (2)).

$$n(t) = S \cdot [1 - \exp^{-K \cdot (t-t_o)^2}] \tag{2}$$

where n = Development of the equipment efficiency (%); S = Possible saturation (%); t = Time (year); t_o = Time (year) in which the equipment was introduced; K = Constant, which describes the growth rate of the curve.

In this paper we summarize the calculation methodology proposed in TREM in 4 main steps:

(1) determination of reference periods and forecast period,
(2) modelling input data collection,
(3) modelling of energy demand in a *reference year* and model calibration, and
(4) prediction of aggregate national level energy demand.

2.1. Determination of reference periods and forecast period

Prior to the execution of a modelling exercise in TREM, two periods of study must be determined; a Reference Period and a Forecast Period. The reference periods are established by each modeller, however, it is recommended that the reference period is as long as possible to obtain more robust and reliable results (Beer et al., 2009; Martinez-Soto & Jentsch, 2020). This is especially relevant when considering uncertainties associated with outliers such as variations in temperatures due to climate change or changes in the growth rates of the number of dwellings (Vahid et al., 2015). If only one reference year is used, it may not be possible to identify whether that year was representative of the long-term period does not allow the identification of possible variations in time or of trends. The reference period in this sence 'feeds' the model with existing data from the residential building stock and its associated energy demand. Additionally, in this period, model calibration is carried out in order to adjust the average 'measured' final energy consumption data in a year other than the reference year. This is due to the fact that the use of measured final energy consumption data from a given year can lead to errors in the prediction, in particular, if measurements were carried out in an exceptionally warm or cold year. In this work, the reference period was defined from 1990 to 2010 for the USA and the UK, and from 1992 to 2010 for Australia and Chile (reliable sources of data for the decade before 1990 and 1992 could not be identified due to the scarcity of relevant data sources in Australia and Chile). The year 2010 was considered as the *reference year* for the calculation of the residential sector energy demand for all countries examined in this study.

The forecast period corresponds to the years for which the energy demand is predicted and the uncertainties in the results were quantified. In this work, the forecast period included the years between 2011 and 2030 for the long term prediction of energy demand. Additionally, in order to have a previous reference of the accuracy of the predictions, the results of the prediction energy demand between 2011 and 2015 were compared with the existing statistical data for each country. The year 2015 was considered as last year because all the case study countries have full energy consumption data up to this year.

2.2. Modelling input data collection

The input parameters required for TREM can be classified into six groups:

(1) number of dwellings of the entire stock,
(2) outdoor air temperature,
(3) dwelling archetype,
(4) energy consumption according to dwelling archetype,
(5) heating equipment efficiency, and
(6) national statistics on final energy consumption in the residential sector.

The data collection for each country was based on these six groups, where data was mainly extracted from national statistical datasets available of each country. Table 1 shows a summary of the required input parameters and the sources from which they were extracted.

The following sub-sections present the input generation procedure for each one of the six input categories in more detail.

2.2.1. Number of dwellings of the entire stock

The case study countries have notable differences in their total number of dwellings. In the last year of the reference period (2010), there were 118 million dwellings in the USA (USCB, 2018), 4–24 times more dwellings than in Australia (9 million dwellings), Chile (5 million dwellings) and the UK (22 dwellings).

The annual number of dwellings is considered to be an essential input to run TREM simulations in TREM, however, censuses in Australia, Chile and the USA, are not conducted every year. To address this, mathematical adjustments were applied in this study (Equation 3) to determine the number of dwellings for years between censuses periods in case study countries. The adjustment was calculated using the annual amount of building permits issued between years of the different censuses corresponding to each country. In the case of Australia, the censuses for the years 1991, 2001, 2006 and 2011 (ABS, 2003, 2016) were considered, for Chile the years included 1992, 2002 and 2017 (INE, 2007, 2017) and for the USA 1990, 2000 and 2010 (USCB, 2018). In the case of UK, an annually updated online database exists (DCLG, 2011, 2016), so data on the number of dwellings is readily available on an annual basis.

$$V_{ti} = V_{ti-1} + V_{p,ti} - \frac{\left[\left(\sum_{t0+1}^{tf} V_p\right) - (V_{tf} - V_{to})\right]}{(A_{t0,tf} - 1)} \tag{3}$$

where V_{ti} = annual number of dwellings adjusted for one year t_i between each Census; V_{ti-1} = number of dwellings in the previous year $(t_i - 1)$ per year of analysis; $V_{p,ti}$ =

Table 1. Input parameters of the TREM model with associated sources from the four countries under study.

Input Parameters	Australia	Chile	UK	USA
Number of dwellings	ABS (2003, 2016)	INE (2007, 2017)	Hughes, Palmer, Cheng, et al. (2013); Hughes, Palmer, and Pope (2013)	USCB (2018)
Outdoor air temperature	AGBM (2018)	DGA (2015)	Met Office (2016)	NOAA (2018)
House archetype (year of construction, area-specific heat loss)	ABS (2003, 2012)	CDT (2010), Romero Ramos (2011)	Hughes, Palmer, Cheng, et al. (2013); Hughes, Palmer, and Pope (2013)	USCB (2018)
Energy consumption according to housing type	ABS (2012)	CDT (2010), Romero Ramos (2011)	Hughes, Palmer, Cheng, et al. (2013); Hughes, Palmer, and Pope (2013)	EIA (2009)
Efficiency of the applied equipment	DP[a]	CDT (2010)	Hughes, Palmer, Cheng, et al. (2013); Hughes, Palmer, and Pope (2013); Anderson et al. (2010)	DP[a]
National statistics on final energy consumption in the residential sector (for comparison with the results of the simulation with TREM)	DEE (2016)	DPPE (2015)	DBEIS (2017)	EIA (2017)

Note: ABS: Australian Bureau of Statistics; INE: National Institute of Statistics; AGBM: Australian Government Bureau of Mereorology; DGA: Dirección General Aeronáutica; CDT: Corporación Desarrollo Tecnológico; DEE: Departament of the Environment and Energy; DPPE: División de Prospectiva y Politica Energética; DBEIS: Department for Business, Energy & Industrial Strategy; EIA: Energy Information Administration.

[a]Predetermined data from (Martinez & Jentsch, 2015) and available to be used in the TREM.

number of new dwellings according to building permits in the year of analysis t_i; V_p = number of new dwellings according to building permits between the year following the initial census in the year t_o and the final census in the year t_f; V_{tf} = number of dwellings in the year of the final census t_f; V_{t0} = number of dwellings in the initial census year t_o; $A_{t0,tf}$ = number of years between the year following the year of the initial census $(t_0 + 1)$ and the year of the final census t_f

2.2.2. Outdoor temperature

The main climate variable that is used to perform the energy simulations is outdoor air temperature. In Australia, Chile and the USA, the outdoor temperature varies considerably both temporally during the same month and spatially across different regions. For example, for the month of July in the year 2010 the spectre of outdoor temperature in Australia varied from 0°C (Canberra) to 31°C (Darwin) (AGBM, 2018), in Chile it varied between −22°C (Balmaceda) to 24°C (Calama) (DGA, 2015) and in the USA from −10°C (Montana) to 34°C (Florida) (NOAA, 2018). These variations directly impact domestic energy consumption: if a dwelling is located in areas of low temperatures, it will commonly have a higher heating load (EIA, 2009). On the contrary, if it is located in an area of high temperatures, there will usually be a greater energy consumption as a result of air conditioning use (Romero Ramos, 2011).

For this reason, in Australia, USA and Chile, geographic areas are classified into climatic zones. In the case of Chile, based on the National Norm (NCH 1079), 7 thermal zones were considered (INN, 2008; MINVU, 2006). For Australia and the USA, seven and five climate zones were identified respectively (BCA, 2018; EIA, 2009). Compared to the other case study countries, outdoor temperatures in the UK do not vary to that extent spatially. For example, in July 2010, the maximum mean outdoor air temperature difference between Wick Airport in Scotland and Eastbourne in England, two geographically distant locations, was only 3.8°C (Met Office, 2016). The division of the country into climatic zones was, therefore, not considered necessary for this work. A summary of the different climatic zones considered for each country is shown in Table 2. It should be mentioned that in TREM, the modelling is primarily implemented for each climatic zone (see. Equation 1) in order to quantify the uncertainties associated with the different climatic conditions. Subsequently, the results are aggregated into a range of national values of energy demand to compare it with the existing real values at the same level of disaggregation used in national statistics.

2.2.3. Dwelling archetypes

In TREM, dwellings can be classified according to building type, construction age group and/or climate region. In this work, for the UK, a total of 42 dwelling archetypes based on seven housing forms (end terrace, mid terrace, semi-detached, detached, bungalow, converted flat, purpose built flat) and 6 construction age groups (pre-1919, 1919–1944, 1945–1964, 1965–1980, 1981–1990, post-1990) were used. These were obtained by clustering the detailed building typology published by Hughes, Palmer, and Pope, (2013) and Hughes, Palmer, Cheng, et al. (2013). In this database, the residential building stock of the UK was divided into 14,951 dwelling types, which were classified based on their form and year of construction. In the case of Australia and Chile, 28 dwelling archetypes based on data of Australian Bureau of Statistics (ABS, 2003, 2012; CDT, 2010; Romero Ramos, 2011),

Table 2. Names climatic zones countries Australia, Chile and the USA.

Country	Climatic zones
Australia	Zone 1: hot and humid summer, warm winter Zone 2: warm and humid summer, temperate winter Zone 3: dry and hot summer, warm winter Zone 4: dry and hot summer, cool winter Zone 5: warm temperate Zone 6: soft temperate Zone 7: cool temperate
Chile	Zone 1: desert with abundant clouds Zone 2: normal desert Zone 3: warm temperate with winter rains and high cloud cover Zone 4: warm temperate with winter rains Zone 5: rainy with Mediterranean influence Zone 6: temperate cold rainy without dry season Zone 7: temperate cold rainy without dry season
USA	Zone 1: verycold/cold Zone 2: mixeed-humid Zone 3: dry mixed/hot dry Zone 4: hot-humid Zone 5: marine

respectively, were used. For the clustering, 7 climatic zones (see Table 2) and 4 types of form (detached houses, semi-detached houses, apartments and others) were considered for each country. In the case of the USA, 20 dwelling archetypes based on data by the USA Census Bureau (USCB, 2018) were used. For the dwelling archetypes, five climatic zones (see Table 2) and 4 types of form (detached houses, semi-detached houses, apartments and mobile houses) were used.

2.2.4. Energy consumption according to dwelling archetype

The values of energy consumption per dwelling archetype help to characterize the level of consumption of the residential building stock in each case study country. Significant differences were found between average energy consumption by dwelling between the different residential building stocks (ABS, 2012; CDT, 2010; EIA, 2009; Hughes, Palmer, Cheng, et al., 2013; Hughes, Palmer, & Pope, 2013; Romero Ramos, 2011). For example, it was observed that average residential energy consumption in the USA is higher than in the other case study countries (Figure 3). This country (USA) has an average energy consumption of 23.9 MWh / a (EIA, 2017). This is for example 14.5 MWh / a higher than the energy consumption in a Chilean dwellings, which is the lowest average housing energy consumption observed in this study (9.4 MWh / a) (DPPE, 2015). The average dwelling energy consumption for Australia and the UK are 16.2 MWh / a and 20.9 MWh / a, respectively (DBEIS, 2017; DEE, 2016).

High residential energy consumption in the USA could be attributed to the gradual improvement in standards of living and income of the US. families since 1978, which has generated an increase in the acquisition and use of home appliances (EIA, 2009). For example, in 1978 only 23% of dwellings used air conditioning, but that percentage tripled in 2009, when 61% of dwellings used air conditioning (EIA, 2009). Also, the use of washing machines increased from 74% to 82% and the use of dishwashers increased from 35% to 59% during the years 1978–2009 (EIA, 2009). This increase in the use of electrical appliances led to the USA being one of the countries that consumes the most

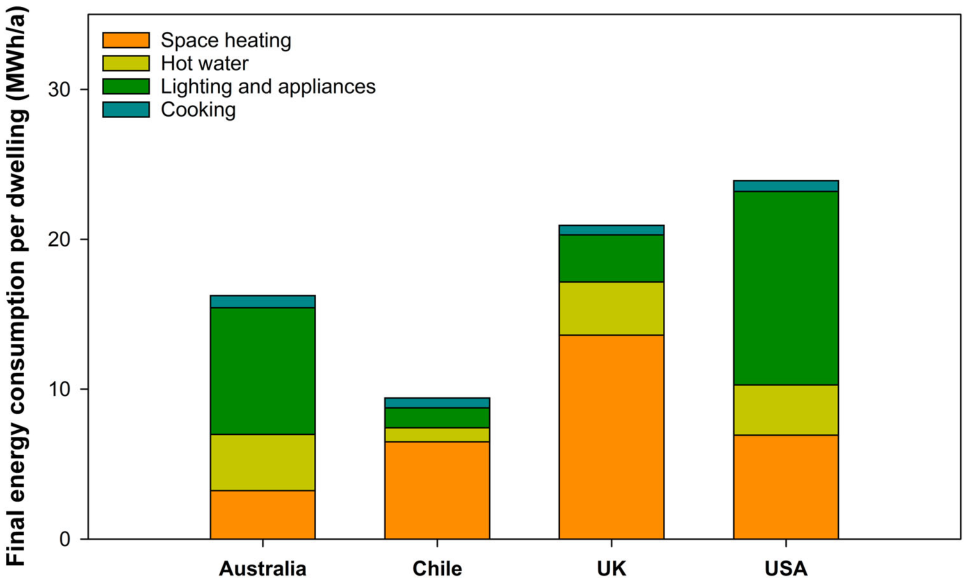

Figure 3. Comparison of the energy consumption of average dwellings according to the area of use: Heating, Hot Water, Lighting and Appliances and kitchen for the different countries considered as case studies. Here 2010 was considered as the year of reference. Sources: data on final energy consumption in the residential sector: (DBEIS, 2017; DEE, 2016; DPPE, 2015; EIA, 2017).

electricity in the world (IEA, 2009). While the substantial contribution of air conditioning (AC) to energy demand is relevant in the US, however the prevalence of AC is currently much lower in other countries. For example, in Chile only 3% and in the UK only 0.6% of residential buildings currently have AC equipment installed (CDT, 2010; Statista, 2021). As such, for the purposes of quantifying cooling demand across the case study countries, it was included within the 'appliances' category.

Figure 3 shows illustrates both the differences in energy consumption of lighting and appliances and differences in other energy end uses, such as space heating, hot water provision and cooking (DPPE, 2015). The differences in energy consumption per dwelling in space heating, hot water provision or cooking are directly related to the climate (outdoor temperature, solar radiation, air speed), the building characteristics (building type, insulation, living space, orientation), the need for and the efficiency of building services systems (space heating and cooling, hot water provision), social and societal factors as well as the economic conditions (thermal comfort expectations and practices, the penetration of heating/cooling systems, the presence and use of appliances) (Yu et al., 2011).

The average dwelling energy consumption values presented above were assigned to energy end uses and dwelling archetypes following the domestic building stock subdivision set up in the building stock module in order to calculate the energy demand in the reference year.

2.2.5. *Efficiency of heating equipment*

The individual efficiency of heating equipment decreases over time (Martinopoulos et al., 2018). However, the average overall efficiency of new equipment improves every year

(Shorrock & Dunster, 1997). For example, Martinez and Jentsch (2015) demonstrated that the average efficiency of heating equipment in Germany increased by 20% over a period of 20 years (from 60% to 80%) (Martinez & Jentsch, 2015). As a result, in the energy model TREM the use of saturation curves (S-curves) for determining the development of the equipment efficiency is proposed (Martinez-Soto & Jentsch, 2020).

Heating equipment efficiency is directly related to the energy source used. The predominant energy source of heating equipment in Chile (39%) is firewood followed by gas (34%), electricity (24%) and paraffin (3%) (DPPE, 2015). In Australia, the principal energy source for heating is natural gas (61%) followed by electricity (20%), wood (16%) and solar energy (3%) (Anderson et al., 2010). In the USA, the largest energy source for space heating is natural gas with 50%, followed by electricity (35%), oil (6%), LPG (5%) and wood (2%) (DPPE, 2015). In the UK, the commonest heating energy source is gas (76%), followed by biomas (8%), oil (7%), electricity (6%) and solid fuel (3%) (DBEIS, 2017). It can be deduced that in Chile the average efficiency of the equipment is lower compared to the heating equipment in the other countries, since the equipment that uses firewood as an energy source has greater energy losses in the process of transforming the final energy (ex: gas, oil, paraffin, among others) to useful energy or use (ex: thermal, lighting, mechanical) (Hatt et al., 2012).

In Chile, efficiency factors for heating equipment varies between 0.39 and 0.95 depending on the energy source used by the equipment, which can be gas, electricity, firewood or paraffin (CDT, 2010). The efficiency factors of the hot water equipment is 0.70 for equipment of the gas type and 0.81 for equipment of the electric type (CDT, 2010). For this, an average value was calculated and the model was entered as the initial value. For the simulations of Australia and the USA, no reliable data sources were found on the efficiency of the equipment. For this reason, the S-curves of TREM were used. For the UK, the Cambridge Housing Model energy model database was used (Hughes, Palmer, & Pope, 2013; Hughes, Palmer, Cheng, et al., 2013). In this database, the efficiency value of the equipment is available for each type of dwelling.

2.2.6. Real data on energy consumption at the country level

Actual energy consumption data for each country were used in the model both for the calibration of the model and for the comparison of energy demand predictions for part of the forecast period (in this case between 2011 and 2015). These data are published annually by government institutions. In the case of Australia, it is the Department of Environment and Energy (DEE, 2016), in Chile the National Energy Balance (DPPE, 2015), in the UK Department for Business, Energy & Industrial Strategy (DBEIS, 2017) and the in the USA the Energy Information Administration (EIA, 2017).

It is noteworthy that energy consumption data for the US residential sector is divided into two types according to their state of transformation: *primary energy* and *total final energy*. *Primary energy* corresponds to the energy that is recorded for the first time in a statistical energy balance before any transformation (EIA, 2017). For this reason, in this work, we used the total final energy value adjusted with the average percentage of difference based on the data published by the Energy Information Administration (EIA), added to the amount of biomass consumption since the year 2006,[1] in order to determine the *final energy* consumption.

Global data on the final energy consumption in the residential sector of each country, as well as the energy consumption by dwellings, shows considerable differences between the countries. Chile and Australia have the lowest average total final energy consumption in the residential sector (57 and 113 TWh/a respectively) (DEE, 2016; DPPE, 2015), followed by the UK (528 TWh/a) (DBEIS, 2017) and finally the USA is the country with the highest average energy consumption (2923 TWh/a) (EIA, 2017). The latter is between 5 and 51 times higher than the other countries under study. This could be potentially attributed to the fact that the USA has a greater number of dwellings and, in addition, the individual consumption of each dwelling is greater, as discussed in subsection 2.2.4.

In summary, the process of data collection of the input parameters turned out to be different for each of the case studies. There was greater difficulty in compiling two particular input parameters: (a) efficiency of heating equipment and (b) energy consumption according to housing type. This is due to the fact that in countries such as Australia, Chile and the USA there are few studies related to measuring the efficiency of the heating equipment in residential settings. For this reason, updated databases were used up to 2016. With the complete compilation of all the required data as input parameters for each country, the simulations were carried out in TREM in order to determine the energy demand until the year 2030 for each country considered in this work as a case study.

2.3. Modelling of energy demand in a reference year and model calibration

The first step in model calibration is carried out in relation to the measurements of energy consumption for heating. The individual values of energy consumption for heating can be measured in extremely cold or warm years, which leads to obtaining a non-representative consumption data if it is not normalized according to an average climate (Martinez-Soto & Jentsch, 2020). For this reason, to determine the final energy consumption values, a calibration by degree days is performed for heating, due to the annual variations of external temperature.

Following the first calibration, the determination of the final energy demand for the reference year is carried out. With the results obtained plus the statistical data of the final energy consumption, a second calibration is carried out in order to adjust the energy demand with the actual energy consumption in the reference year.

2.4. Prediction of aggregate national level energy demand

To determine the aggregate national level energy demand, two simulations were carried out simultaneously, both in the building stock module and final energy demand module were carried out. In the building stock module, data of the number of buildings in the reference year and rates of demolition of buildings with and without construction replacement, new buildings based on demographic factors and renovated buildings were used to predict the future building stock for the next years. In the final energy demand module, data on the probability distribution of the useful energy demand values in the reference year and data on future equipment efficiency were used to determine the probable energy demand by area of use and dwelling archetype. The sum of the final energy demand of each archetype multiplied by the corresponding number of dwellings that each archetype represents for each year of the forecast period, then represents the total final energy demand in the housing sector of the given country.

3. Results

Energy demand prediction results up to the year 2030 for each one of the case study countries are illustrated in Figures 4–7. Figures 8–11 present the comparison between the actual energy consumption according to statistical data and the bands of probabilities of the final energy demand generated by the energy model TREM for the year 2015, for each of the countries under study.

3.1. Predictions of energy demand until 2030

3.1.1. Australia

Figure 4 shows that the actual final energy consumption in Australia had a progressive increase at an average rate of 1.6% during the entire reference period (1992–2010) (DEE, 2016). This resulted from a slight increase in the average energy consumption per dwelling observed in the last two decades (0.4 MWh/a from 1990 to 2010) and additionally the number of dwellings grew at an almost constant rate of 1% per year and a small standard deviation ($\sigma = 0.01$) (DEE, 2016). The largest difference in actual energy consumption was observed between 2001 and 2002 (2.5 TWh/a) (DEE, 2016), but this

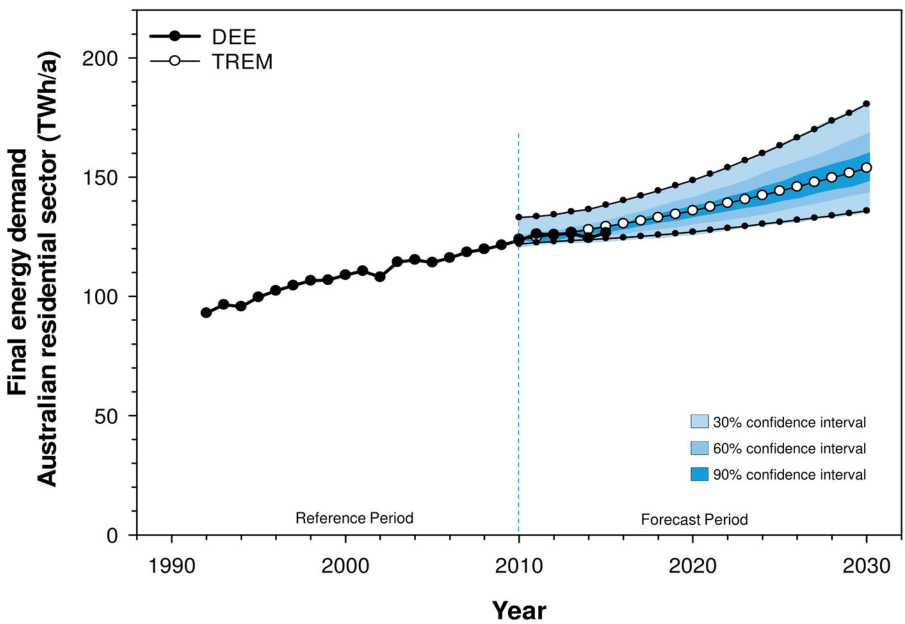

Figure 4. Comparison for Australia between actual energy consumption according to the Department of the Environment and Energy and the results of predictions of energy demand obtained with the energy model TREM. Data for the actual final energy consumption: Department of the Environment and Energy (DEE, 2016).

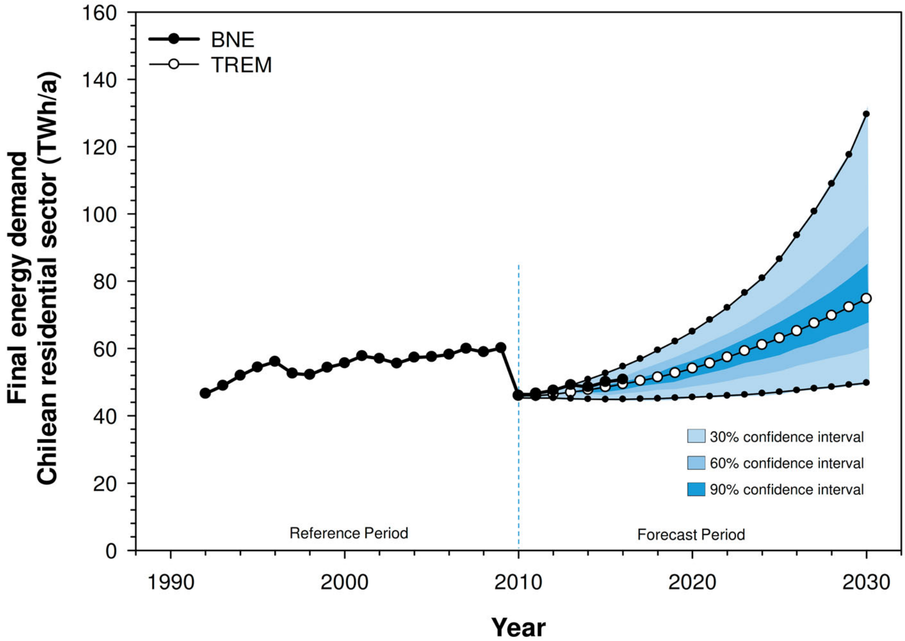

Figure 5. Comparison for Chile between the actual energy consumption according to the National Energy Balance and the results of energy demand predictions obtained with TREM. Data for actual final energy consumption: Foresight and Energy Policy Division of the Ministry of Energy (DPPE, 2015).

difference is minimal in percentage terms (2.2%) in relation to the average net value of those years (109 TWh/a).

Modelled prediction results show that energy demand in Australia in the forecast period (2011–2030) will continue increasing at an average annual rate of 1.1%. This rate is 0.5% lower than what was observed in the reference period. This is because in modelling it was considered that the efficiency of the heating equipment will have an improvement due to the reduction of wood and increase of electricity as energy source, which finally causes a deceleration in the increase in energy demand (Ryan & Murray, 2016).

Based on the simulations, it is expected that energy demand in the year 2030 will increase by 25% compared to 2010 (from 123 to 153 TWh/a). This increase will be directly influenced by the continuous increase in the number of dwellings (see sections 2.2.1 and 2.3) and, to a lesser extent improvements in domestic appliances/equipment efficiency. In Australia, starting in 2012, the energy efficiency programme that includes energy rating labelling for household appliances began to be implemented (COAG, 2009). It is hoped that this programme will increase building fabric thermal efficiency and decrease future energy demand, however it is likely that the impact will be noticeable in the long term.

Figure 4 shows a comparison between the actual energy consumption according to the Department of the Environment and Energy (DEE) and the results of the prediction of energy demand made with the energy model TREM for the period between the years 2011 and 2015. The average difference between actual energy consumption and

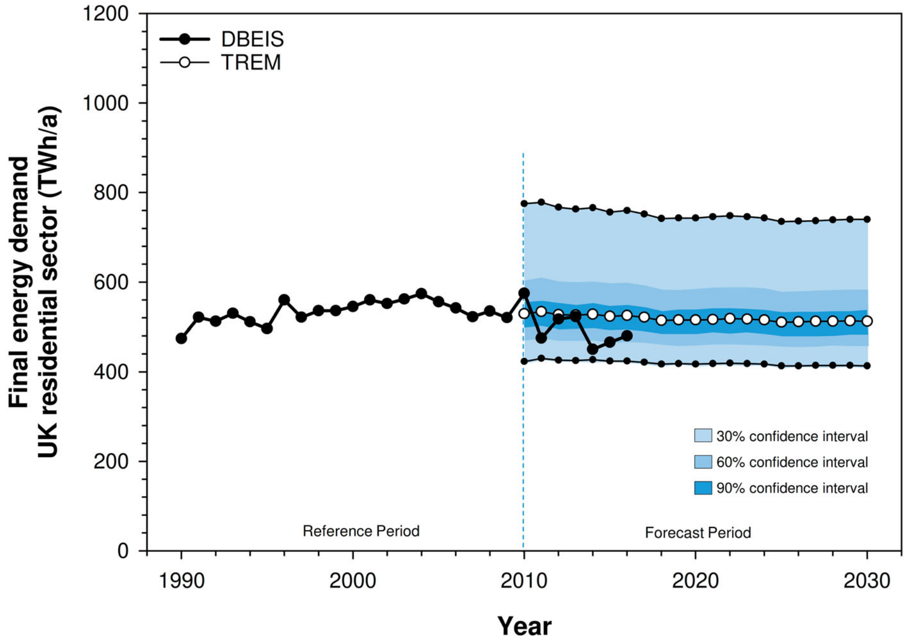

Figure 6. Comparison for the UK between the actual energy consumption according to the DBEIS (Department for Business, Energy & Industrial Strategy) and the results of the predictions of energy demand obtained with the energy model TREM. Data for the actual final energy consumption: Department for Business, Energy & Industrial Strategy (DBEIS, 2017).

the central estimate of predicted energy demand is less than 1%. In addition, most of the data (five of six years) on actual energy consumption for the period 2011–2015 are within the confidence interval of 60%, which in summary shows the high degree of accuracy of the results of the modelling.

3.1.2. Chile

Figure 5 shows that final actual energy consumption in the Chilean residential sector increased steadily at an average rate of 2% between 1992 and 2009 (DPPE, 2015). On the other hand, between 2009 and 2010, energy consumption decreased drastically by 24%. This is due to a change in the method used to estimate biomass energy consumption in the National Energy Balance (DPPE, 2015), which is still used to date. The methodological change consisted in the use of a projected energy demand software, where the data with which this software is 'fed' comes from a national household consumption of firewood survey (DPPE, 2015). This new method, implemented in 2014, was used to correct data on energy consumption as of 2010 and, additionally, it allowed direct coverage of the entire national territory (DPPE, 2015). After the correction of the actual energy consumption, it is observed that the trend in the period between 2010 and 2015 follows the same past trend, since its average rate of increase is equal to that of the period 1992–2009 (2%) (DPPE, 2015). For this reason, this aspect did not have major repercussions in the modelling, since the trend has remained similar and it was only necessary to adjust the energy demand in the reference year using the calibration indicated in section 2.3.

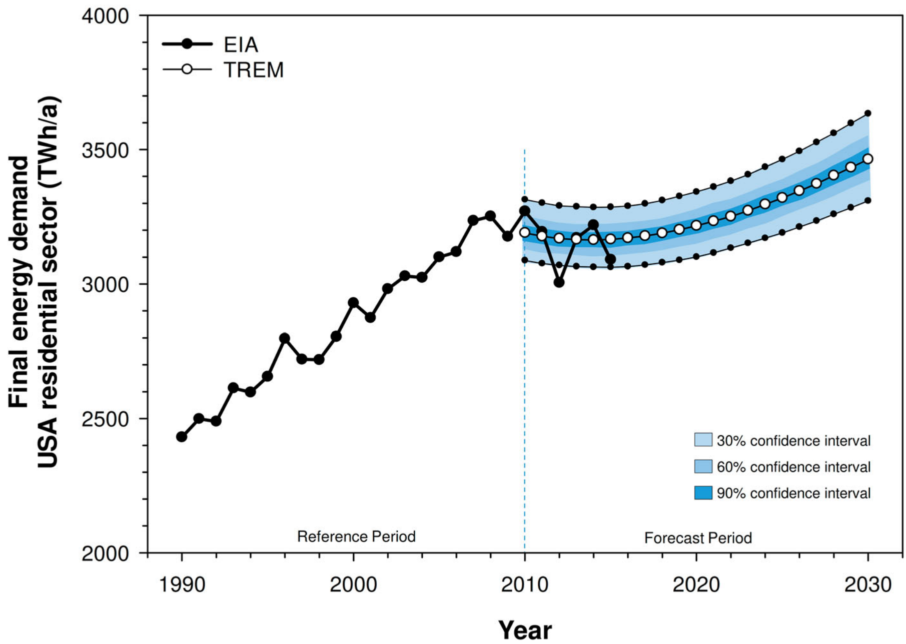

Figure 7. Comparison for the USA between the actual energy consumption in the residential sector according to the Energy Information Administration and the results of energy demand predictions obtained with the TREM energy model. Data for the actual final energy consumption: Energy Information Administration (EIA, 2017).

This continuous increase in energy consumption in Chile is due to the high annual growth rate of housing in Chile, which varies between 2% and 3% during the reference period (INE, 2007) and the additional impact of the increase in the level of income per capita and the improvement in the quality of life of the Chilean population (Hatt et al., 2012), which has increased the use of household appliances and higher energy consumption per dwelling, similarly to the trend observed in the USA during the years 1978 and 2009 (EIA, 2017).

The model results show that the energy demand in Chile will continue increasing at an average rate of 2%. This is because it is estimated that the growth rate of the residential building stock of the reference period will be maintained as in the last two decades i.e. between 2% and 3% (INE, 2007, 2017). It is also expected that the constant improvement in the level of income per capita and the people's living standards will continue to gradually increase (Hatt et al., 2012). This leads to an amplitude in the widths of the 90% confidence intervals in the modelling of the energy demand due to the consideration of an annual rate of housing growth of 3%. In this case, it is estimated that the maximum value of energy demand for the year 2030 would reach 74 TWh / a, that is to say, 63% higher respect to the energy consumption of the year 2010.

Since 2000, energy saving policies in housing have been implemented in Chile (DCLG, 2011), but it is unclear in which year these regulations have a perceptible impact in terms of a decrease in global energy demand, since the rate of increase in the number of existing dwellings built before the thermal regulations (year 2000) represents the 80% of the building stock and have scarce or no thermal insulation (Martinez-Soto, 2016).

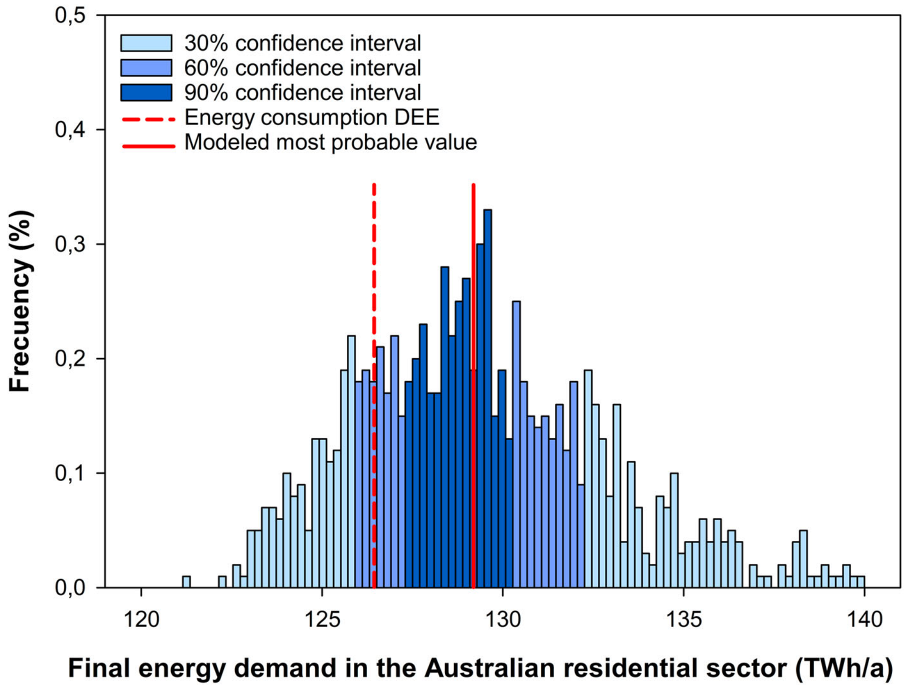

Figure 8. Comparison for Australia between the actual energy consumption in the residential sector according to the Department of the Environment and Energy and the probability bands of the final energy demand generated by the energy model TREM for the year 2015. Data for the actual final energy consumption: Department of the Environment and Energy (DEE, 2016).

Finally, in the period between 2010 and 2015, it can be seen that the actual energy consumption with the most probable energy demand prediction for that period has an average difference of 2%. Additionally, it is observed that all the data of the real energy consumption are within the probability band generated by the energy model TREM which indicates a high accuracy of the results of the modelling.

3.1.3. United Kingdom

Energy consumption trends in the UK changed during the reference period (1990-2010) compared to the trend up until 2006. Figure 6 shows that this trend was positive between 1990 and 2005, that is, an increase of energy consumption. However, this trend has been negative with fluctuations since 2006 (DBEIS, 2017). This change in the trend could be attributed to the energy saving measures applied since 1970 and the 'rush for gas' in the 1980s, which sought in the first instance to reduce the impacts of the oil crisis and currently seek to reduce energy consumption and CO_2 emissions (Ray et al., 2008). Additionally, in the last five years there has been an increase in outdoor temperatures, which has generated a decrease in dwelling heating consumption (DECC, 2015). This is reflected in a clear decrease in energy consumption with a decrease rate of 2.5% between 2010 and 2016 (DBEIS, 2017).

The energy demand and consumption prediction results show a decrease for the next years at an average decrease rate of 0.2%. This means that the energy demand in the year 2030 is expected to decrease by 12% with respect to energy consumption in 2010. This

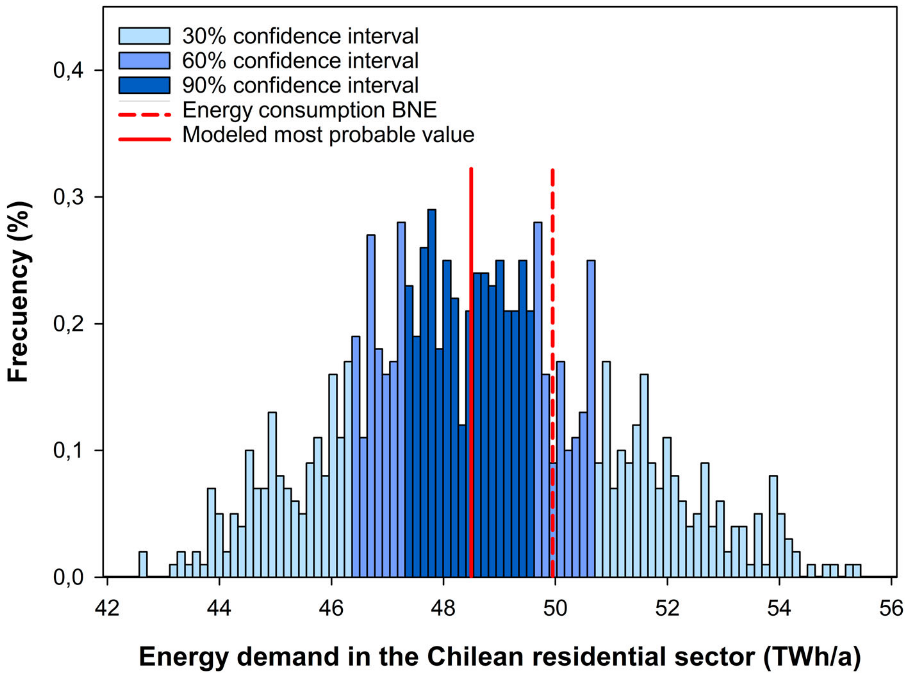

Figure 9. Comparison for Chile between the actual energy consumption in the residential sector according to the National Energy Balance (BNE) and the probability bands of the final energy demand generated by the energy model TREM for the year 2015. Data for actual energy consumption final: Foresight and Energy Policy Division of the Ministry of Energy (DPPE, 2015).

decrease will be due to the efficiency in the implementation of energy saving measures applied in previous years and the continuous improvement in the coming years. For example, it is expected that by the year 2050 two thirds of the dwellings will have been built after the construction regulations were implemented, with new and renovated dwellings being more energy efficient (Ray et al., 2008).

Lastly, the comparison of energy consumption data with energy demand data between the period of 2010–2016 shows that there is an average difference of 6%. Although this value is high compared to the results obtained for Chile and Australia, it can be seen that most of the actual energy consumption values are within the confidence interval of 60%.

3.1.4. United States

Figure 7 shows that the actual final energy consumption in the residential sector according to the Energy Information Administration (EIA) has grown drastically in recent decades. Additionally, it is observed that energy consumption has had large fluctuations compared to other countries (up to 12%). The most significant difference was observed in 2012, when the actual energy consumption was 190 TWh / a compared to the previous year (2011) (EIA, 2017), and subsequently increased by 167 TWh / a the next year (2013). This is due to the fact that in 2012 outdoor temperatures had an average increase of 11% and 8% compared to the external temperatures of 2011 and 2013, respectively

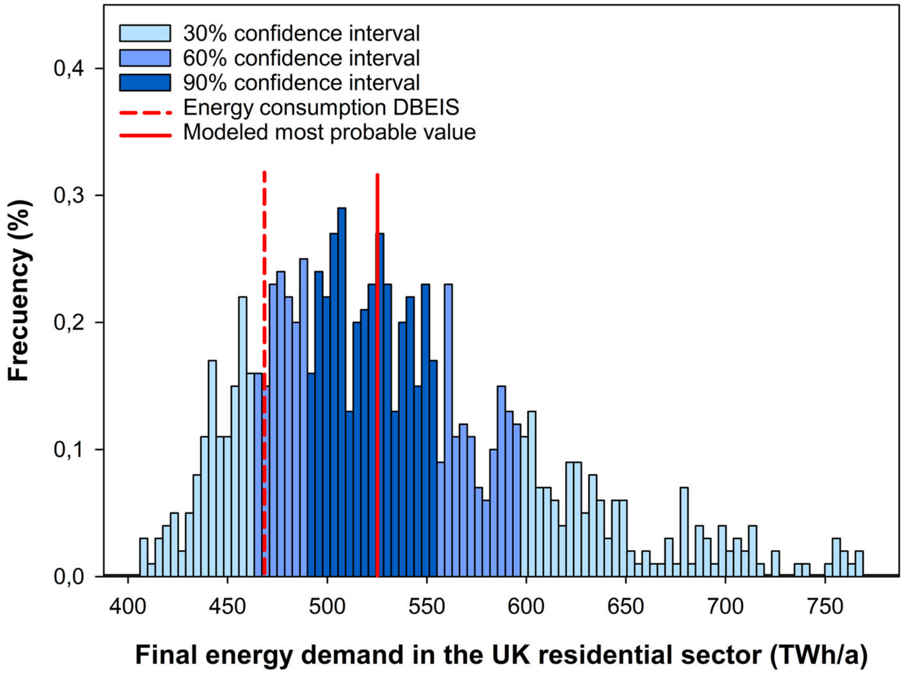

Figure 10. Comparison for the UK between the actual energy consumption in the residential sector according to the DBEIS (Department for Business, Energy & Industrial Strategy) and the probability bands of the final energy demand generated by the energy model TREM for the year 2015. Data for the actual final energy consumption: Department for Business, Energy & Industrial Strategy (DBEIS, 2017).

(NOAA, 2018). This gives an indication of the impact that climate has on energy consumption and that in the context of climate change, references from past years do not necessarily represent a stable pattern for the future. Climate change is expected to increase cooling loads and decrease heating loads in temperate climates. The specific trade-off will be very context specific but this is not factored into TREM. This limitation of the approach represents an aspect that could be improved in the future.

Modelled energy demand prediction results show a decrease with an average rate of 0.2% between 2010 and 2013. This is explained by the increase in outdoor temperatures, which produces a decrease in energy demand for heating and cooling. The implementation of energy saving measures of recent years contributes to the decrease in energy consumption, especially in the area of use of lighting and household appliances (Hatt et al., 2012). However, it is estimated that, as of 2014, the energy demand continued to increase at an average rate of 0.6%. This is due to the fact that, on the one hand, outdoor temperatures remained relatively low, as has happened in the last five years, and on the other hand, there was a continuous increase in the number of dwellings.

The majority (five of six) of actual energy consumption values between 2010 and 2015 are within the probability band generated by the energy model TREM. The only energy consumption value that is not within the probability bands is the energy consumption of the year 2012. This is due to the fact that that year the average outside temperature was extremely high in relation to the average value of the other years (11%). However,

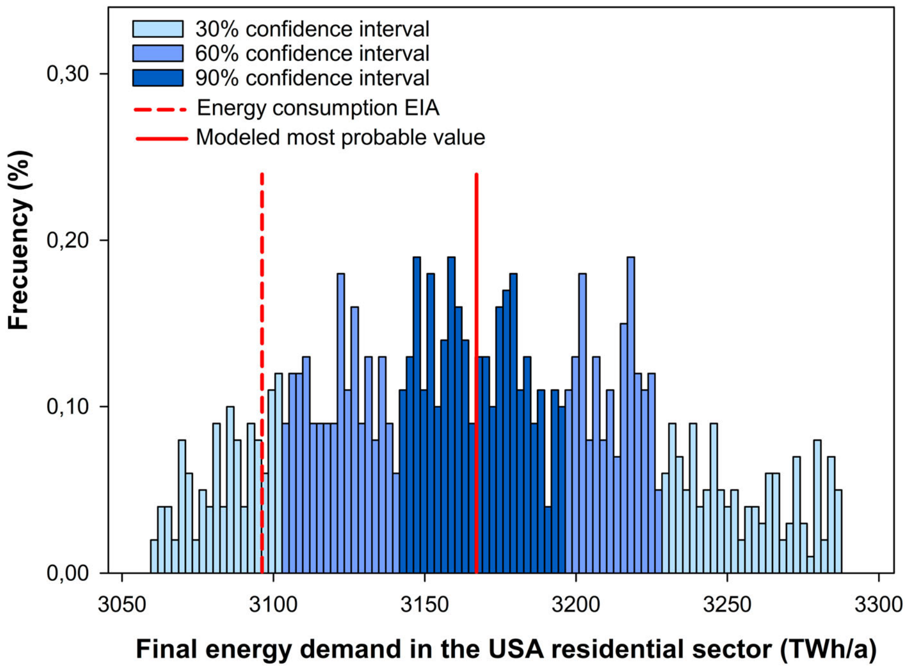

Figure 11. Comparison for the USA between the actual energy consumption in the residential sector according to the Energy Information Administration and the probability bands of the final energy demand generated by the energy model TREM for the year 2015. Data for the Actual final energy consumption: Energy Information Administration (EIA, 2017).

it should be mentioned that said energy consumption value (3004 TWh / a) is within the 100% probability band, which indicates that the possible minimum value of energy demand (3000 TWh / a) if it was within the possible values given by the modelling.

3.2. Comparisons between actual energy consumption in the residential sector and energy demand probability bands for the year 2015

The last year of the 'forecast period' where there are data on total energy consumption in all countries, was 2015. For this reason, a comparison between actual energy consumption in the residential sector and energy demand probability bands for each case study country are presented in this sub-section. Figures 8–11 show a comparison of the actual final energy consumption and the probability bands of the final energy demand for 2015 generated by the energy model TREM for the four countries under study: Australia, Chile, UK and USA. It can be seen that the actual energy consumption of almost all countries (except the USA) is located within the probability band of the results generated by TREM in the confidence interval of 60%. Also, the difference between energy consumption according to statistical data (dotted red line) and the most probable value of energy demand according to the energy model TREM (red line) is shown.

This difference, for the case of Australia is 2.5 TWh / a, for Chile it is 1.6 TWh / a, for the UK it is 58 TWh / a and for the USA it is 75 TWh / a. However, it can be seen that the lower and upper limits of the probability bands of the USA, Australia and Chile, are similar to each other, with lower limits of −3%, −4% and −8% (absolute differences −103.8, −5 and −3.6 TWh / a, respectively), and upper limits of 4%, 7% and 8% (absolute differences +120.3 + 9.1 and +4.1 TWh / a, respectively). In the case of the UK, its lower limit and upper limit of the probability bands are −24% and 31% (absolute differences −99.7 and +233.1, respectively).

From the results obtained on the possible fluctuations of the results for a particular year, it can be concluded that these are similar in percentage terms for the case studies from Australia, Chile and the USA, but different from those observed for the UK. On the one hand, it is observed that the probability bands for the energy demand are narrow for Australia, Chile and the USA and wide for the UK. This is because most of the trend in the input parameters for the energy demand modelling in the UK residential sector have the same trend. For example, they have an ascending rate in the number of dwellings per year, and also an ascending rate in energy consumption per dwelling. On the contrary, in the UK there is an increase in the growth rate of the residential building stock (1%) (DCLG, 2016), but a decrease in the trend of energy consumption per dwelling (DBEIS, 2017; DCLG, 2016). These two opposite tendencies result in the probability band for the UK being wider than the probability band of the other countries.

4. Discussion

During the modelling process, strengths and weaknesses of the calculation methodology proposed in TREM were identified.

The first aspect identified is related to the susceptibility of the width of the probability bands when different trends are used. It should be noted that the results of the model are not unique values to predict energy demand, but bands of probabilities in which the estimated energy demand could fluctuate. These variations for a comparison in 2015 in percentage terms for Australia are from −4% to 7%, for Chile from −8% to 8%, for the UK of the −24% to 31% and for the USA from −3% to 4%. These variations are due, on the one hand, to the uncertainties associated with the input parameters and, on the other hand, to the compatibility of the trends. Similar trends in the input parameters (e.g. sustained increase in the number of dwellings and increase in energy consumption per dwelling) produce narrower probability bands than opposite trends (e.g. sustained increase in the number of dwellings and decrease in energy consumption per dwelling).

The comparisons between the results of the modelling and the real values of energy consumption for each country located that the greatest difference reaches 6% in the case of Unites States. Excluding also the case of the USA, it can be seen that the majority of the real energy consumption values are within the 60% confidence interval. In energy demand predictions for the U.S. residential sector, it was observed that one value of the actual energy consumption was outside the probability band. This is due to the fact that in a specific year (2012), the outdoor temperatures had an atypical increase (11%) compared with the other years and led to a decrease in energy consumption for heating. In TREM, climate data from the last decades are used to determine a spectrum of possible variations in the outside temperature. Nevertheless, in the context of climate change, references from past years do not necessarily represent a stable pattern of climate data for the prediction of future climate events. This leads to the existence of energy consumption values under atypical climatic conditions, which cannot be recorded in the demand predictions made with TREM. This limitation of the approach should be addressed to improve TREM in the future.

Using TREM, three bands of probabilities defined by three confidence intervals (30, 60 and 90%) were considered to illustrate the uncertainties in the results. Until now, there has been no agreement on the appropriate percentages to define the confidence intervals for the probability bands in which the results of the modelling should be shown. For example, Hughes, Palmer, Cheng, et al. (2013, 2015) used the 2.5%, 50% and 97.5% confidence intervals for the Cambridge Housing Model. Similarly, Branger et al. (2015) with the model Res-IRF used the 1%, 5%, 50%, 95% and 99% confidence intervals.

In the case of TREM, on one hand, a 90% confidence interval is used to represent scenarios where trends in the input variables produce greatly different effects on energy demand (increases or decreases). For example, an increase in energy efficiency measures (producing a decrease in energy demand) and an increase in the number of buildings (producing an increase in energy demand). On the other hand, for scenarios where trends in input variables produce similar effects on energy demand a 30% confidence interval is used and an intermediate band (60%) that represents moderate effects of the uncertainties in the input variables in the results of energy demand is assumed.

The results of the energy demand showed that for the cases studies analysed, the use of a band as narrow as that defined by the 30% confidence interval requires further discussion. This is especially relevant when most of the results are in the band defined by the confidence interval of 60 or 90%. While this aspect was not addressed in previous work (Martinez & Jentsch, 2015), the work presented in this paper provides the opportunity to consider it. Defining appropriate confidence intervals for modelling is important for all models that are capable of quantifying uncertainties in the results, but is of particular relevance in this work where case studies that represent very distinct contexts are modelled.

As is mentioned in section 1.2, we consider the use of forecasting of different scenarios (e.g. technology advancements) to be a good approach by which to explore answers to the question: *What would happen if certain energy saving measures are applied?* However, this should also consider *when* the prediction will occur and *how likely* it is to occur. The results of the energy models show immediate effects associated with the application of energy saving measures on energy demand, which is not consistent with reality since time frames for the implementation of measures or availability of new technologies must be considered. This is especially relevant when considering the uncertainties associated with the possibility of developing and implementing new technologies. In considering future improvements in the modelling, the inclusion of an additional algorithm which allows the quantification of the period of implementation of improvement measures or intervention of new technologies should be included. The use of saturation curves (Equation 2) for new technologies can offer a possible approach to implementing this.

The aims of this work related to quantify the prediction uncertainty of residential sector energy demand until the year 2030 in four case study countries (Australia, Chile, UK and the USA) was achieved. This indicates that the Model used (TREM) can be used to model different case studies with different boundary conditions. However, additional cases with other countries are still required in order to confirm these conclusions and to continue to verify the transferability and accuracy of the model. It is also suggested that in the long term and in the context of global warming, greater focus is given on the energy demand of air conditioning. Most recent work has focused on AC in hotter countries and looked at the 2050s; and UCL/UKERC (Crawley et al., 2020) work in the UK suggests that 5–32% of English households will have air conditioning by 2050 (a lower range than previous estimates based on simpler assumptions).

5. Conclusions

This paper discussed energy demand prediction for the residential sector until the year 2030 for four case study countries: Australia, Chile, the UK and the USA. These predictions were generated using the energy model TREM (Transferable Energy Model), which uses a limited number of input parameters (the number of dwellings, the indoor and outdoor temperature, the type of housing, energy consumption values according to housing type and heating equipment efficiency).

The prediction results show that for Australia, Chile and the USA the energy demand for the year 2030 will increase by 25%, 63% and 6%, respectively, compared to the energy consumption of the year 2010. These predictions are based on the assumption that the number of dwellings in these countries will have a constant increase in average energy consumption (mainly in the use of lighting and household appliances) and a building stock growth rate over 1%. In the case of the UK, it is expected that energy demand by 2030 will decrease by 12% with respect to energy consumption in 2010. This is due to the impact of energy saving measures that have been implemented in the last 30 years. In the other countries, national energy saving measures have been planned in the last decade, but it is still uncertain when they will have an impact on energy consumption trends.

Additionally, measured energy consumption in the case study countries was compared with the most probable values of energy demand determined with TREM in a part of the period of prediction between the years 2011 and 2015, in order to determine the accuracy of predictions. The results of the comparisons show that the difference between the real and modelled values of energy consumption does not exceed 3%. It was, thus, concluded that the model can accurately predict national level energy consumption.

The results presented in this paper allow us to evaluate the future impact of the current implementation of energy saving measures that are being carried out in the case study countries and enhance our understanding of the quantitative relationship of the variations of modelling input parameters in residential energy demand prediction. This paper offers a useful database that can help quantify the range of possible variations of the impact the application of energy saving measures may have in housing in different countries.

Note

1. In the USA, as of 2006, biomass consumption was not considered within the total energy balance.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Aner Martinez-Soto http://orcid.org/0000-0001-5087-9859

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