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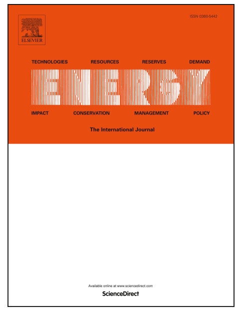

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Credit authorship contribution statement

Giorgio Besagni: Conceptualization, Data curation, Investigation, Methodology, Writing - original draft, Writing - review & editing.

Lidia Premoli Vilà: Formal analysis, Investigation, Visualization, Writing - original draft,

Marco Borgarello: Conceptualization, Data curation, Investigation, Writing - original draft, Writing - review

Andrea Trabucchi: Formal analysis, Investigation, Writing - original draft, Writing - review & editing

Marco Merlo: Writing - review & editing

Jacopo Rodeschini: Formal analysis, Investigation, Methodology, Writing - original draft, Writing - review & editing.

Francesco Finazzi: Formal analysis, Investigation, Methodology. Writing - original draft, Writing - review & editing.

Electrification pathways of the Italian residential sector under socio-demographic constrains: looking towards 2040

Giorgio Besagni*[1], Lidia Premoli Vilà[1], Marco Borgarello[1], Andrea Trabucchi[1,2], Marco Merco[2], Jacopo Rodeschini[3], Francesco Finazzi[3]

[1] Ricerca sul Sistema Energetico - RSE S.p.A., Power System Development Department, via Rubattino 54, 20134, Milan, Italy

[2] Politecnico di Milano, Department of Energy, Via Lambruschini 4, 20156, Italy

[3] Università degli studi di Bergamo, Department of Management, Information and Production Engineering, viale Marconi 5, 24044 Dalmine (BG), Italy

* Corresponding author: Giorgio Besagni, giorgio.besagni@rse-web.it, Ricerca sul Sistema Energetico - RSE S.p.A., Power System Development Department, via Rubattino 54, 20134 Milan (Italy)

Abstract

What are the required costs to sustain the electrification of the residential sector? What are the achievable primary energy savings? This paper tries to answer these questions, for the Italian residential sector, by providing coupled energetical and economic evaluations of the electrification pathways. To this end, this paper extends *MOIRAE*, a bottom-up modelling approach previously proposed by the authors. First, the input data have been upgraded by coupling, using ad-hoc statistical methods, different datasets provided by the Italian Institute of Statistics. Second, to estimate households' time-variation, a socio-demographic model has been developed, validated, and implemented. Third, an economic model of fixed and variable costs for electrical and thermal appliances has been implemented. Subsequently, the modelling approach has been calibrated against detailed consumption data for the different Italian regions and validated against historical data. Finally, *MOIRAE* has been employed to unveil the electrification pathways with and without household budget constraints, aiming at replacing natural gas, *LPG*, diesel, and fuel oil energy carriers with electrical energy. For the different scenarios investigated, the changes in primary energy consumptions and the variation of variable and fixed costs have been included to consider both the energetic and the economic point of view.

Keywords Electrification pathways; residential sector; bottom-up; primary energy forecast; economic model

Nomenclature

Abbreviations

ARERA	Italian Regulatory Authority for Energy, Networks, and Environment
AVQ	Aspects of daily life ISTAT dataset
CAGR	Compound Annual Growth Rate
DHW	Domestic Hot Water
ECH	Energy Consumptions of Households ISTAT dataset
GFK	Growth from Knowledge
GSE	Gestore dei Servizi Energetici
HBS	Household Budget Survey ISTAT dataset
IEA	International Energy Agency
ISTAT	Italian national institute of statistics
LPG	Liquefied Petroleum gas
MAPE	Mean Absolute Percentage Error
MISE	Ministry of Economic Development
MOIRAE	Bottom-up MOdel to compute the energy consumption of the Italian Residential sector
NIC	Italian consumer price index for the whole nation
OECD	Organisation for Economic Co-operation and Development
PNIEC	Integrated National Plan for Energy and Climate
RSE	Ricerca sul Sistema Energetico
VAT	Value Added Tax

Symbols

$y_{x,yr}$	The generic expense for the x-i product annualised to year y	$[-]$
$\alpha_{x,y,10}$	NIC coefficient for transforming the expense from year y to 2010	$[-]$
$\alpha_{x,10,13}$	NIC coefficient for transforming the expense from the year 2010 to 2013	$[-]$
d_{st}	Weighted Hamming distance between family s and t	$[-]$
n	Total number of variables	$[-]$

w_v	Weight for the v-i variable	$[-]$
TE	Thermal energy consumption	$\left[\frac{kWh}{year}\right]$
EE	Electrical energy consumption	$\left[\frac{kWh}{year}\right]$
z	Days of presence at home	$\left[\frac{days}{year}\right]$
$y_{heating-\max}$	Maximum number of days when heating systems can be utilised	$\left[\frac{days}{year}\right]$
h	Frequency of use of household appliances, declared by families	$\left[\frac{hours}{day}\right]$
d	Frequency of use of household appliances, declared by families	$\left[\frac{days}{week}\right]$
η_{th}	Thermal appliance efficiency	$[-]$
P_{th}	Thermal power provided by the thermal appliance	$[kW]$
$\xi_{heating}$	Heating system performance variation coefficient, related to building properties and climatic region	$[-]$
$\dot{V}_{w,t}$	Water flow rate across the heating *t-type* terminal	$\left[\frac{l}{hour}\right]$
ΔT_w	Water temperature difference	$[°C]$
n_t	Number of heating terminals	$[-]$
ρ_w	Water density	$\left[\frac{kg}{l}\right]$
$c_{p,w}$	Water specific heat capacity	$\left[\frac{kWh}{kg*K}\right]$
$n_{occupants}$	Number of occupants	$[-]$
V_{DHW}	Daily water consumption per occupant	$\left[\frac{l}{occupants*day}\right]$
$\gamma_{heating}$	Partial load coefficient of the heating system	$[-]$
γ_{DHW}	Partial load coefficient of the domestic hot water system	$[-]$

γ_k	Calibration coefficient	$[-]$
PE	Primary energy consumption	$[TJ]$
S_{tot}	Total expenditure	$\left[\frac{€}{year}\right]$
S_{inv}	Investment expenditure	$\left[\frac{€}{year}\right]$
$S_{O\&M}$	Variable expenditure	$\left[\frac{€}{year}\right]$
S_{app}	Investment expenditure for appliance cost	$\left[\frac{€}{year}\right]$
S_{inst}	Investment expenditure for appliance installation	$\left[\frac{€}{year}\right]$
LHV_j	Lower heating value	$\left[\frac{MJ}{kg}\right]$
$C_{j,r,cons}$	j-fuel cost related to r-region and fuel consumption	$\left[\frac{€}{kg}\right]$
f_{reg}	Regional corrective factor	$[-]$
f_{sex}	Sex corrective factor	$[-]$
f_{age}	Age corrective factor	$[-]$
N	Number of inhabitants	$[-]$
n	Percentage of people	$[-]$
N_f	Total number of family components	$[-]$
$coef\_red$	Carryover coefficient	$[-]$
e	Relative error	$[-]$
N^C	Number of inhabitants computed from the dataset	$[-]$
N^I	Number of inhabitants from official ISTAT data	$[-]$
c_{sex}	Sex error correction coefficient	$[-]$
c_{age}	Age class error correction coefficient for the i^{th} family in the year y	$[-]$

$coef\_red'$	Carryover coefficient with error correction	$[-]$
y_t	Actual value	$[-]$
$\hat{y}_t$	Forecasted value	$[-]$
n	Number of samples	$[-]$

Subscripts

a	The age group of the family component c
c	c-family component
i	i-household
j	Fuel
k	Appliance technology
MOIRAE	Computed by MOIRAE
r	Region of the family component c
REF	Reference
s	Sex of the family component c
th	Thermal energy
x	Product
y	Year

1 Introduction

It is known that the residential sector is characterised by high energy consumption, accounting for 26.1% of the total primary energy demand in the *EU* region (2018) [1]; conversely, it accounted for 27.8% in Italy (2016) [2]. Besides, the heating sector of households mainly relies on natural gas (share: 32.1% [1]), thus leading to 775.53 million tonnes of CO_2 emissions in the EU-27 (2018, share: 30.47% of total emissions [3]); conversely, it accounted for 111.80 million tonnes in Italy [3]. Even if there has been a slight decrease in greenhouse emissions in advanced economies in the last few years (-3.2% between 2018 and 2019 [4]), additional efforts are needed to comply with the objectives of the *COP21* climate agreement [5]. Understanding the "*country-scale*" implication relies on a detailed description of the "*household-scale*". In this sense, the changes that continuously affect the household-scale should be taken into account. In this perspective, the last decades were characterised by improvements in the living conditions of European citizens, thus leading to an increase in the elderly population; conversely, the number of children for each family has remained almost stable in the range of 1.45 - 1.55 live births per woman [6, 7]. This trend leads toward the progressive ageing of the European population, with Italy being the country with the oldest demographic in the continent, with a median age of 46.3 years (Figure 1) [6]. The main consequence of this phenomenon is that, despite its steady increase in the last 20 years, the total Italian population is expected to shrink in the following decades (Figure 2), due to the death of older people and the lower number of children that will replace them [6].

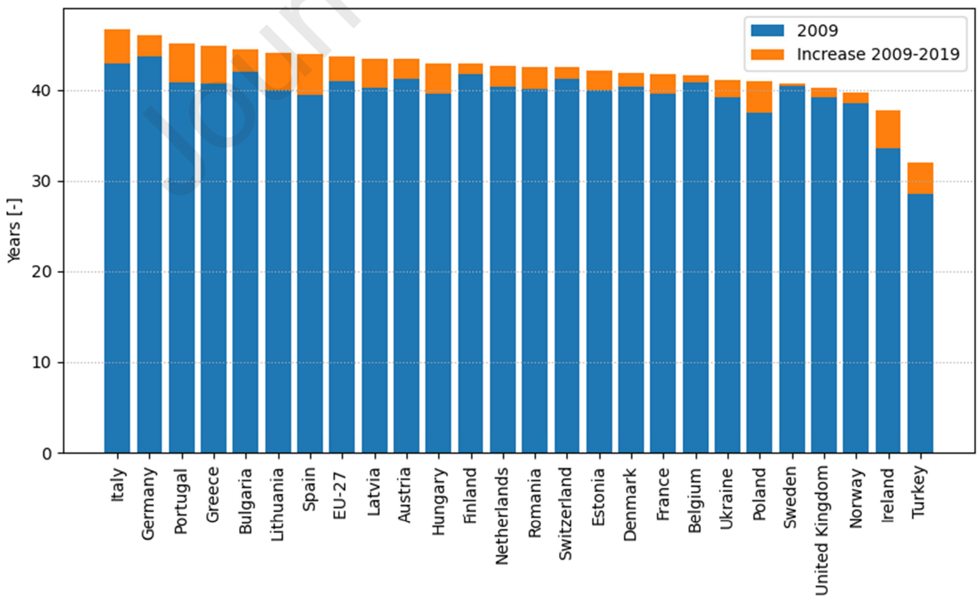


Figure 1: Median age of the population in the *EU* between 2009 and 2019 [6]

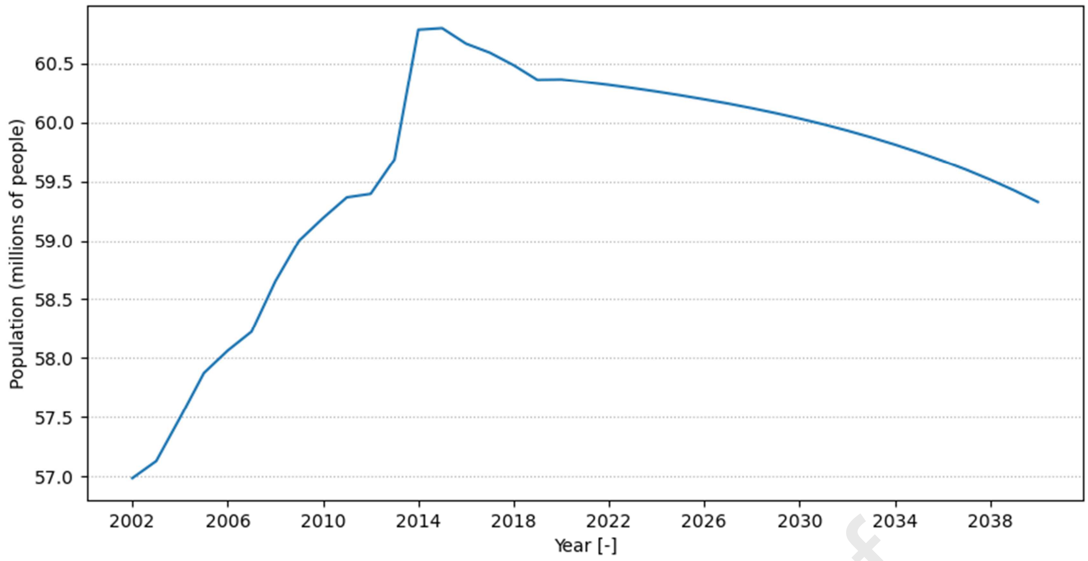


Figure 2: Forecast of the Italian population between 2002 and 2040 according to ISTAT (Italian Institute of Statistics) [8, 9]

The population structure changes influence energy consumption and should be taken into account when developing forecasting scenarios: different household structures are characterised by different consumption patterns [10]. Considering that the household energy consumption is given by the connection between the "*demand-side*" and the "*supply-side*", it is clear that the ageing of the population is likely to change this equilibrium point, thus leading to a change in the "*country-scale*" energy consumption. Different household structures are characterised by different budget constraints, which cannot be ignored when discussing energy policies' effects on different households.

For the sake of clarity, a brief overview of some papers discussing this broader topic is proposed in the following. Chancel [11] studied the differences in carbon emissions between different cohorts by analysing the results of different consumer budget surveys (USA and France, 1980-2000). In the first case, no significant differences were found between age groups; conversely, in the latter, emissions reach a peak in people born between 1930 and 1955, with CO_2 production 20% higher concerning other cohorts, probably due to the use of less efficient infrastructures, economic marginalisation of later cohorts and a more environmental-friendly behaviour of younger generations. Yamasaki and Tominaga [12] studied the reason behind the larger energy consumption of elderly households by analysing the results of household budget surveys (Japan): large households, consumer durables stock, a small number of household members, and a more considerable time of home occupancy were linked to high energy consumption. They also found considerable differences in elderly household consumption in Western countries concerning the Japanese case due to cultural differences. Bardazzi and Pazienza [13] studied the differences in energy consumption forecasts of households in dependence on age cohorts by analysing historical data (Italy, 1997-2016) from the Italian Institute of Statistics (*ISTAT*). In this case, the older cohort is considered responsible for higher energy consumption (2% increase per year of age for electricity and natural gas), and it is estimated that energy demand in the country is likely to increase due to the ageing of the population. Frederiks et al. [14] studied the influence of socio-demographic and psychological factors on household energy consumption by reviewing previous studies. Contrarily to the previous papers discussed, the authors found no significant relationship between energy consumption and population aging. A particular set of literature is devoted to the application of the STIRPAT model, developed during the 1990s by Dietz and Rosa [15, 16] and based on a stochastic approach to the IPAT model. Zhang and Tan [17] applied the STIRPAT approach, disaggregating population data in different variables (i.e., population intensity, growth rate, education, living standard, age structure) to study the influence of each factor in the different provinces studied (China, 1997-2012). The paper results show that education and urban expenditure positively correlate with carbon emissions, with some differences in their impact between urban and rural regions, while ageing has variable effects in different parts of the country. Liddle [18] determined the influence of demographic factors over energy consumption by summarising the results of different cross-country studies, realised using both STIRPAT and empirical methods. The author found out that urbanisation is proportional to energy consumption, but he ascribed this behaviour to the fact that urban areas are characterised by higher incomes concerning rural areas. Instead, he pointed out that population density appears to be inversely proportional to energy consumption in building and transport. Cole and Neumayer [19] (1975-1998) used the environmental Kuznets curve (EKC) framework, describing pollution as a U-shaped function of per capita income. Their findings remarked a proportional influence of population size over CO_2 emissions and a small correlation between age structure and carbon production. York [20] found correlations between population and energy consumption by analysing demographic data and detailed projections (European countries, 1960-2000). His results show a highly elastic correlation between population growth and energy consumption (2.665% increase in energy consumption for a 1% increase in population). Also, urbanisation and ageing seem to cause an increase in energy consumption. The forecasts produced in the paper suggest that European energy requirements are likely to decrease in the forthcoming years, due to a decrease in the total population, despite the steady increase in median age. To sum up, an agreement is far from being achieved: the effects of some parameters, like age [11-13], vary depending on the countries [11] and the region within the country itself [17]. It can be assumed that the effect of socio-demographic parameters on energy consumption and carbon emissions depends on the particular cultural framework analysed and that there is no general determinant correlated with higher energy consumption.

The above part of the introduction discussed the influence of socio-demographic variables; a comprehensive view cannot neglect its economic side. To comply with the European Union's decarbonisation objectives for 2030 [21], profound investments are needed. Vellini et al. [22] estimated the economic burden due to the application of different decarbonisation scenarios (REF [23], EUCO27 [24], EUCO40 [24], NES [25]), taking as a reference the Italian framework: they found highly variable results, ranging from 2 to 10 billion €/year depending on the different scenarios and computation assumptions. It seems that the broad adoption of natural gas and solar energy has a high impact on the increase in mitigation costs, as does total coal phase-out. Sofia et al. [26] applied a cost-benefit analysis on the PNIEC (*Piano Nazionale Integrato per l'Energia ed il Clima*) scenario for Italy [27], showing positive results for all the areas considered. In particular, while the energy sector has a cost-benefit ratio of just 1.14, transport shows a rate of 7.79, due to the health benefits of pollutant reduction and the substantial decrease in traffic congestions caused by the broad adoption of public transportation [26]. Prina et al. [28] compared the *PNIEC* scenario to an optimised result, obtained using a modified version of the EnergyPLAN model and called "*Advanced 2030*". Despite the similar costs of the two scenarios (around 64 billion €/year), Advanced 2030 was able to reduce carbon emissions by 10% more than the PNIEC scenario, due to a larger share of renewable energy sources and higher electrification in heating and transport. Viesi et al. [29] used the EnergyPLAN model to analyse decarbonisation scenarios on a smaller scale, considering the Autonomous Province of Trento case study in Northern Italy, obtaining up to 50% emissions cuts by 2030 with respects to 1990, with just a 14% increase in annual costs. The OECD [30] tried to address carbon mitigation costs by analysing eight case studies (five with variable renewable energy shares, one with low renewable prices, and two with low interconnection conditions). Flexibility problems in power systems are highlighted as cost-critical factors in the cases with high penetration of renewable energy sources, increasing generation costs up to 70% in the case with 75% of variable renewable sources share. Also, the impact of renewables on the energy market is significant, as hours with a zero-price will inevitably increase, thus leading to higher energy prices in other periods of the day. The same document contains suggestions to tackle these problems, such as maintaining short-term markets for efficient dispatch and introducing carbon pricing and capacity remuneration. As some bottom-up models for energy estimation are provided with economic constraints and can be used to study the relationship between family expenditures and energy consumption, it is essential to mention a few of them. The FORECAST model [31] has been developed to simulate long-term scenarios for energy demand in different sectors; in particular, it can be used to study decarbonisation scenarios taking as inputs technological parameters, behavioural assumptions, and energy policies. The NEMESIS model [32] is used both for learning "Business as usual" scenarios and decarbonisation paths; it uses economic and demographic inputs (interest rates, price of commodities, total population, ...) to compute energy consumption, among other outputs, in different sectors, for EU countries, USA and Japan. The EnergyPLAN model [33] has the primary purpose of assisting the design of energy planning strategies based on technical and economic analyses of energy systems and investments. The model takes as input demand, renewable energy sources, generation capacity, import/export strategies, and can compute energy production, consumption, and costs for areas varying from small municipalities to entire countries. For a more detailed discussion of bottom-up models, the work of Besagni et al. [34]is to be taken as a reference.

Based on the above state-of-the-art, it is clear that a comprehensive bottom-up modelling approach evaluating both technical and economic aspects is not reached yet. Thus, this paper contributes to the present discussion, and it aims to build a model able to predict the evolution of residential energy consumption and the required costs to sustain the residential sector's electrification. This objective is reached by extending *MOIRAE*, a bottom-up modelling approach previously proposed by the authors [34], which is later applied to the Italian case study. This paper is structured as follows: Section 2 describes the main assumptions and computations used to build the sub-models, section 3 is dedicated to the validation of the results obtained from the implementation of the improved model, while section 4 deals with analysing the energy consumption data acquired and the considered electrification scenarios. Finally, section 5 contains a summary of the main results and outcomes.

2 Methods

MOIRAE estimates the primary energy consumption in Italian households starting from a dataset released by *ISTAT* [34, 35], that provides information regarding energy consumption patterns for lighting, heating, cooling, and domestic hot water services, together with socio-demographic data, building characteristics, and energy expenditures. These data are coupled with energy balance equations of household appliances and additional input data offered by Growth from Knowledge (GFK) [36] and by Assoclima [37]. The output produces an estimate of energy consumption disaggregated by family and by different energy sources (electricity, natural gas, Diesel, LPG, biomass, fuel oil, and coal). As each family is provided with a carryover universe coefficient, the total primary energy consumption in the Italian residential sector can be easily computed (see Eq. (1) in ref. [34]). In the forthcoming sections, the modification of MOIRAE proposed by the present paper is presented and discussed.

2.1 Input data

As the dataset utilised in the first version of *MOIRAE* does not provide information about the expenditures incurred by Italian families, it is not possible to use it to perform economic analyses. Thus, an aggregation is performed to associate families in the "*Household Budget Survey*" (*HBS*) [38] and "*Aspects of daily life*" (*AVQ*) [39] ISTAT data sets with families in the "*Energy Consumption of Households*" dataset (*ECH*) [35] (datasets for research purposed provided to *RSE* by *ISTAT*) to have a complete description of the families. Both HBS and AVQ datasets cover 2014, 2015, and 2016. The number of families in each data set is 16804, 15013, and 15409, respectively, for HBS, 18856, 19149, and 18490, respectively, for AVQ. The *ECH* data set only covers 2013 and includes 20000 families. In the preliminary phase of the aggregation process, a search is made to identify the standard variables in *ECH*, *HBS*, and *AVQ* data sets used to compare any two families. All socio-demographic variables, the household's descriptive variables, and the family's socio-economic variables are considered essential. At the end of the search, 50 socio-demographic variables are retained. Expenditures in the HBS data set must be carried back to 2013 to be time-aligned with the *ECH* data set. To do this, the "*Italian consumer price index for the whole nation*" (viz., *NIC* data) [40, 41]) is used. Expenditures in the years 2014, 2015, and 2016 are first carried back to 2010 through Eq. (1), then forward to 2013 through Eq. (2):

$$y_{x,10} = \frac{y_{x,y}}{1+\frac{\alpha_{x,y,10}}{100}} \tag{1}$$

$$y_{x,13} = y_{x,10} * \left(1+\frac{\alpha_{x,10,13}}{100}\right) \tag{2}$$

Assessing the similarity between two families requires a distance measure. Among the available distances [42], in this work, we adopt a modified version of the Hamming distance. Eq. (3) gives the weighted Hamming distance d_{st} between family *s* and *t*, where operator *!=* returns one if the values for a given variable are different and 0 if they are equal.

$$d_{st} = \sum_{v=1}^{n} \left(x_{sv} \mathrel{!=} x_{tv} \right) w_v \tag{3}$$

The variables *number of components*, the *region of residence*, *macro area,* and *municipal type* have a weight equal to 10^5 ensure that the optimal association has these variables equal in their values. This value has been selected because it is much larger than the maximum distance achievable by comparing two families where these four variables coincide, that is equal to n-4, where n is the total number of variables to be compared. This way, it is possible to consider in the aggregation just families where these 4 variables coincide, as they will have much smaller distances. The remaining variables have a weight equal to one. The aggregation process is divided into two phases. For each aggregation phase, a base data set must be selected: the data set for which each family is associated with a family of the other data set. For the first phase, *HBS* is the base data set, while *ECH* is the base data set in the second phase. It follows that the aggregated data set is aligned with *ECH* because each family of *ECH* is associated with a family of the other two data sets. In the first phase, HBS families are associated with AVQ families based on the weighted Hamming distance. The result of this phase is a first aggregated data set; in the second phase, the aggregated data set is aggregated with *ECH*. In this way, new virtual families with additional features are obtained. The aggregated data set has 20000 families described by 2910 variables. Note that a family in *HBS* and *AVQ* data sets can be associated several times to a family in *ECH*. The following indices are used to measure the performance achieved in the aggregation process: average distance, family maximum matching frequency, family average matching frequency, and family matching frequency. The average distance describes how much two families are different on average concerning the weighted Hamming distance; the family maximum matching frequency gives the maximum number of times that a given family is used for aggregation.

In contrast, the family average matching frequency and the family matching frequency, intended as the number of total families of a data set associated with the base data set, provide information on the degree of coupling between two data sets. Table 1 reports the above indices computed between *HBS* and *AVQ* and between the aggregated data set obtained by the first phase and ECH. In the first phase of the aggregation process, *HBS* is the base data set. Hence, family maximum matching frequency describes the maximum number of times an *AVQ* family has been associated, while family matching frequency describes the total number of *AVQ* families associated with *HBS* families. In the second phase, *ECH* is the base data set; in this case, family maximum matching frequency gives the maximum number of times a virtual family from the first aggregation step has been associated, while family matching frequency gives the total number of virtual families from the first step which is associated with *ECH* families. Thus, the ECH dataset has been preserved as-is and the obtained families are "*half-virtual*". In particular, the variables within the ECH dataset are the ones used to compute household's energy consumption (as shown in the previous paper regarding MOIRAE [34]); Thus, electrical and thermal energy consumptions have been computed from ISTAT official data. These data are also the one used in the calibration/validation procedure. On the other hand, economic computations rely on additional variables.

Table 1: Performance indexes achieved in the various phases of the aggregation process

	HBS, AVQ			*ECH*
	2014	2015	2016	2013
Average distance	26.09	114.75	176.82	96.07
Family maximum matching frequency	22	30	21	24
Family average matching frequency	2.08	1.98	2.05	1.60
Family matching frequency	8048	7572	7494	12515

2.2 Socio-demographic variations of households between 2002 and 2040

The main limitation of the first version of *MOIRAE* is due to the specific input dataset; this dataset was released as part of a study performed in 2013 by the Italian Institute of Statistics (ISTAT) ("Household energy consumption") [35].

ISTAT provides [8] data regarding Italy's main socio-demographic variables for all years since 1952, together with population forecasts stretching for the forthcoming years. In particular, three parameters are used to compute the forecasting of the carryover coefficients:

- region: inhabitants of each of the 20 Italian regions;
- sex: male and female populations of the country;
- age: population share of 3 different age classes (0-14 years, 15-64 years, 65+ years).

These data are extracted for two distinct periods: the first one considers historical data recorded by *ISTAT* from 2002 to 2019, while the second one, covering the 2020-2040 period, is composed of projections performed by *ISTAT* itself, with a confidence band of 80%. These data also offer some fascinating insight over the changes in the Italian population structure over almost 40 years: for example, the elderly population is expected to grow significantly in the following years, while the other age cohorts will most likely shrink in numbers; at the same time there is a displacement from rural regions to the most industrialised ones. In the end, by comparing the data provided by ISTAT with the output of the improved *MOIRAE* model, it is possible to study correlations between socio-demographic data and household energy consumption.

To compute the carryover universe coefficient for each year (in above-defined ranges), the initial coefficients, referred to in 2013, are modified following the procedure described in Figure 3. At first, the 2013 coefficients are multiplied by a series of factors representing the changes in a demographic variable between 2013 and the new reference year. The first factor represents changes in population inside the region where the family resides:

$$f_{reg,i,y} = \frac{N_{r,y}}{N_{r,2013}} \tag{4}$$

The second factor is computed by considering the changes in sex distribution inside the single families during the years:

$$f_{sex,i,y} = \frac{\sum_{c=1}^{N_f} \frac{n_{s,y,c}}{n_{s,2013,c}}}{N_f} \tag{5}$$

The third factor takes into account the variation of the age groups of the single-family members during the years:

$$f_{age,i,y} = \frac{\sum_{c=1}^{N_f} \frac{n_{a,y,c}}{n_{a,2013,c}}}{N_f} \tag{6}$$

In the end, to compute the carryover coefficients in the new reference year from the old ones, it is necessary to apply Eq. (7):

$$coef\_red_{i,y} = coef\_red_{i,2013} * f_{reg,i,y} * f_{sex,i,y} * f_{age,i,y} \tag{7}$$

These equations can be implemented directly into *MOIRAE* to obtain a time-variant output. From the new coefficients received, it is possible to compute estimates for the Italian population divided by region, sex, and age. This way, the model results can be compared to the respective *ISTAT* data used as input. The errors related to the difference between the variables computed using the novel sub-model and the reference *ISTAT* variables can improve the coefficient's estimate by using a feedback loop, raising the similarity between input and output data. The first step is to compute the base model's relative errors for regions, sexes, and age groups concerning the ISTAT data. They are calculated using Eq. (8), Eq. (9), and Eq. (10):

$$e_{r,y} = \frac{N_{r,y}^I - N_{r,y}^C}{N_{r,y}^I} \tag{8}$$

$$e_{s,y} = \frac{N_{s,y}^I - N_{s,y}^C}{N_{s,y}^I} \tag{9}$$

$$e_{a,y} = \frac{N_{a,y}^I - N_{a,y}^C}{N_{a,y}^I} \tag{10}$$

As each family is composed of elements that can differ by sex or age, for each component of the dataset, two parameters must be defined to consider all its members' relative errors. These parameters are defined in Eqs. (11 - 12):

$$c_{sex,i,y} = \frac{\sum_{c=1}^{N_f} e_{s,y,c}}{N_c} \tag{11}$$

$$c_{age,i,y} = \frac{\sum_{c=1}^{N_f} e_{a,y,c}}{N_c} \tag{12}$$

After that, each carryover universe coefficient in the dataset is combined with the regional relative error $e_{r,y}$ and the two parameters $c_{sex,i,y}$ and $c_{age,i\,y}$, as shown in the Eq. 13:

$$coef\_red'_{i,y} = coef\_red_{i,y} * \frac{(1+e_{r,y})+(1+c_{sex,i,y})+(1+c_{age,i,y})}{3} \quad (13)$$

Hence, carryover coefficients can be computed in two modes: (i) by performing just the basic coefficient calculation, without correcting the error; and (ii) by applying the feedback loop. They are to be used as additional input for the *MOIRAE* model, appropriately modified to repeat its computations for different years. Carryover coefficients sub-model output is deeply analysed in Supplementary material S.1, which the interested reader might refer to.

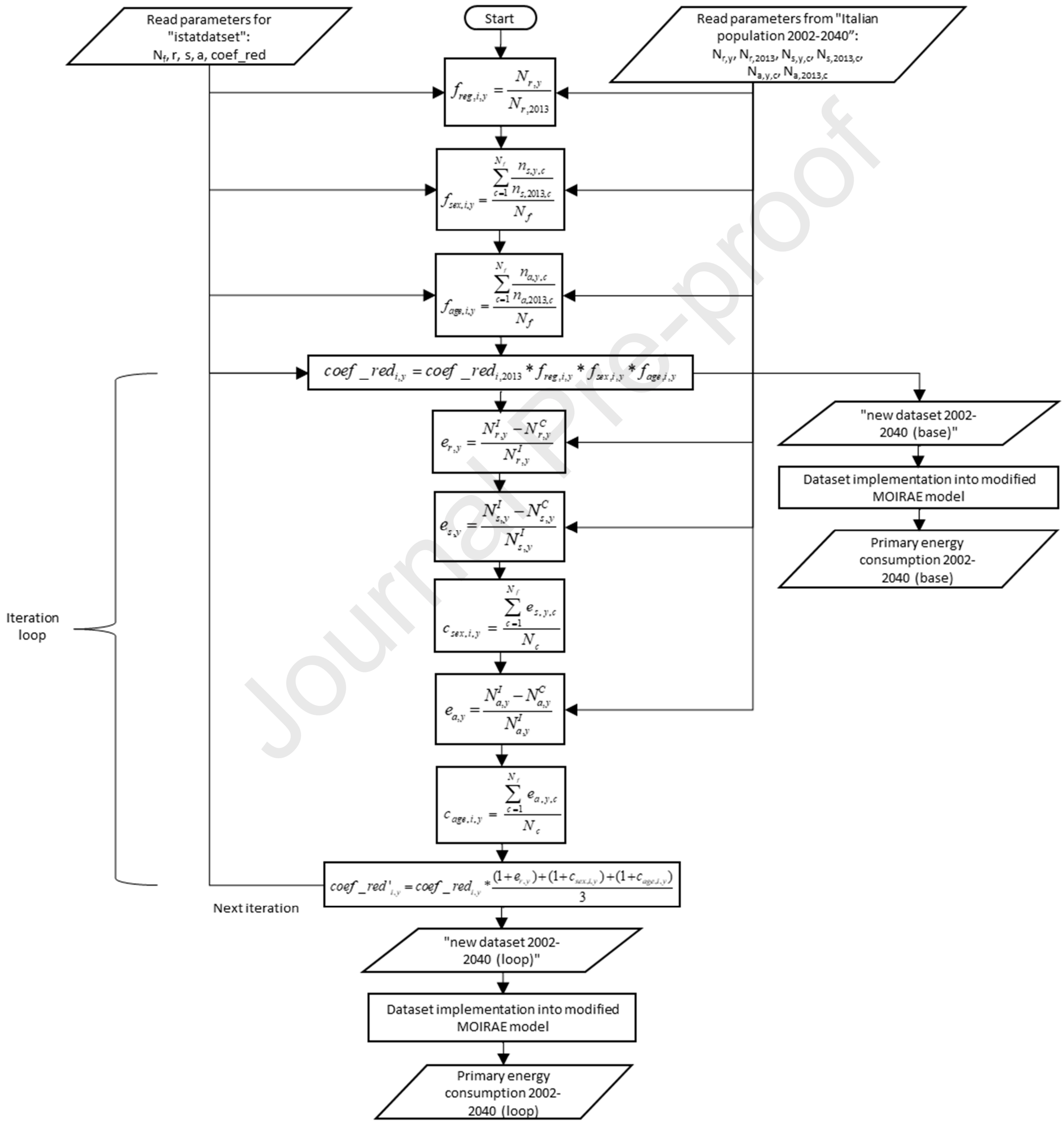


Figure 3: Procedure to compute the carryover coefficients for different years

2.3 Energy consumption model: calculation procedures

The first version of *MOIRAE* was validated against data provided in IEA final balances [43], showing an overestimation of natural gas and *LPG* primary energy consumption. Thermal energy consumption in households is due mainly to heating and domestic hot water heating systems (*DHW*). Thus an improvement in thermal energy consumption prediction on these final uses is needed to increase capability predictions. Based on the thermal energy consumption functions defined and implemented in *MOIRAE*, it is proposed to include a partial load coefficient in the heating and *DHW* thermal energy consumption equations, in an attempt to take into account variations in the load profiles of the systems and to calibrate the model outcomes. Partial load coefficients are assumed to depend on the family and the region's energy carrier, as variables representing boiler efficiency variation due to fuel and socio-demographic behaviour. All model assumptions described by Besagni et al. [34] are kept unchanged, and the structure and notation are defined as the original equations. $\gamma_{heating_{i,r,j}}$ and $\gamma_{DHW_{i,r,j}}$ are the partial load coefficients of heating and domestic hot water, respectively, not present in the original equations and representing performance variations due to changes in the operating conditions (e.g., off-design mode). Thus, the heating and DHW thermal energy consumption functions in *MOIRAE* have been modified as described in Eq. (14-15).

$$\begin{aligned} TE_{i,heating,j} &= \sum_{j=1}^{fuel\_type}\left[\sum_{k=1}^{heating\_type} TE_{i,heating,k,j,r}\right] = \\ &\sum_{j=1}^{fuel\_type}\left[\sum_{k=1}^{heating\_type} P_{th,i,k,j} h_{i,k,j} d_{i,k,j} y_{heating-\max} \xi_{heating,i} \gamma_{heating,i,r,j}\right] = \\ &\sum_{j=1}^{fuel\_type}\left[\sum_{k=1}^{heating\_type} n_t \frac{\dot{V}_{w,i,k,t}\rho_w c_{p,w}\Delta T_{w,i,k,t}}{\eta_{th,i,k,t}} h_{i,k,j} d_{i,k,j} y_{heating-\max} \xi_{heating,i} \gamma_{heating,i,r,j}\right] \end{aligned} \tag{14}$$

$$\begin{aligned} TE_{i,heating,j} &= \sum_{j=1}^{fuel\_type}\left[\sum_{k=1}^{heating\_type} TE_{i,DHW,k}\right] = \\ &\sum_{j=1}^{fuel\_type}\left[\sum_{k=1}^{heating\_type} \frac{V_{DHW,i}\rho_w c_{p,w}\Delta T_w n_{occupants,i}}{\eta_{th,i,k,j}} \gamma_{DHW,i,r,j} z\right] \end{aligned} \tag{15}$$

Even if MOIRAE results on global validation of electricity show a more accurate prediction concerning the year 2013, an overall calibration of the model is needed to ensure better performances in a scenario analysis perspective. Thus, GSE regionalisation data [44] obtained for the year 2018 (listed in Supplementary material S.2) are used to calibrate cooking, heating, cooling, and domestic hot water services for all energy sources. As MOIRAE's bottom-up approach does not consider the energy consumption of centralised systems (assumption#6 in ref. [34]), GSE data must be modified to rule out centralised systems energy consumption. The *ISTAT* input dataset carried to 2018 by the carryover coefficient model described in paragraph 2.2 is utilised to extrapolate information on centralised systems diffusion in Italy, disaggregated by region and energy carrier; then, *GSE* data are refined proportionately to systems diffusion to obtain a consistent result to compare to MOIRAE output, disaggregated by final service, region, and energy source accordingly. In conclusion, the ratio between primary energy consumptions computed by MOIRAE and from GSE data defines calibration coefficients $\gamma_{k,r,j}$, related to *k-technology*, *r-region,* and *j-fuel*, to be implemented into the model's functions utilising Eq. 16-18:

$$EE_{i,k_{calibrated}} = EE_{i,k_{MOIRAE}} * \gamma_{k,r,el} \tag{16}$$

$$TE_{i,k,j_{calibrated}} = TE_{i,k,j_{MOIRAE}} * \gamma_{k,r,j} \tag{17}$$

Where:

$$\gamma_{k,r,j} = \frac{PE_{k,r,j_{REF}}}{PE_{k,r,j_{MOIRAE}}} \tag{18}$$

In conclusion, the model's accuracy for all years is expected to increase, decreasing the primary energy consumption estimation error. All coefficients introduced are better clarified in Supplementary material S.2 comparing *GSE* and *MOIRAE* results and characterising their values.

2.4 Economic model: calculation procedures

To further improve *MOIRAE* as a support tool for the residential sector's decision-making process, an economic sub-model is included [45]. In this context, to estimate the average price of electrical appliances, data from Growth from Knowledge (*GFK*) [36] and released to RSE, regarding market researches with 2013 – 2018 coverage years, are used; these data were already adopted in the original *MOIRAE*, to build the technological framework. Thus their application for economic evaluation is consistent. In this regard, *MOIRAE* assumption#1 [34], concerning data coupling between *ISTAT* and *GFK* datasets, is applied and kept unchanged to match appliances age and energy labels. For the specific case of air-conditioners and heat pumps systems, data gathered and elaborated by Assoclima [37] are employed. For other thermal appliances such as boilers, internal *RSE* databases are used. For energy systems requiring distribution systems, such as ambient and water heating, additional costs related to dismantling, installation, and labour have to be taken into account when needed; in this regard, regional price lists [46] are utilised as a reference. However, all listed databases are related to the household appliances market until the current year. Hence the Statista database on consumer market outlook [47] is used to forecast prices until 2040, selected objective year in the following scenario analysis. The Statista database is built on national statistics (such as *ISTAT* or *GFK* for Italy), company data, association data, or other third-party studies; moreover, it provides critical parameters, for instance, *CAGR*[1], adjusted for the expected impact of COVID-19. All prices are listed in Supplementary material S.3. The total expenses of the whole

[1] CAGR: compound annual growth rate

residential sector for the installation of new household appliances is determined by summing up the *k-appliance* expenses for the *i-households* bearing the substitution (Eq. (19)).

$$\begin{aligned}
S_{tot,y} &= \sum_{i=1}^{Total_numer_of_households} S_{tot,i,y} * coef_red_{i,y} = \\
&\sum_{i=1}^{Total_number_of_households} \sum_{k=1}^{Appliances} \sum_{j=1}^{Energy_carrier} (S_{inv,k,i} + S_{O\&M,k,i,j}) coef_red_{i,y} = \\
&\sum_{i=1}^{Total_number_of_households} \sum_{k=1}^{Appliances} \sum_{j=1}^{Energy_carrier} (S_{app,k,i} + S_{inst,k,i} + S_{O\&M,k,i,j}) coef_red_{i,y}
\end{aligned} \tag{19}$$

Investment costs are assessed concerning the type of technology chosen and technical characteristics, and when required, supplementary costs related to distribution system integration and appliance installation are determined. Lastly, variable costs are considered based on energy consumption calculated by *MOIRAE*, disaggregated by energy carrier. Variable expenses are calculated as described by Eqs. (20-21):.

$$S_{O\&M,k,el,i} = EE_{k,i} * C_{el,r,cons} \tag{20}$$

$$S_{O\&M,k,el,i} = \frac{TE_{k,i,j}}{LHV_j} * C_{j,r,cons} \tag{21}$$

The costs for electricity and natural gas are obtained from data provided by *ARERA* for customers in the protected market [48], taking into account the taxes on excise duties, *VAT*, and regional surcharges [49]. Conversely, the costs of *LPG* and diesel for domestic use are derived based on the statistics on the average monthly prices of fuels provided by *MISE* [50]. As these data are provided until the current year, *RSE* data on price forecasts on natural gas and electricity is utilised for the coming years; the projections consider energy-matter costs and taxes like *VAT* and regional surcharges (described in Supplementary material S.3). *LPG* and diesel trends are finally assumed consistent with the natural gas one.

2.5 Methodology application to other countries

Despite the application of *MOIRAE* to the specific Italian case, it should be noted that the same approach proposed can be applied for other countries or broader region (e.g. Europe), employing specific assumptions as input. In particular, values such as the representative micro-data, the efficiencies, the coefficients, the powers and the energy consumptions should be derived from the specific selected-region market; for further information on the specific assumptions to be modified in the MOIRAE energy model see section 2.4 of the methodology proposed by the reference [34]. The carryover universe coefficient extension can be applied to other countries taking into account the particular socio-demographic variations, made available by national statistics institutions. The investment costs for the purchase of appliances and energy systems, and the variable costs related to fuels, have been determined based on the Italian market (e.g. from GFK, Assoclima and ARERA datasets); the same approach can be adapted to other specific regions with the ad-hoc market investigation. However, all the considered values can be exploited as a first estimation, at least within the European area. Lastly, it should be noted that these observations are comparable to the required input information for many other energy simulation and optimisation models. Moreover, micro-data characterising households behaviour spectra, energy consumptions, expenditures should be available.

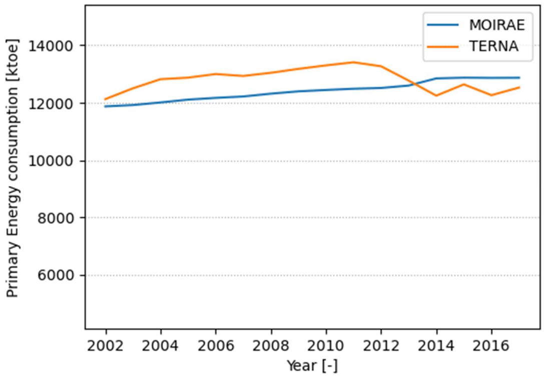
3 Model validation

After completing the calibration of the model (Supplementary material S.2), it is possible to compare historical balances to the primary energy consumption output, to perform validation; for the purpose, balances from Terna [51] are considered for electric consumption, while *IEA*'s data [43] are used for all the other sources. It is essential to remark that the current MOIRAE version does not consider centralised systems; this means that the model results are expected to be lower than the historical data, where centralised systems are included. Table 2 shows the primary energy comparison for all energy sources. In most cases, consumption computed by *MOIRAE* is lower than the historical data, as expected. However, there are some instances where the model's estimations are higher, like biomass (Figure 4.e) and sometimes electricity (Figure 4.a) and *LPG* (Figure 4.d). If the differences between the two curves are almost always around 20% for natural gas (Figure 4.b), for diesel the error decreases steadily from 80% in the early 2000s to 40% in the mid-2010s (Figure 4.c). Fuel oil (Figure 4.f) is a particular case: as the calibration coefficients for fuel oil computed using GSE's data are almost all equal to 0, energy consumption computed by MOIRAE for this carrier is equal to 0 for all years, leading to a constant error equal to 100%. Luckily, the impact of this issue on total consumption is relatively low, due to the negligible amount of energy consumption due to fuel oil; nonetheless, further calibration is needed to obtain realistic results. By looking at the *MAPE* (the average of the percentage errors for each year) of the model for each source, it can be seen that the average error of the model in a couple of cases (diesel, fuel oil) is exceptionally high, exceeding 60%, while for the rest of the sources it is relatively contained. Electricity is the source with the lowest error, with a value of around 5%. In the end, the MAPE on the total energy consumption is slightly more than 10%, relatively high, but still acceptable. Even if lower values of MOIRAE's primary energy are expected, due to centralised systems exclusion from *MOIRAE* computation, it is impossible to calculate the error contribution due to the model's intrinsic error. Also, *MOIRAE* considers just socio-demographic changes when estimating the evolution of energy consumption, while in reality, many factors are to be considered, like efficiency improvements and changes in the general behaviour of the population. The inclusion of procedures to consider these elements is thus strongly advised to perform the model's proper validation.

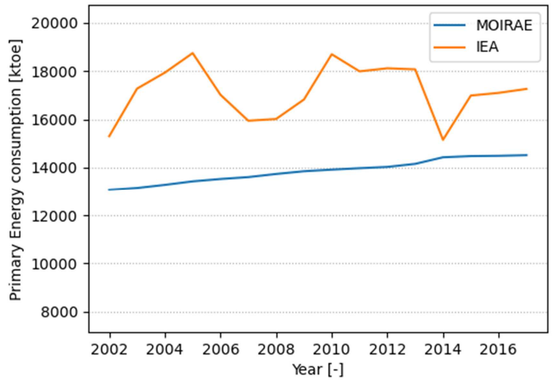
Table 2: Comparison between MOIRAE and Terna[51]/IEA[43] balances*

	Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	MAPE
Electricity:	**MOIRAE [ktep]**	11876.29	11922.62	12012.98	12111.40	12171.84	12220.71	12318.05	12398.69	12446.32	12489.45	12516.49	12600.24	12848.82	12874.18	12866.81	12870.74	-
	TERNA [ktep]	12129.13	12504.10	12821.63	12875.11	13000.17	12933.99	13043.65	13179.95	13301.26	13409.05	13270.46	12771.96	12249.40	12640.81	12265.69	12530.69	-
	Difference [%]	-2.08%	-4.65%	-6.31%	-5.93%	-6.37%	-5.51%	-5.56%	-5.93%	-6.43%	-6.86%	-5.68%	-1.34%	4.89%	1.85%	4.90%	2.71%	4.81%
Natural Gas:	**MOIRAE [ktep]**	13071.43	13150.34	13281.27	13427.15	13525.42	13604.29	13734.17	13847.29	13914.66	13973.88	14027.19	14153.47	14425.94	14475.73	14487.67	14513.55	-
	IEA [ktep]	15301.00	17273.00	17937.00	18746.00	17017.00	15942.00	16015.00	16821.00	18698.00	17990.00	18117.00	18073.00	15151.00	16986.00	17097.00	17261.00	-
	Difference [%]	-14.57%	-23.87%	-25.96%	-28.37%	-20.52%	-14.66%	-14.24%	-17.68%	-25.58%	-22.32%	-22.57%	-21.69%	-4.79%	-14.78%	-15.26%	-15.92%	18.92%
Diesel:	**MOIRAE [ktep]**	596.56	600.72	606.56	613.23	618.27	622.42	628.24	633.31	636.36	638.98	641.82	648.05	661.04	664.08	665.24	667.05	-
	IEA [ktep]	4003.59	3320.67	3600.37	3550.35	3144.07	2477.49	2393.78	2321.31	1912.99	1797.63	1593.47	1510.79	1161.67	1291.32	1171.88	940.16	-
	Difference [%]	-85.10%	-81.91%	-83.15%	-82.73%	-80.34%	-74.88%	-73.76%	-72.72%	-66.73%	-64.45%	-59.72%	-57.11%	-43.10%	-48.57%	-43.23%	-29.05%	65.41%
LPG:	**MOIRAE [ktep]**	1039.12	1042.92	1050.36	1057.85	1062.60	1066.47	1074.72	1081.29	1084.77	1087.84	1089.61	1096.14	1116.48	1118.39	1117.48	1117.54	-
	IEA [ktep]	1475.92	1538.61	1502.31	1552.90	1428.63	1359.34	1459.42	1383.54	1372.54	1246.06	1207.57	1193.27	1081.09	1086.59	1119.59	1149.28	-
	Difference [%]	-29.59%	-32.22%	-30.08%	-31.88%	-25.62%	-21.55%	-26.36%	-21.85%	-20.97%	-12.70%	-9.77%	-8.14%	3.27%	2.93%	-0.19%	-2.76%	17.49%
Biomass:	**MOIRAE [ktep]**	5686.41	5710.32	5755.86	5801.01	5829.51	5851.51	5900.30	5937.23	5956.77	5973.06	5985.74	6026.11	6134.06	6145.82	6143.00	6145.92	-
	IEA [ktep]	2160.00	3491.00	2244.00	3905.00	4697.00	6513.00	7674.00	7380.00	7163.00	4602.00	6637.00	6633.00	5676.00	6393.00	6173.00	6757.00	-
	Difference [%]	163.26%	63.57%	156.50%	48.55%	24.11%	-10.16%	-23.11%	-19.55%	-16.84%	29.79%	-9.81%	-9.15%	8.07%	-3.87%	-0.49%	-9.04%	37.24%
Fuel Oil:	**MOIRAE [ktep]**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-
	IEA [ktep]	330.58	323.68	224.99	221.05	139.14	86.84	88.81	86.84	39.47	34.54	14.80	3.95	0.99	0.99	0.99	0.99	-
	Difference [%]	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	-100.00%	100.00%
Total:	**MOIRAE [ktep]**	32269.82	32426.92	32707.04	33010.63	33207.65	33365.40	33655.49	33897.82	34038.88	34163.21	34260.85	34524.01	35186.34	35278.20	35280.19	35314.80	-
	TERNA+IEA [ktep]	35400.22	38451.05	38330.31	40850.41	39426.01	39312.66	40674.67	41172.63	42487.26	39079.28	40840.31	40185.97	35320.16	38398.70	37828.15	38639.11	-
	Difference [%]	-8.84%	-15.67%	-14.67%	-19.19%	-15.77%	-15.13%	-17.26%	-17.67%	-19.88%	-12.58%	-16.11%	-14.09%	-0.38%	-8.13%	-6.74%	-8.60%	13.17%

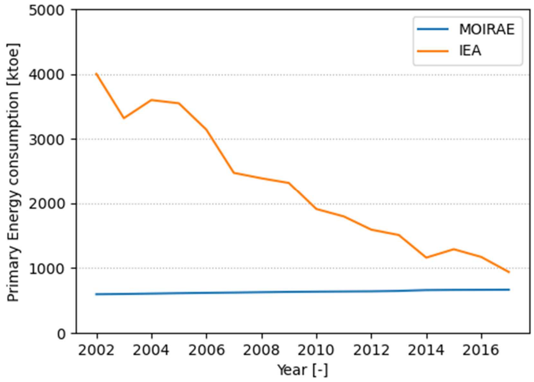
*: Centralised systems are considered only for Terna and IEA balances and not for MOIRAE estimations



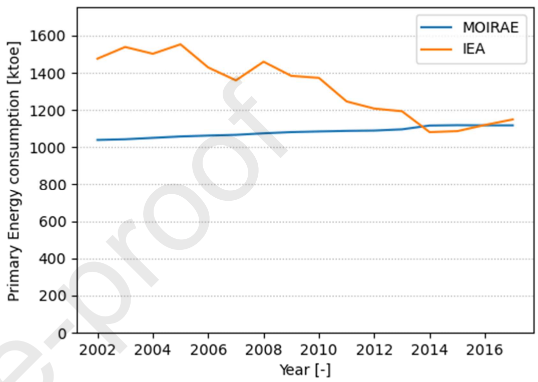
(a) Primary energy consumption from electricity



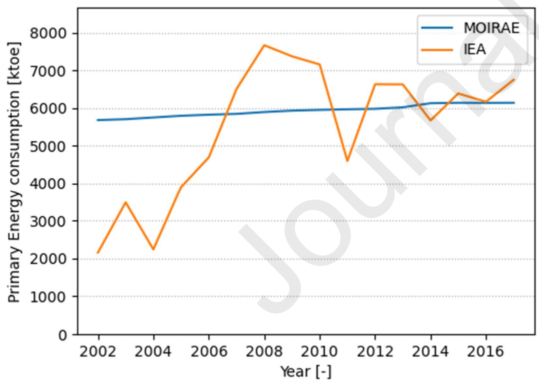
(b) Primary energy consumption from natural gas



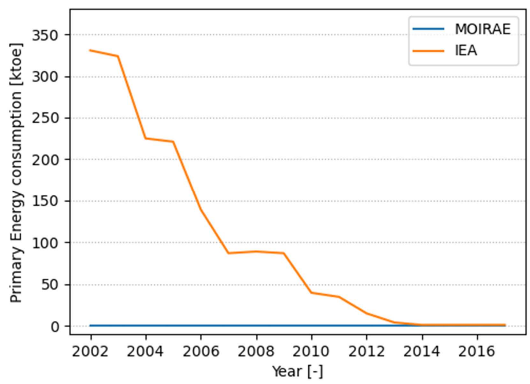
(c) Primary energy consumption from diesel



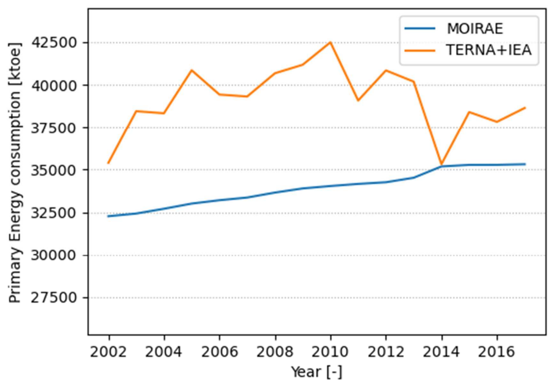
(d) Primary energy consumption from LPG



(e) Primary energy consumption from biomass



(f) Primary energy consumption from fuel oil



(g) Total primary energy consumption comparison

Figure 4: Comparison between primary energy consumptions computed by the MOIRAE model and historical balances from Terna and IEA

4 Results

4.1 Primary energy consumption forecasting

The total primary energy consumption trend in the whole study interval can also be considered, taking into account carryover coefficients forecasts for the 2020-2040 period (Figure 5). Energy consumption is forecasted to grow during the years, while the total Italian population is expected to decrease; this is coherent with the findings of Bardazzi and Pazienza [10], and it means that, due to changes in demographic structure, the per capita energy consumption in Italy is going to increase significantly. As Italian households' primary energy consumption has been analysed, considering the socio-demographic framework, it is essential to study how energy consumption changes between different population components. *MOIRAE* bottom-up perspective allows us to explore the variations in these categories' total energy consumption over time. Figure 6 shows the changes in energy consumption divided by region, sex, and age class concerning 2013. The energy consumption evolution differs significantly between North and South, with areas in the former heavily increasing their energy consumption during the years, while the others are characterised by a stable or even decreasing outcome over time. Both sexes increase their consumption steadily during the years, with women having a slightly higher increase concerning men. Looking at age classes, elders have a considerable increase in their energy consumption during the whole study period, due to the evolution of the Italian population; children and adults are expected to decrease their energy consumption in the next two decades. In this paper, only socio-demographical variations in the forthcoming years will be investigated, including the effect of population ageing and changes in the demographical variables [13]; indeed, this study focuses on the perspective of the household (i.e. the economic burden on households for an electrification pathway, described in section 4.2) rather than precisely describe the primary energy values at specific years. However, technological changes and households behaviours variations should be taken into account to achieve a precise and reliable result in a broader perspective (i.e. primary energy consumption and savings at country-level). For instance, the recent Italian legislation regarding energy communities [55], where different prosumers can exchange energy between each other, is not considered in this study, despite being a potential topic of interest for the next few years, also due to the positive public opinion regarding renewable energy [54, 56]. Also, in the previous decades, energy efficiency in developed countries has always been continuously increasing [52, 57], and forecasts highlight how this trend is going to carry on in the future [58]; this means that ignoring efficiency evolution in the model will lead to an overestimation of residential energy consumption forecasts, in a similar way to how the models' results for 2000 are underestimated compared with the historical data. The implementation of projections of energy efficiency of appliances is a matter of future studies. The starting point would be the existing body of knowledge on the topic. For instance, the implementation of digital technologies and automation system inside residential buildings (the so-called Smart Homes) could potentially optimise the utilisation of appliances, improving home comfort at the same time [59, 60]. Also, 4th generation district heating is a promising tool for reducing residential energy consumption, as a single heat distribution system could supply entire neighbourhoods and towns, heavily improving energy efficiency [61]; this type of technology could also contribute in the development of smart energy systems, fostering the implementation of variable energy sources [62] and contributing to the development of 100% renewable energy systems [63], which are expected to provide a certain number of benefits, not just environmental but also social and political, due to decarbonisation [64].

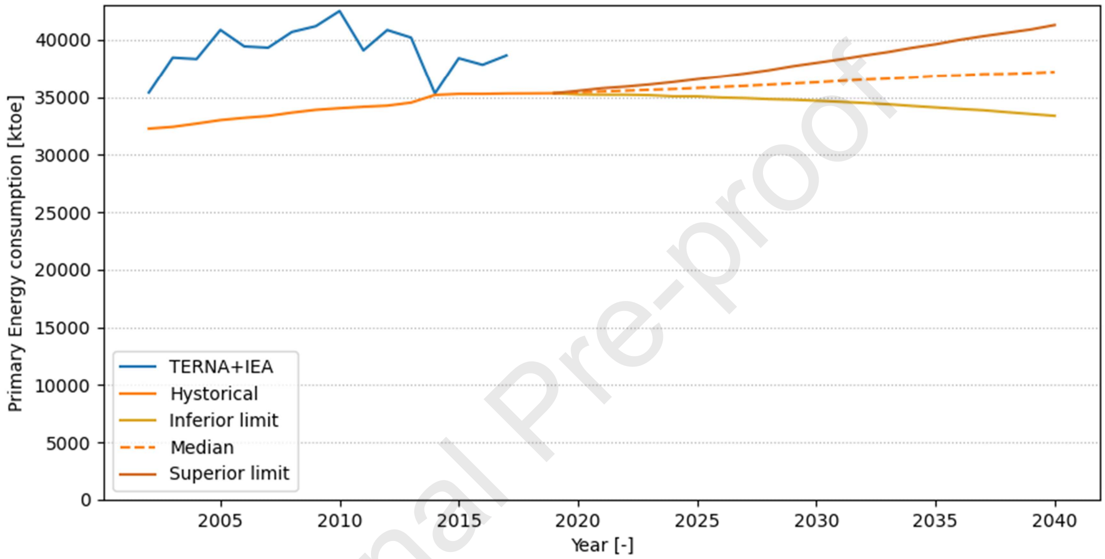
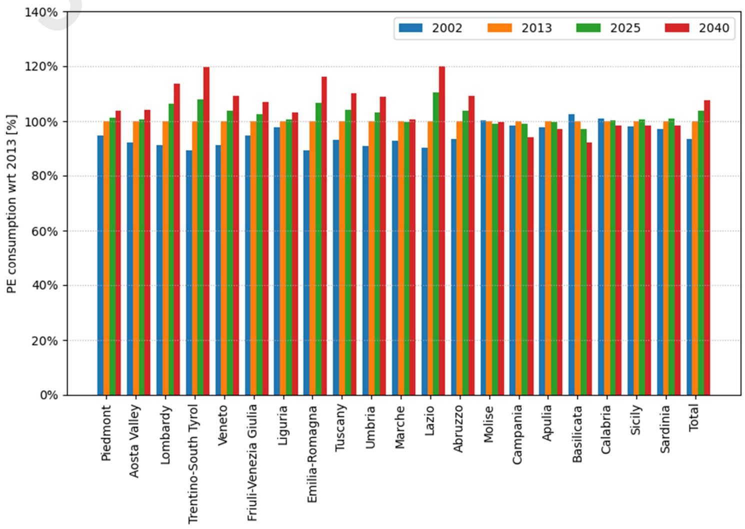
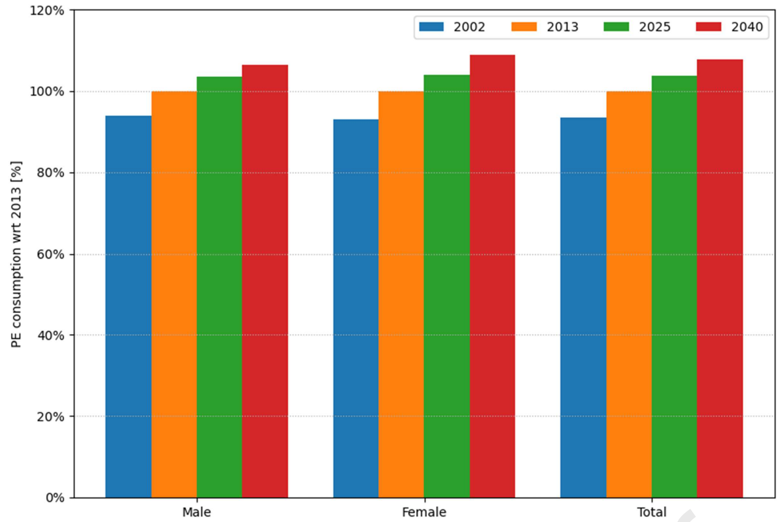


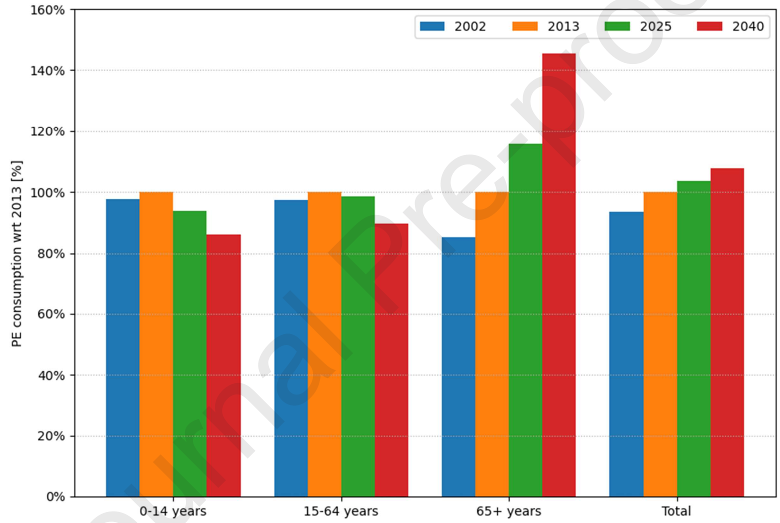
Figure 5: Forecast for total primary energy consumption in Italy computed using the MOIRAE model



(a) Primary energy evolution during the years by region



(b): Primary energy evolution during the years by sex



(c) Primary energy evolution during the years by age class

Figure 6: Primary energy consumption evolution in Italian residential sector

4.2 Electrification pathways

In this section, modified *MOIRAE* is exploited to study the electrification pathways for the Italian residential sector; for the purpose, natural gas, *LPG*, diesel, and fuel oil energy consumptions are replaced with electricity consumption by substituting thermal energy systems with electrical ones; conversely, biomass is considered to be a renewable source, in agreement with what is stated in the Integrated National Energy and Climate Plan (*PNIEC*, see ref. [65]), defining targets and methods for a decarbonisation plan; in *PNIEC*, biomass-based systems are taken into account for energy efficiency improvements. However, they are not considered for the electrification scenario. The primary energy consumption forecasting procedure defines the baseline case where appliances for heating, cooking, and *DHW* in households are kept unchanged, whereas their replacement induces a variation on the overall residential energy consumption, estimated by improved *MOIRAE*. It Is noted that the results are strictly related to the assumptions and constraints described in the following section, and limitations arising from both the original model and developed sub-models should be taken into account; for instance, centralised systems, the substitution of appliances due to obsolescence, efficiency improvements and population behaviour changes are not considered.

4.2.1 Methods and scenarios

The residential sector's electrification allows a decrease in the total primary energy from non-renewable sources, increasing the share of renewable energy production, and reducing carbon-based emissions [66]. Moreover, the developed economic sub-model can support an analysis under household budget constraints, which can induce a variation to socio-demographic behaviour towards decarbonisation choices [67]; thus, the proposed scenarios are considered both with- and without- household financial resources. Four scenarios are investigated:

Scenario #1. Electrification of the cooking sector. Traditional ovens and stoves are replaced with electric ovens and induction stoves, respectively.

Scenario #2. Electrification of the heating sector. Thermal heating appliances are replaced with heat pumps, based on the criteria described by Besagni et al. [34].

Scenario #3. Electrification of the DHW sector. Thermal *DHW* appliances are replaced with heat pumps.

Scenario #4. Total electrification of the residential sector. Criteria applied in Scenarios#1, #2, and #3 are used jointly.

Heat pumps are selected to replace thermal appliances [68, 69] as a key-role technology for deep decarbonisation paths in the residential sector, besides allowing to fulfil energy needs for both heating and cooling [70]. Moreover, taking into account scenario#4, the investment on a unique heat pump system for both heating and *DHW* systems could be convenient, also considering the benefit from an integrated cooling system, thus enabling a single system aimed at home comfort improvement. The procedure used to define the criteria for heat pump system selection is kept unchanged from the former analysis performed by Besagni et al. [34]. Each scenario is then further analysed with and without household budget constraints:

Scenario i). Without household budget constraints. Scenarios#1, #2, #3, and #4 are investigated as the reference analyses [34], improved with the carryover coefficient and economic sub-models; appliances are replaced only based on the thermal primary energy consumption, not considering household financial resources.

Scenario ii). With household budget constraints. Scenarios#1, #2, #3, and #4 are investigated considering household financial resources. All assumptions from scenario i) are kept constant, and the criteria displayed in Figure 7 and discussed in the following are added to consider the economic capability of households.

As far as scenario (ii) is considered, based on the input data, the following variables are chosen to define the household budget:

(1) Current economic resources:
   i. Excellent
   ii. Adequate
   iii. Scarce
   iv. Insufficient

(2) Economic resources variation:
   i. Greatly improved
   ii. Slightly improved
   iii. Almost constant
   iv. Slightly worsened
   v. Greatly worsened

(3) Absolute poverty:
   i. Yes
   ii. No

Combining these variables can characterise financial resources available for each family, as displayed in Figure 7, where households are clustered in order of economic capability. Such procedure allows us to consider, in the decarbonisation pathway, first households who most likely have an energy-related budget to grant appliances substitution and gradually involve households who presumably need economic support. Moreover, families in absolute poverty (accounting for 6.4% of families in Italy in 2019 [71]) are entirely not involved in the process. In this way, the electrification process is subdivided into a blockchain in which each cluster represents a specific condition related to the combination of variables (1) and (2). Within each cluster, households are ordered based on the amount of thermal primary energy consumption to be replaced, following the same conditions as scenario i). The carryover coefficients sub-model is then exploited to set the analysis over a 20-years' time horizon, from 2021 to 2040, to evaluate long-term goals to Climate neutral Europe as presented in the European Green Deal [72].

Conversely, economic sub-model is utilised to estimate appliances substitution costs incurred by households. Thanks to MOIRAE's bottom-up perspective, each cluster can be singled out and further investigated under the economic and socio-demographic point of view to strengthen the residential sector (i.e., energy-related incentives). For each scenario taken into account, once total primary electrical energy consumed by electrical appliances replacing thermal appliances is defined, it is assumed linear electrification of the residential sector (i.e., 5% of $PE_{el_{new}}$ every year from 2021 to 2040); all assumptions and constraints, except for economic ones, are kept unchanged among different scenarios.

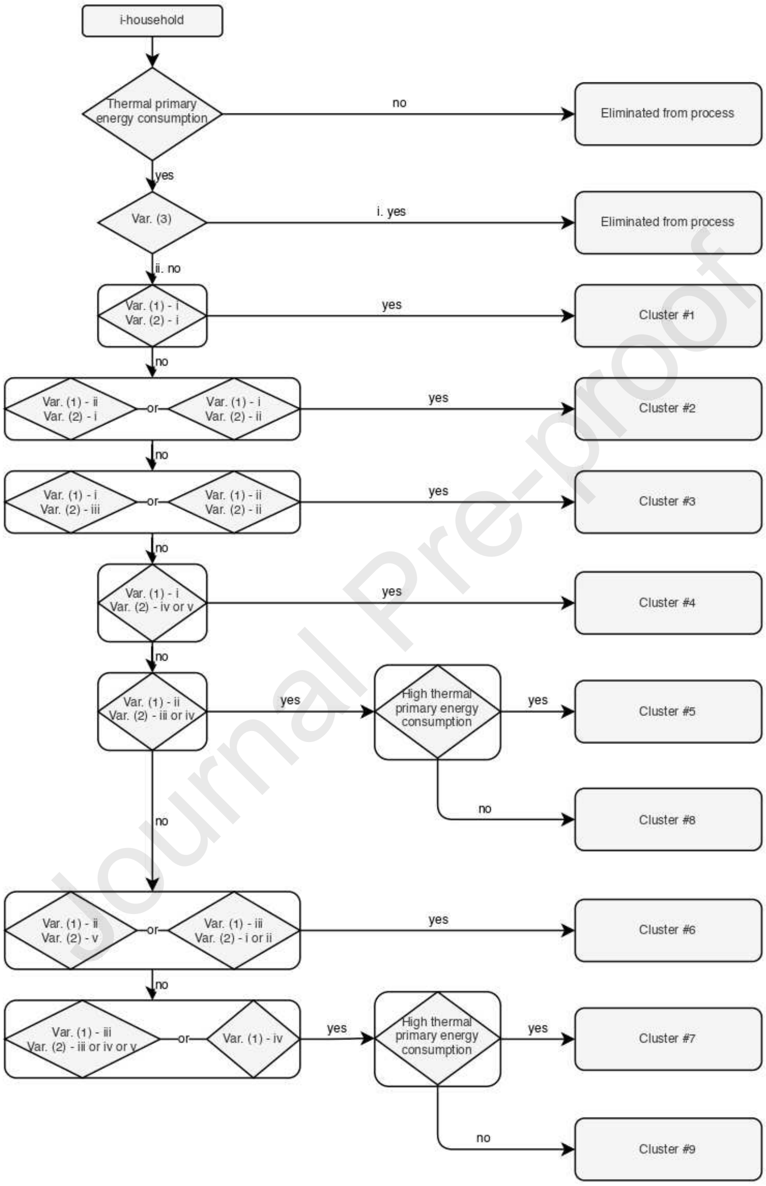


Figure 7: **Electrification pathways: blockchain process for household budget constrains selection.**

4.2.2 Results and discussions

The results of the above-described analyses are displayed in Table 3 and Figures 8-15. Table 3 shows the values of total primary energy consumption forecasted for all scenarios considered, and their variation as per cent concerning "base" case scenario, where no substitution occurs. Figures 8-15 show the electrification pathways: Figures 8, 10, 12, and 14 show total primary energy evolution and electrification-related costs as a function of the year, from the year 2021, represented by a vertical grey line; conversely, Figures 9, 11, 13 and 15 show the geographical dimension of replaced electrical primary energy in the years [2021-2025] (sub-script a), [2026-2030] (b), [2031-2035] (c) and [2036-2040] (d). The indexes i) and ii) refer to the scenario mentioned above i) and ii), in which household budget constraints presence is compared. Supplementary material S.4 lists the costs needed to sustain the electrification process in terms of investment costs for purchasing appliances, operational electricity costs for new appliances and fuel variable costs for thermal appliances gradually replaced; that is, only expenses related to involved appliances are taken into account. For the sake of clarity, further analyses characterising households' socio-demographic features and the corresponding details on technologies are presented in Supplementary material S.5 and S.6, respectively. While analysing the results, it is important to recall two main assumptions in the energy consumption forecasts: (1) the evolution of appliances technologies is not taken into account; (2) electricity is taken from the national grid. The first assumption is related to the fact that the input dataset referred to the year 2013 is kept as a basis to define technologies and population behaviour; thus, factors such as energy efficiency improvements (for appliances substitution other than the ones analysed in the scenarios) or decline (for appliances ageing), changes in energy-related behaviour of the population, or purchasing of new appliances, are not considered. The second assumption is related to *MOIRAE* primary energy methodology (see Eq.(1) in ref. [34]); indeed, the electrical energy to primary energy consumption conversion factor is set to 2.42, as an indicator of the actual national energy mix for electricity production.

Moreover, the linear electrification assumption (5% of total electrical primary energy added per year) results in a general linearisation of the variable cost curves. Indeed, fuel and electricity costs are proportional to thermal and electrical energy consumptions. Conversely, fixed prices for purchasing new appliances (and installation/distribution-related costs) are related to a thermal appliance to be substituted (as an indicator of the type of technology required to meet household energy needs).

It is observed that the electrification for the cooking service (Figure 8-9) leads to a cumulated increase of 1.2% of total primary energy consumption (+0.46 Mtoe) under the assumptions mentioned above, for both scenarios i) and ii), concerning the base-case scenario. The families involved in the process are located mainly in Lombardy, Lazio, and Veneto, due to their high population density. For total electrification, the fixed costs related to the substitution of appliances amount to 16.20 and 16.32 billion€, with an average price per year of 0.81 and 0.82 billion€ for scenario i) and ii), respectively. The main difference is noted between years 2029 and 2030 (Figure 8), due to the shift of families involved from previously-defined cluster#6 to cluster#7, meaning that, in case scenario ii), from the year 2030, the families affected are more likely not to have the financial resources to bear the appliances substitution; this observation can be applied for all below-described scenarios, as it is linked to the methodology adopted for ordering the household involved in the scenario ii) process. Moreover, scenario ii) presents a noteworthy geographic distinction from the scenario i), applying to a greater extent to the Emilia-Romagna region from 2021 to 2025 (Figure 9.a) and Lombardy from 2026 to 2030 (Figure 9.b), suggesting a broader financial availability of the households in these areas. Considering the number of households involved (nearly the total number of Italian households) which should bear the costs of such a scenario, and considering the impact on total primary energy consumption, intrinsically related to carbon-based emissions, the electrification of the cooking service should not be regarded as the only (or the prevailing) pathway to be pursued. This outcome agrees with Lombardi et al. [73], who proposed an analysis of the same sector's electrification and confirming the need for a synergic effect between electrification strategies and higher penetration of VRES in the energy system. The injection of biofuels directly in the natural gas national grid could be more affordable and practical for this sector [74, 75].

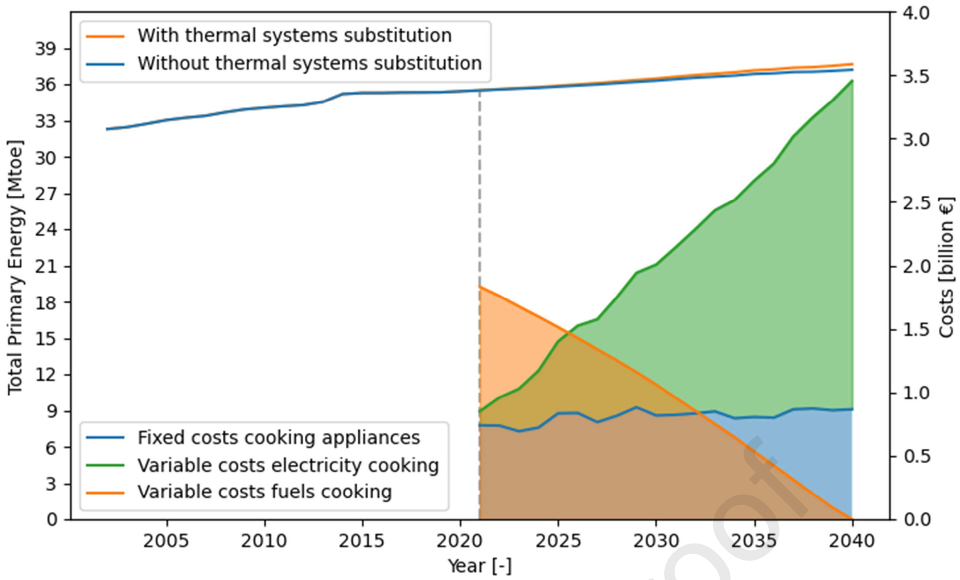
Regarding the heating service substitution, shown in Figure 10-11, it is noted a relevant primary energy consumption saving of 7.81 Mtoe (-21.0% concerning base-case scenario), even with the above-mentioned limiting assumptions, thus suggesting the deployment of heating pumps is valid and effective. The households bearing the substitution of these systems are mainly located in the northern part of Italy, in particular Lombardy, Veneto, and Emilia-Romagna, mostly due to the related climatic zone and elevated population density. The Sardinia region does not have a methane grid and already has a high distribution of systems employing electricity and biomass. Hence this region is involved only in the latter years of the electrification process, with a contribution of only about 0.8% of total primary energy replaced. For the process, an average of 1.48 and 1.52 billion€ per year is needed, with a total amount of 26.68 and 30.39 billion€ for the entire heating appliances substitution in the scenario i) and ii), respectively. In the years 2026-2030, there's a more significant contribution of Lombardy and Veneto in scenario ii) (Figure 11.b), suggesting more considerable financial resources in these areas concerning Emilia-Romagna. Central and southern regions display less contribution to total electrification due to climatic and building properties, as discussed by Ballarini et al. [76]. In this context, a wider penetration and local exploitation of renewable energies could contribute beneficially to ensure deep decarbonisation; as stated by Neirotti et al. [68], higher deployment of power generation low-carbon sources leads to both lower primary energy consumption and carbon-based emissions. Nevertheless, the heating system's electrification is expected to alter the daily load curves, suggesting a technical assessment of the electricity grid is needed [77, 78].

Electrification scenario#3 (Figure 12-13) demonstrates a lesser effective deployment of heat pumps for DHW service. Indeed, it is noted a total primary energy consumption increase of 1.1% concerning the base-case scenario (+0.43

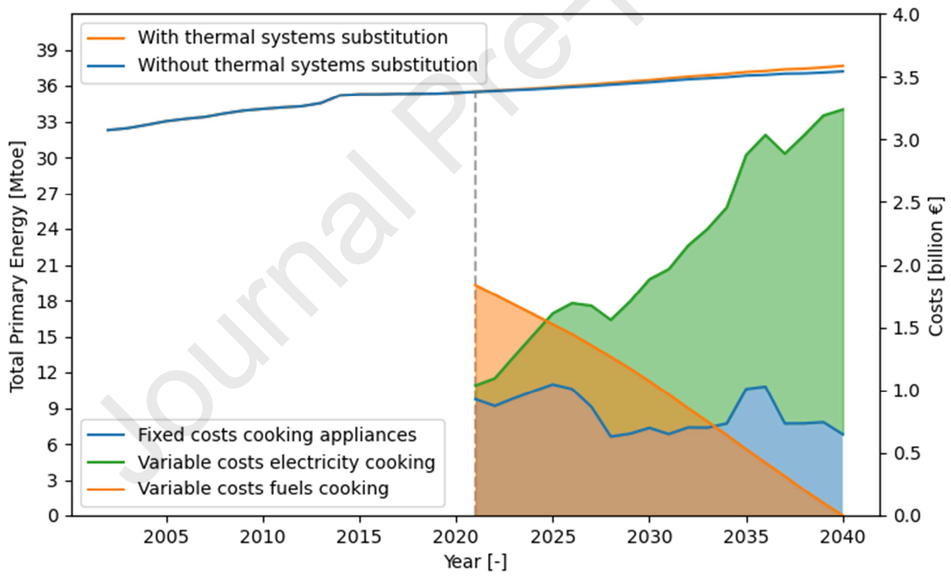
Mtoe). The families involved in the process are mainly located in Lombardy, Veneto, and Emilia-Romagna regions, with a higher contribution from Veneto. For total electrification, the fixed costs related to appliances substitution amount to 27.22 and 27.15 billion€, for scenario i) and ii), respectively, with an average cost per year of 1.36 billion€ for both. Similarly to the cooking service substitution, from 2029 to 2031, scenario ii) deviates from scenario i) due to households' involvement represented by cluster#7 (Figure 12).

Moreover, scenario ii) shows an earlier involvement of the Veneto region in the process (Figure 13.b), suggesting a broader financial availability for the households in this area combined with the more general usage of thermal-based DHW systems. A more evident advantage for decarbonisation purposes could be highlighted by coupling DHW heat pump to solar power generation systems [79, 80] or in integration with district heating [81]. Once again, it is stressed the importance of VRES power generation associated with end-user services electrification.

Regarding the complete electrification of the residential sector (Figure 14-15), all the advantages and disadvantages mentioned above are combined with a significant heating sector contribution. Indeed, it is noted a total primary energy saving of 6.92 Mtoe (-18.6% concerning base-case scenario), as a result of the minor increase due to cooking and DHW services (+0.89 Mtoe). Similarly to the heating service substitution, Lombardy, Emilia-Romagna, and Veneto regions are the most involved in the process in the earlier years (Figure 15.a-b). Total fixed costs for scenario i) and ii) amount to 83.10 and 83.41 billion€, respectively, with an average per year of 4.16 and 4.17 billion€, similarly to the estimated values by Vellini et al. [22] (ranging from 2 to 10 billion €/year depending on the different scenarios considered). In 2026-2030, Lombardy and Veneto contribute a more significant amount to total electrical primary energy added under the household budget constraints scenario, as a combination of scenarios #1, #2, and #3 observations. End-use services electrification costs are expected to be 9.73 and 9.41 billion€ in 2030 for scenario#4.i) and #4.ii), respectively, correspondent to around 27-28 billion€ of possible domestic value creation, comparable with the value calculated by Prina et al. [28] (approximately 34.8 billion€/year for PNIEC scenario), stating fuel costs decrease, although these costs should also be addressed to all energy efficiency related improvements (e.g., building, mobility, ..).

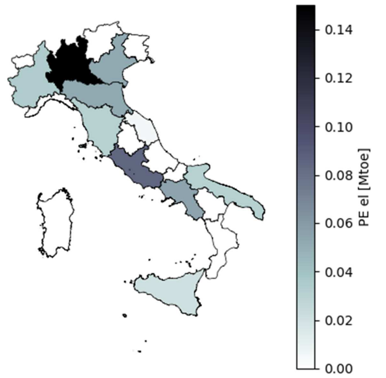


i) Electrification pathway for the cooking service without household budget constraints

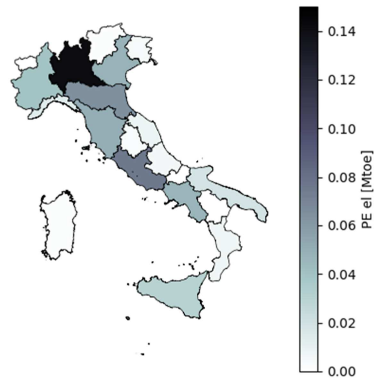


ii) Electrification pathway for the cooking service under household budget constraints

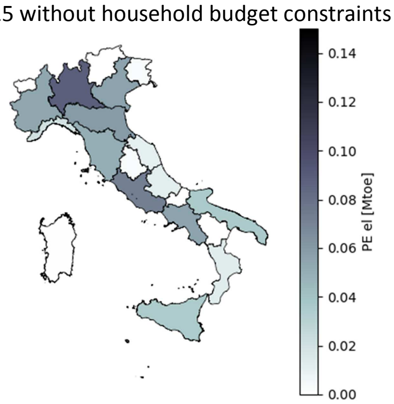
Figure 8: Scenario #1: electrification of the cooking sector.



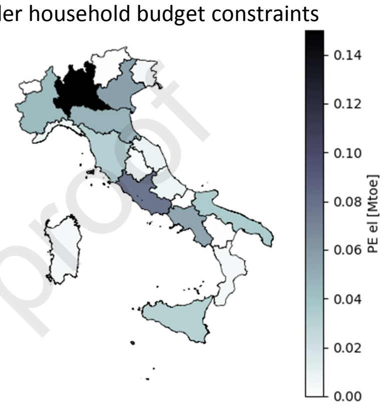
a.i) New primary energy consumption – years from 2021 to 2025 without household budget constraints



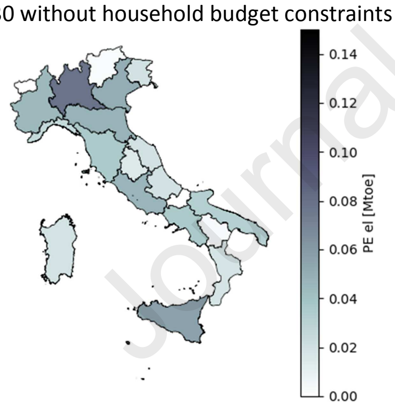
a.ii) New primary energy consumption – years from 2021 to 2025 under household budget constraints



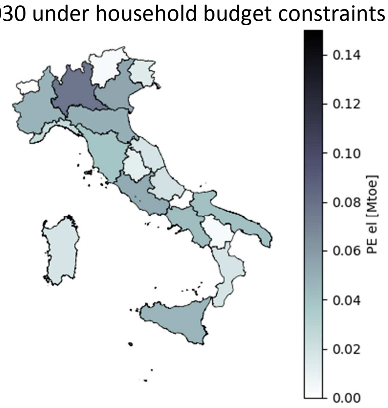
b.i) New primary energy consumption – years from 2026 to 2030 without household budget constraints



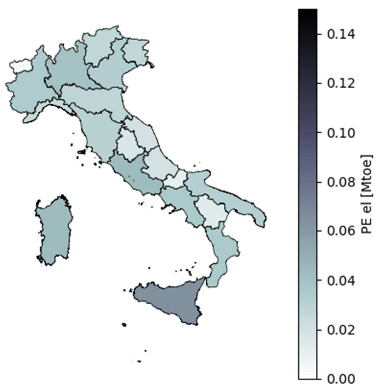
b.ii) New primary energy consumption – years from 2026 to 2030 under household budget constraints



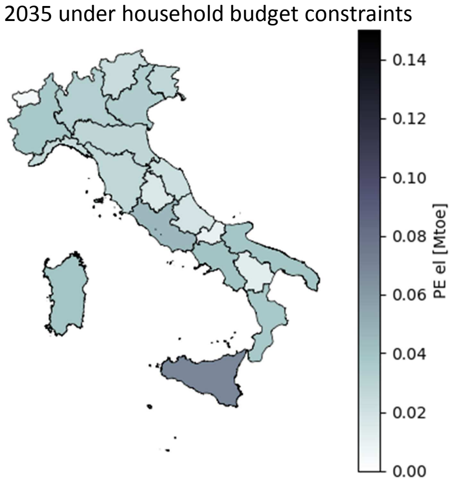
c.i) New primary energy consumption – years from 2031 to 2035 without household budget constraints



c.ii) New primary energy consumption – years from 2031 to 2035 under household budget constraints

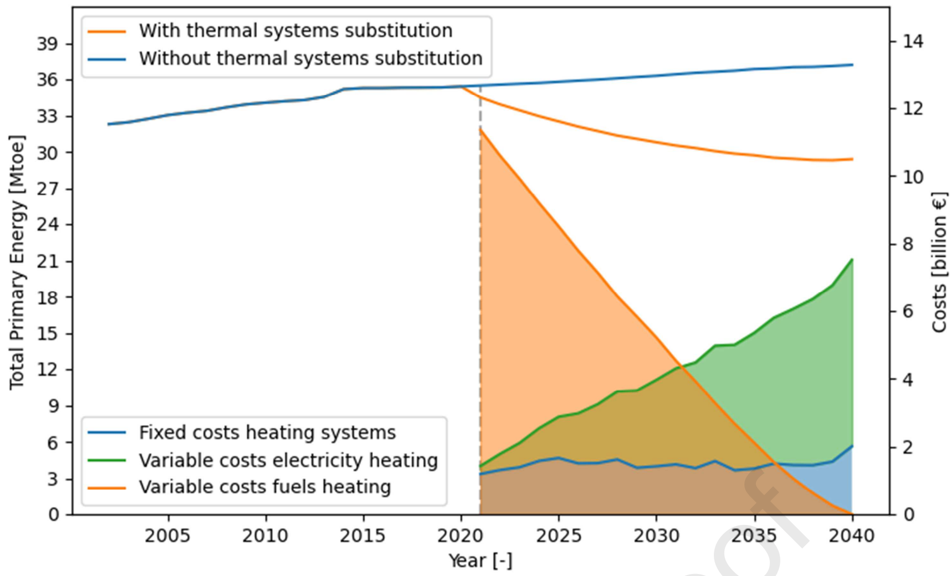


d.i) New primary energy consumption – years from 2036 to 2040 without household budget constraints

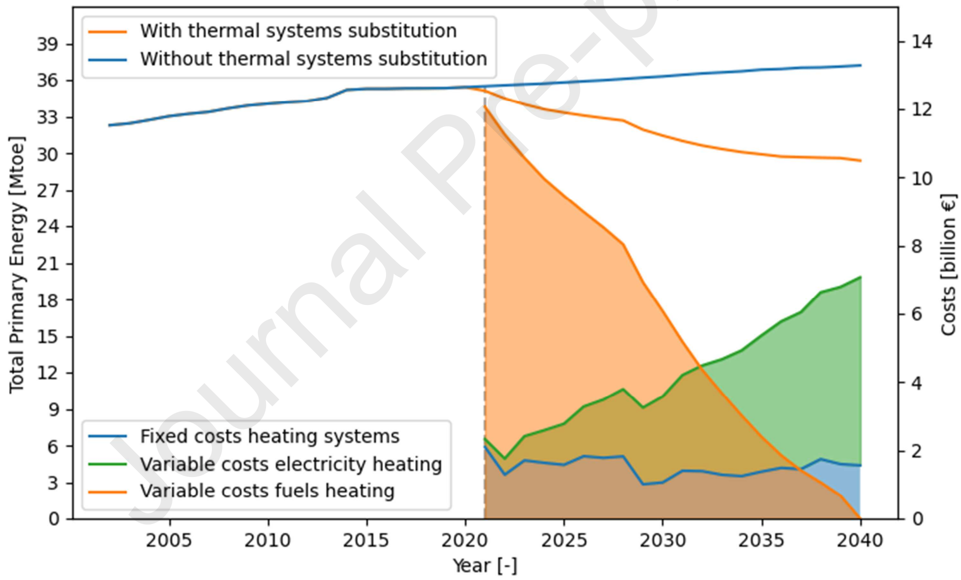


d.ii) New primary energy consumption – years from 2036 to 2040 under household budget constraints

Figure 9: Scenario #1: electrification of the cooking sector: geographic dimension.

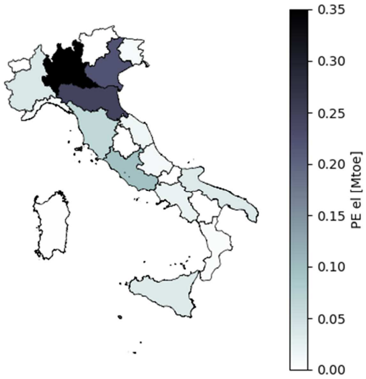


i) Electrification pathway for the heating service without household budget constraints

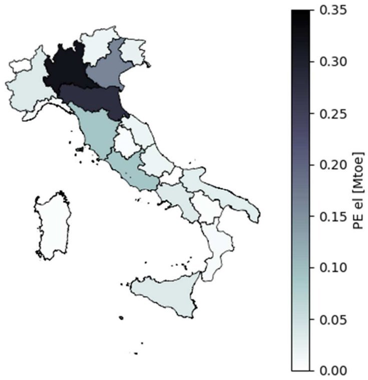


ii) Electrification pathway for the heating service under household budget constraints

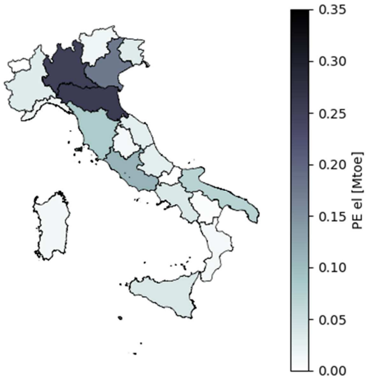
Figure 10: Scenario #2: electrification of the heating sector.



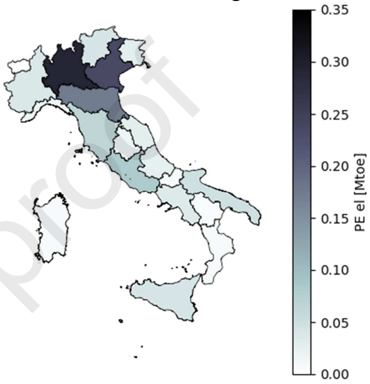
a.i) New primary energy consumption – years from 2021 to 2025 without household budget constraints



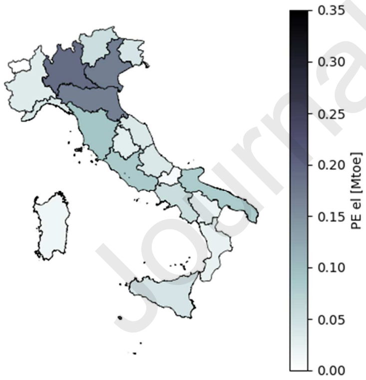
a.ii) New primary energy consumption – years from 2021 to 2025 under household budget constraints



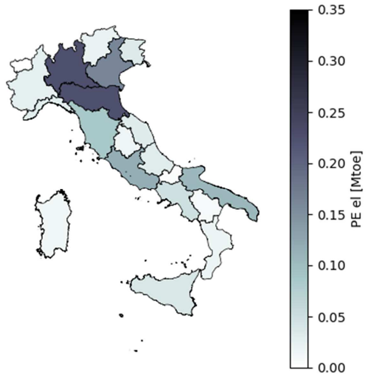
b.i) New primary energy consumption – years from 2026 to 2030 without household budget constraints



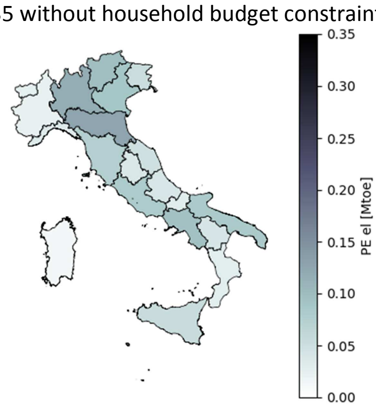
b.ii) New primary energy consumption – years from 2026 to 2030 under household budget constraints



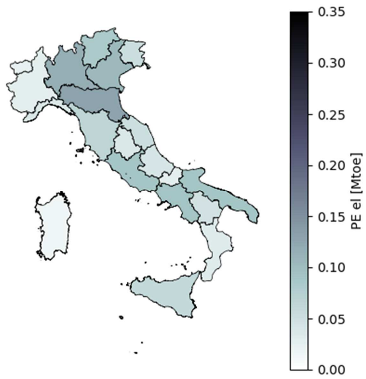
c.i) New primary energy consumption – years from 2031 to 2035 without household budget constraints



c.ii) New primary energy consumption – years from 2031 to 2035 under household budget constraints

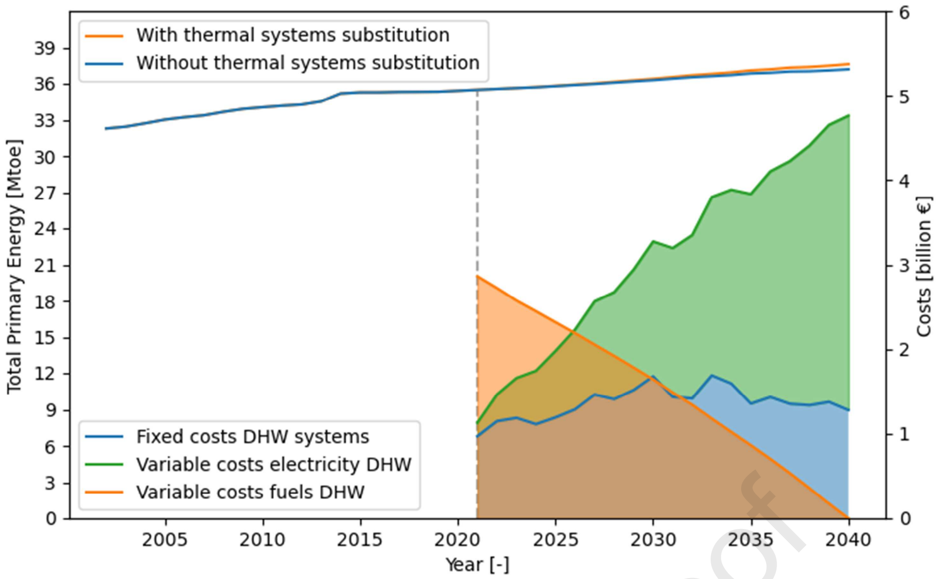


d.i) New primary energy consumption – years from 2036 to 2040 without household budget constraints

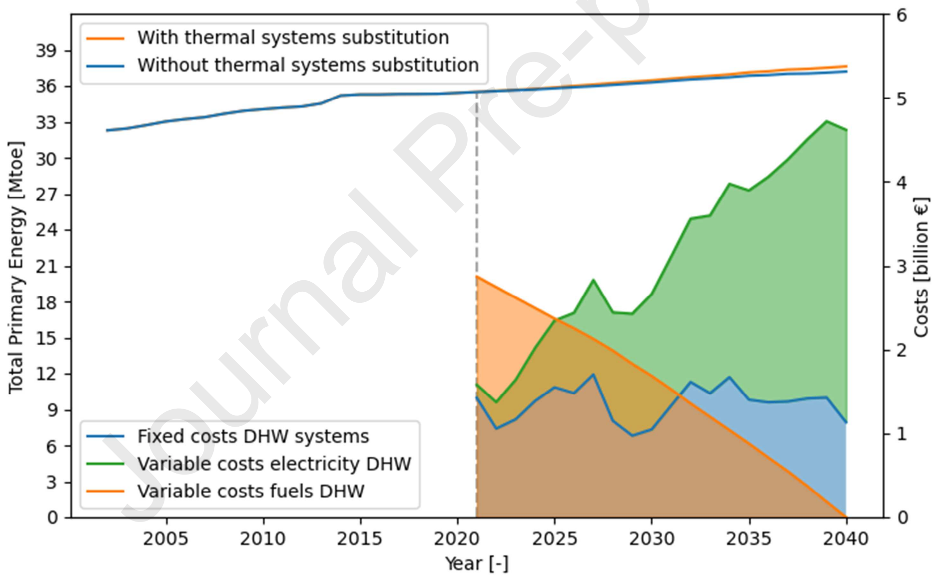


d.ii) New primary energy consumption – years from 2036 to 2040 under household budget constraints

Figure 11: Scenario #2: electrification of the heating sector: geographic dimension.

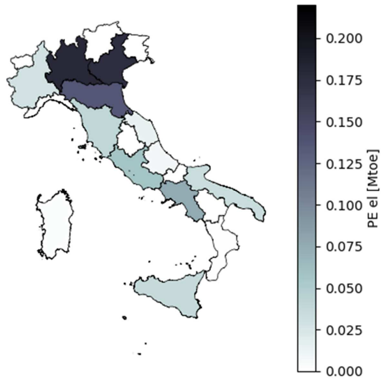


i) Electrification pathway for the DHW service without household budget constraints

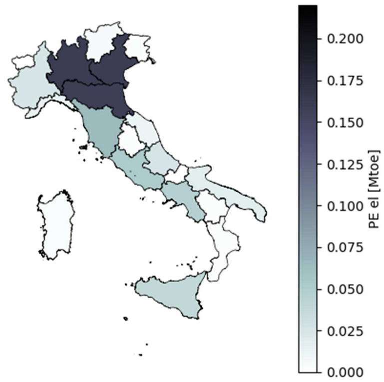


ii) Electrification pathway for the DHW service under household budget constraints

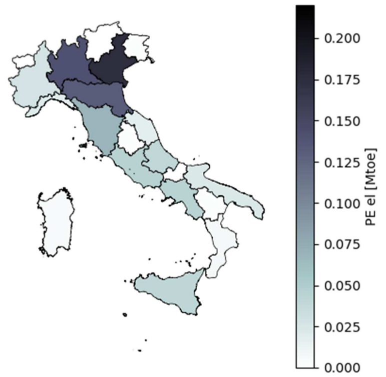
Figure 12: Scenario #3: electrification of the DHW sector.



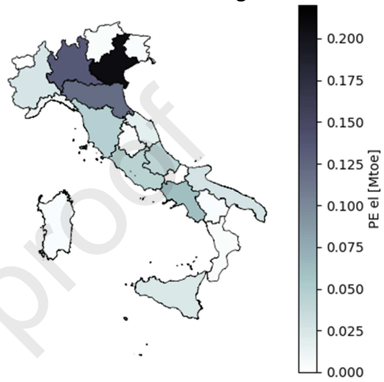
a.i) New primary energy consumption – years from 2021 to 2025 without household budget constraints



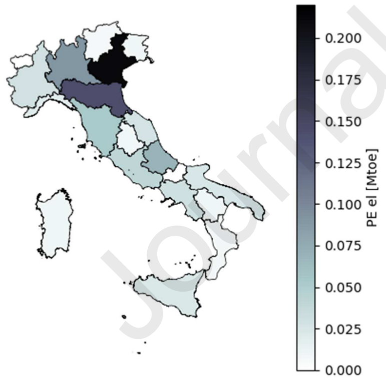
a.ii) New primary energy consumption – years from 2021 to 2025 under household budget constraints



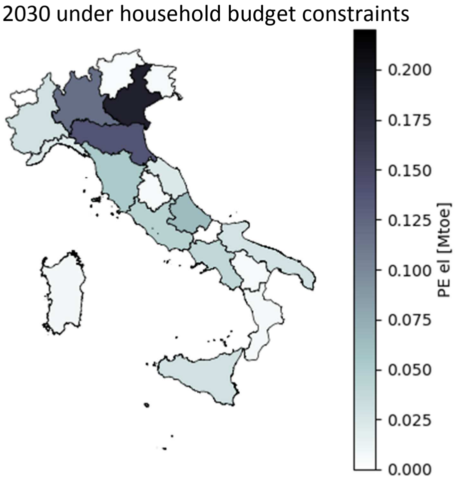
b.i) New primary energy consumption – years from 2026 to 2030 without household budget constraints



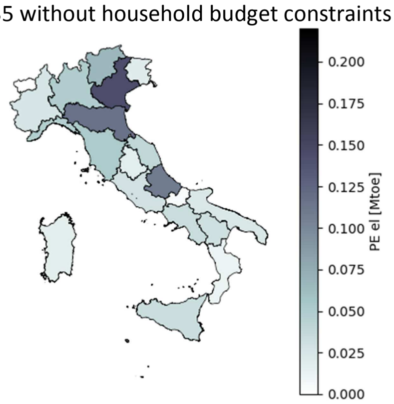
b.ii) New primary energy consumption – years from 2026 to 2030 under household budget constraints



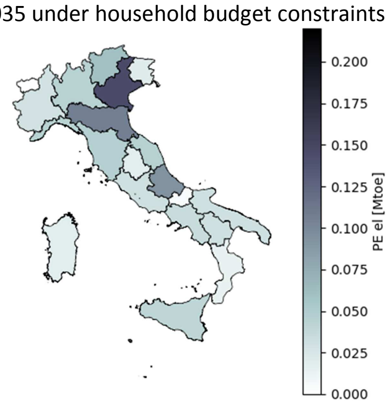
c.i) New primary energy consumption – years from 2031 to 2035 without household budget constraints



c.ii) New primary energy consumption – years from 2031 to 2035 under household budget constraints

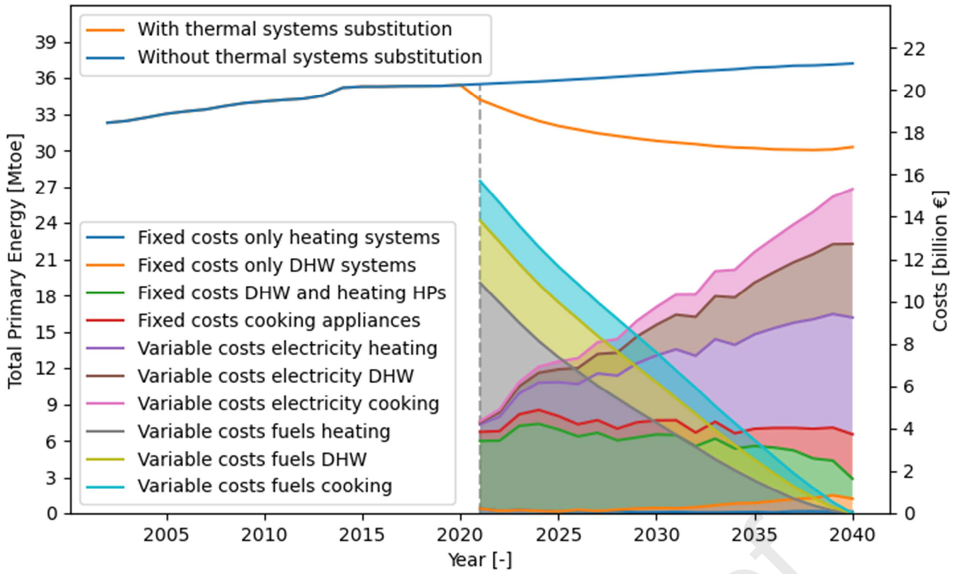


d.i) New primary energy consumption – years from 2036 to 2040 without household budget constraints

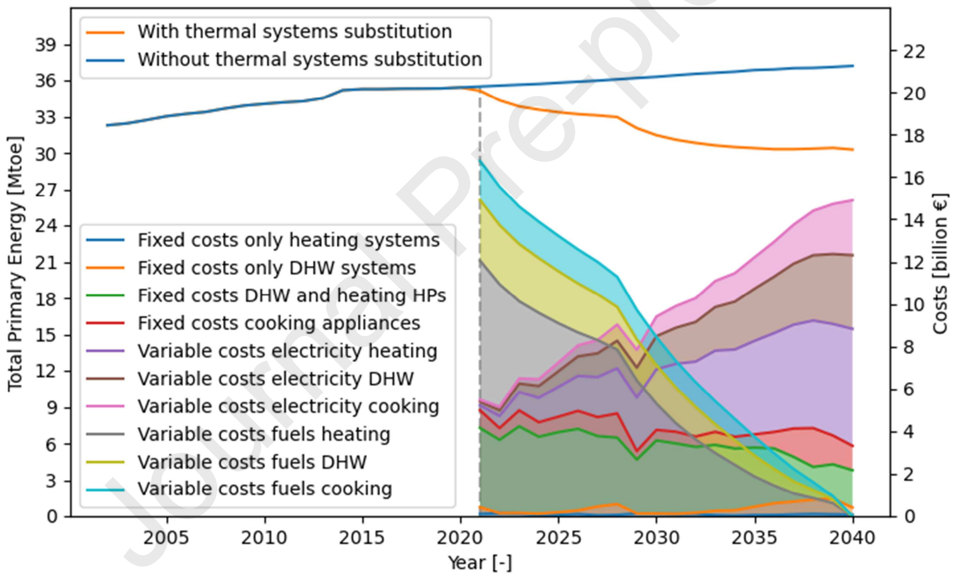


d.ii) New primary energy consumption – years from 2036 to 2040 under household budget constraints

Figure 13: Scenario #3: electrification of the DHW sector: geographic dimension.

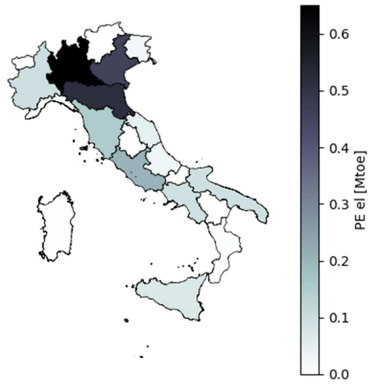


i) Electrification pathway for all services without household budget constraints

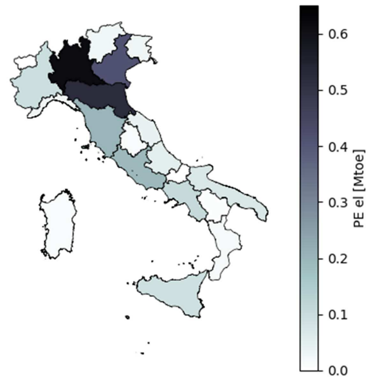


ii) Electrification pathway for all services under household budget constraints

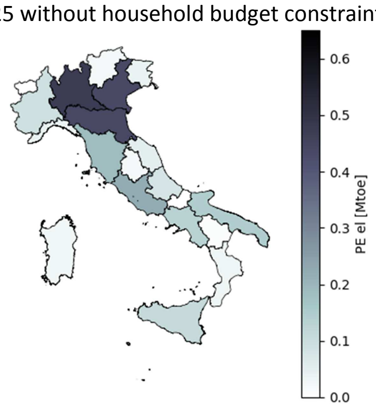
Figure 14: Scenario #4: electrification of the residential sector.



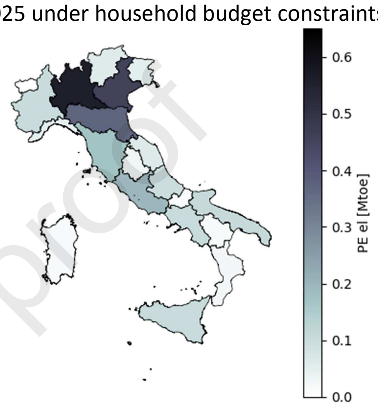
a.i) New primary energy consumption – years from 2021 to 2025 without household budget constraints



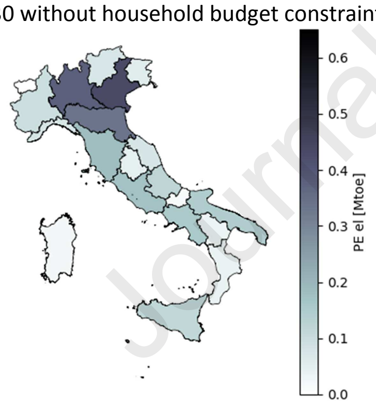
a.ii) New primary energy consumption – years from 2021 to 2025 under household budget constraints



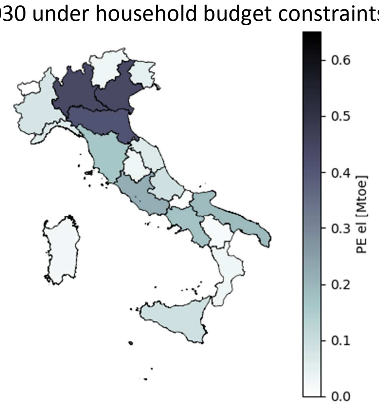
b.i) New primary energy consumption – years from 2026 to 2030 without household budget constraints



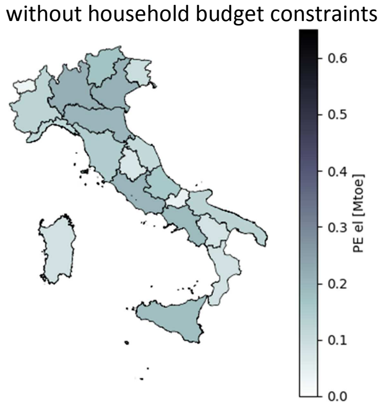
b.ii) New primary energy consumption – years from 2026 to 2030 under household budget constraints



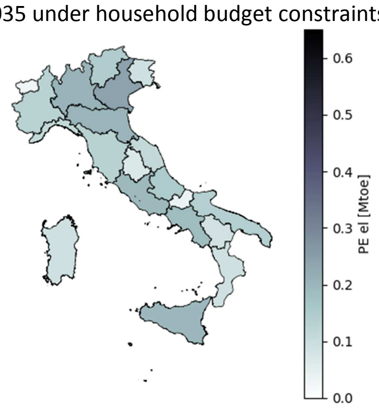
c.i) New primary energy consumption – years from 2031 to 2035 without household budget constraints



c.ii) New primary energy consumption – years from 2031 to 2035 under household budget constraints



d.i) New primary energy consumption – years from 2036 to 2040 without household budget constraints



d.ii) New primary energy consumption – years from 2036 to 2040 under household budget constraints

Figure 15: Scenario #4: electrification of the residential sector: geographic dimension.

Table 3. Total primary energy values [Mtoe] for replacing thermal technologies (cooking, heating, and DHW).

	Year	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
Base	$PE_{tot_{base}}$	35.49	35.56	35.64	35.70	35.80	35.89	35.98	36.09	36.19	36.29	36.42	36.54	36.62	36.71	36.85	36.90	37.01	37.03	37.10	37.19
Scenario #1.i)	$PE_{tot_{\#1.i}}$	35.50	35.59	35.68	35.76	35.87	35.99	36.09	36.22	36.34	36.46	36.61	36.75	36.86	36.98	37.14	37.22	37.36	37.41	37.51	37.65
	% var	0.0%	0.1%	0.1%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.5%	0.5%	0.6%	0.7%	0.7%	0.8%	0.9%	1.0%	1.0%	1.1%	1.2%
Scenario #1.ii)	$PE_{tot_{\#1.ii}}$	35.51	35.59	35.68	35.77	35.88	36.00	36.10	36.23	36.35	36.47	36.61	36.75	36.86	36.98	37.14	37.22	37.36	37.42	37.52	37.65
	% var	0.0%	0.1%	0.1%	0.2%	0.2%	0.3%	0.3%	0.4%	0.4%	0.5%	0.5%	0.6%	0.7%	0.7%	0.8%	0.9%	1.0%	1.0%	1.1%	1.2%
Scenario #2.i)	$PE_{tot_{\#2.i}}$	34.48	33.90	33.41	32.92	32.50	32.06	31.70	31.33	31.05	30.77	30.50	30.30	30.04	29.84	29.70	29.50	29.42	29.32	29.29	29.38
	% var	-2.8%	-4.7%	-6.2%	-7.8%	-9.2%	-10.7%	-11.9%	-13.2%	-14.2%	-15.2%	-16.2%	-17.1%	-18.0%	-18.7%	-19.4%	-20.0%	-20.5%	-20.8%	-21.0%	-21.0%
Scenario #2.ii)	$PE_{tot_{\#2.ii}}$	35.11	34.48	33.99	33.59	33.31	33.07	32.86	32.65	31.91	31.42	30.99	30.61	30.33	30.08	29.90	29.71	29.66	29.62	29.58	29.38
	% var	-1.1%	-3.0%	-4.6%	-5.9%	-6.9%	-7.9%	-8.7%	-9.5%	-11.8%	-13.4%	-14.9%	-16.2%	-17.2%	-18.1%	-18.9%	-19.5%	-19.8%	-20.0%	-20.3%	-21.0%
Scenario #3.i)	$PE_{tot_{\#3.i}}$	35.50	35.57	35.64	35.72	35.82	35.93	36.03	36.15	36.28	36.40	36.54	36.69	36.80	36.93	37.09	37.19	37.33	37.38	37.49	37.62
	% var	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.2%	0.3%	0.3%	0.4%	0.5%	0.6%	0.7%	0.8%	0.9%	1.0%	1.0%	1.1%
Scenario #3.ii)	$PE_{tot_{\#3.ii}}$	35.50	35.59	35.67	35.76	35.87	35.99	36.11	36.24	36.34	36.45	36.59	36.72	36.83	36.95	37.12	37.21	37.35	37.41	37.51	37.62
	% var	0.0%	0.1%	0.1%	0.1%	0.2%	0.3%	0.4%	0.4%	0.4%	0.4%	0.5%	0.5%	0.6%	0.6%	0.7%	0.8%	0.9%	1.0%	1.1%	1.1%
Scenario #4.i)	$PE_{tot_{\#4.i}}$	34.17	33.54	32.94	32.42	32.01	31.71	31.40	31.18	30.97	30.78	30.64	30.51	30.34	30.24	30.18	30.08	30.05	30.03	30.07	30.27
	% var	-3.7%	-5.7%	-7.6%	-9.2%	-10.6%	-11.7%	-12.7%	-13.6%	-14.4%	-15.2%	-15.9%	-16.5%	-17.2%	-17.6%	-18.1%	-18.5%	-18.8%	-18.9%	-18.9%	-18.6%
Scenario #4.ii)	$PE_{tot_{\#4.ii}}$	35.14	34.34	33.83	33.56	33.35	33.19	33.09	32.95	32.04	31.45	31.08	30.82	30.61	30.48	30.39	30.30	30.30	30.34	30.41	30.27
	% var	-1.0%	-3.4%	-5.1%	-6.0%	-6.8%	-7.5%	-8.0%	-8.7%	-11.5%	-13.3%	-14.7%	-15.7%	-16.4%	-17.0%	-17.5%	-17.9%	-18.1%	-18.1%	-18.0%	-18.6%

5 Conclusions

This paper includes time-variant and economic analysis into the *MOIRAE* model developed by Besagni et al. [34], to study the effects of socio-demographic and economic factors on energy consumption forecast. As the model time perspective has been enlarged, additional data were used to calibrate the model, leading to performance improvements. By comparing the energy consumption computed by the model with historical data, the results obtained are variable: if for some energy sources estimation is reasonably good, for others there is a significant difference between the trends of measurements and balances, that can be explained by changes in the efficiency and diffusion of particular technologies, not implemented in the current version of the model. As such, further work on *MOIRAE* is needed to implement these factors into the computations. Nonetheless, the economic input data provided in supplementary material S.3 may be a valuable resource for other researchers interested in residential sector modelling; in this context, the proposed methodology can be applied to other countries following the observations identified in section 2.5. Indeed, the calculation procedures described in this paper can be applied to other countries and for different objectives (e.g. the definition of RES penetration or the employment of different domestic technologies), where micro-data on households are available. Forecasts for energy consumption are disaggregated for different demographics to study their evolution during the years: it has been observed an increase in household energy consumption in the northern and central part of the country, while the South shows no significant changes; also, elders are expected to be responsible for a considerable increase in energy consumption, while the other age classes are forecasted to decrease it gradually. This is in line with many other works mentioned in the paper's introduction, which link older people to higher energy consumption levels and highlight the impact that this can have in countries, like Italy, with a rapidly ageing population. Finally, the analysis is extended to the evaluation of decarbonisation pathways, implementing a supplementary economic sub-model. It has been observed a significant possible primary energy saving due to the heating sector, estimated at around -7.81 Mtoe (-21.0% of total primary energy in reference scenario), achievable with a total investment (fixed) costs of 30.4 billion€, equal to 1.5 billion€/year until 2040.

Conversely, *DHW* and cooking sectors electrification lead to an increase of +0.43 Mtoe (+1.1%) and +0.46 Mtoe (+1.2%), respectively, with stated assumptions, suggesting renewable energy penetration and distributed power generation is needed to make the electrification of these sectors advantageous, particularly considering investment costs related (27.2 billion€, 1.4 billion€/year for DHW and 16.3 billion€, 0.8 billion€/year for cooking services). As a final result, considering the possible primary energy saving of -6.92 Mtoe (-18.6%) and investment costs (83.1 billion€, 4.2 billion€/year) for the electrification of all residential sector, compared to previous results and stated assumptions, focused electrification on only heating service may be more efficient in an optimal cost-benefit scope. This modelling approach makes *MOIRAE* a powerful tool to investigate the impact of household layers electrification, allowing a bottom-up perspective on decision-making policies.

Nevertheless, further development of MOIRAE is required to broaden its perspective further:

- technological projections, such as energy efficiency variations, different technologies market distribution, heating/cooling periods variations due to climate change [82], should be taken into account to accurately estimate primary energy consumption forecast in a scenario analysis [52];
- geographic Information System can be integrated to support the geographical dimension of the analysis, to support infrastructure planning as well as the assessment of demand-side [83, 84];
- energy-related behavioural changes in households should be integrated into the socio-demographic perspective, to investigate the effects on primary energy consumption [53, 54] ;
- the ISTAT micro-data employed can be exploited to model the whole household sector, including the transport sector; indeed, a broader application of MOIRAE may be integrated to analyse the energy flows in a cross-sectoral perspective;
- MOIRAE can be applied to other countries and integrated to existing models; for instance, a hybrid approach (bottom-up and top-down approach integration) may be implemented to tackle both end-use demand side (at bottom" layer) and macro-economic or market-level factors (at "top" layer), e.g. through soft-linking [73, 85, 86];
- energy efficiency strategies, including top-bottom policies, should be considered to improve the economic-based scenario and to evaluate the outcome of energy investment decisions [87-89].

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Highlights

1. Time variable and economic evaluations are included within MOIRAE
2. the model is calibrated with regionalized data
3. the model is validated considering global perspectives in different years
4. electrification pathways of the Italian residential sector are discussed
5. the economical burden of decarbonization pathways is discussed

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: