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Future electricity demand for Europe: Unraveling the dynamics of the Temperature Response Function

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ABSTRACT

Electricity demand is a crucial factor in energy system planning. Understanding future electricity demand is vital for developing effective energy and climate policies, as well as establishing a resilient and sustainable energy system. In light of these considerations, the escalating challenges posed by climate change are anticipated to have a substantial impact on electricity demand. This study, therefore, provides a comprehensive analysis delving into the dynamic nature of Temperature Response Functions (TRFs) of electricity demand across Europe. By examining various factors influencing electricity demand in residential buildings, such as thermal insulation, heating electrification, space cooling, and passive cooling, we aim to understand their collective impact on shaping future Temperature Response Functions. To project electricity demand, our study incorporates these factors into our scenario assumptions. Through a comprehensive investigation of these scenarios, our findings reveal distinctive regional influences of these factors. In regions where heating demand prevails, an initial increase in electricity demand is anticipated due to increased electrification rates. However, improved building thermal insulation is expected to substantially reduce winter electricity demand in the long run. Conversely, in regions with pronounced cooling demand, a notable escalation in electricity demand is foreseen due to increased space cooling penetration rate. Nevertheless, the application of effective passive cooling measurements is expected to mitigate and markedly diminish this increase. By highlighting the differential influences of these factors on electricity demand across Europe, our findings can offer valuable insights and guidelines first for energy system modelers for considering the change in Temperature Response Functions and second for policymakers to develop effective climate change adaptation and mitigation strategies.

1. Introduction

Electricity demand has a significant impact on climate change, primarily due to the substantial greenhouse gas emissions from electricity generated to meet the demand. However, the relationship between electricity demand and climate change is reciprocal, as shifts in climate also impact the need for heating and cooling. Many countries have implemented policies to adapt and mitigate this impact. For instance, Europe introduced the Energy Performance of Buildings Directive (EPBD) in 2002 [1], aimed at enhancing energy efficiency within the European Union's building sector. Such regulations and actions play a pivotal role in influencing electricity demand, offering a promising pathway to avoid a vicious cycle and protect the population from discomforting conditions. Given the growing challenges of climate change, a thorough investigation of varying policy interventions' effects on future electricity demand becomes imperative. Such investigations can provide valuable information for future energy system planning, improve the efficiency of electricity system management, optimize electricity network planning, analyze the effects of extreme weather events on energy systems, and assist policymakers in designing and implementing effective climate change mitigation and adaptation strategies.

Overall, electricity demand can be influenced by various factors. These factors can be broadly categorized into climatic, socio-economic, and calendrical variables. Climatic variables such as temperature [2], sunshine duration [2,3], humidity [4], precipitation [5], and wind speed [4] have been found to impact electricity demand through their effects on heating and cooling needs. Socio-economic factors also play a significant role. These include gross domestic product (GDP) [6,7], population [8,9], personal income [10], electricity prices [11], tourism [12], electrification on heating [13], space cooling [14,15], electric vehicles [16–18], the increasing demand for green hydrogen production [19,20] and so on. Furthermore, calendrical data such as

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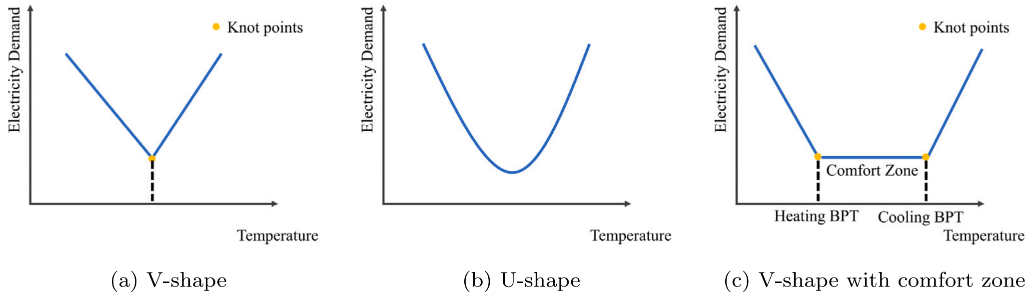


Fig. 1. Typical pattern of Temperature Response Function (TRF).

weekdays [21,22], weekends [21,22], and holidays [23] can influence electricity demand patterns. However, the interactions between demand and these various interrelated factors are complex and ambiguous [24], making it extremely challenging to investigate their impacts in a comprehensive way. As a result, researchers often focus their studies on specific factors or a limited number of factors to gain a more general understanding of their effects on electricity demand.

Among the various factors, temperature is one of the most important factors [4,25–27]. To assess the impact of temperature on electricity demand, a commonly used method is the utilization of Temperature Response Functions (TRFs). TRFs, also known as Temperature Dependence Patterns (TDPs), characterize the nonlinear relationship between temperature and electricity demand. TRFs are often portrayed in three forms across various studies. As illustrated in Fig. 1, these curves commonly manifest in a V-shaped [28,29], or a U-shaped [30,31] pattern, or in a V-shaped pattern with an intermediate comfort zone. All these curves exhibit a consistent trend. In a V-shaped curve, high electricity demand for heating purposes during the cold winter time is shown, followed by a decrease in demand as temperatures rise. Eventually, at a certain temperature, the demand begins to rise again, due to the increased use of cooling appliances during the hot summer months. This inflection temperature is commonly referred to as the Balance Point Temperature (BPT), which is widely used in determining Heating Degree Days (HDD) and Cooling Degree Days (CDD) [32,33]. In comparison, within the V-shaped pattern featuring an intermediate comfort zone, this zone indicates a temperature range where electricity demand exhibits no sensitivity to temperature fluctuations.

The utilization of TRFs stands out in exploring the long-term effects of temperature on electricity demand [34–36], particularly when compared to ‘grey-box’ models like Machine Learning and Artificial Neural Network (ANN), which are usually inadequate for capturing the underlying correlation between different variables and electricity demand. Moreover, unlike TRFs, ‘grey-box’ models are largely limited when applied to future scenarios, due to their difficulty in accurately extrapolating when faced with scenarios that differ significantly from the training data. This constraint makes them more suitable for short-term demand forecasting [5,9,37] rather than delving into the long-term implications of temperature on demand.

Previous studies have proposed various methods to determine TRFs. Typically, this involves the application of non-linear regression analysis. For example, Li et al. [38] utilized a spline function to represent the daily temperature and electricity consumption TRFs in Shanghai, China. Ihara et al. [39] employed multiple regression to analyze the temperature and electric power consumption relationships in business districts of Tokyo, Japan. Wang and Bielicki [40] used a segmented regression technique to determine the hourly temperature and electricity load TRFs for two transmission zones in the United States. Meanwhile, Moral-Carcedo and Pérez-García [41] used a logistic smooth transition regression to determine the daily temperature and electricity demand TRFs for Spain. Wang et al. [40] compared the use of multiple linear regression, adaptive linear filter algorithms, and Gaussian mixture model regression for temperature and hourly electricity consumption TRFs for two specific buildings in Chicago and Des Moines, United States. Hirutal et al. [31] utilized multivariate adaptive regression splines to determine the temperature and electricity demand TRFs at different temporal scales for 10 regions in Japan. Other related studies include [2,42–45]. These studies, which focused on particular geographical regions, and in some cases, individual buildings, can provide valuable insights into the correlation between temperature and electricity demand within specific climate zones. However, such regional foci may limit the generalizability of their findings to broader regions. This limitation arises due to the potential variation in the temperature–electricity demand relationship across various climate zones, given the substantial differences in TRFs across different countries [46].

Due to the limitations of regional studies, some researchers have conducted more comprehensive investigations in a broader geospatial extent. Bessec and Fouquan [46] employed a panel threshold regression model to investigate the nonlinear relationship between temperature and electricity demand for 15 European Union member states. By disaggregating southern and northern countries, they discovered that this nonlinear pattern varies substantially across different countries. This study underscores the need for a more expansive investigation to better understand the influence of temperature on electricity demand. However, it did not develop a sophisticated model for long-term electricity demand projections. More recent studies, such as Victhalia et al. [47], utilized integrated assessment models incorporating empirical data on typical daily and hourly demand patterns across different sectors to calculate future demand projections. Although they took different sectors, socio-economic and technological development into consideration, this study lacks an in-depth analysis of temperature influences. More importantly, the use of 18 °C as the BPT for HDD and CDD calculation for all countries until the year 2100 is biased due to varying TRFs across different countries [46], which can potentially lead to inaccurate estimations [31].

Highlighting these aspects, it becomes evident that the lack of a comprehensive investigation of TRFs on a wider geographical scale stands as a notable limitation in current research. Furthermore, a critical drawback lies in the underlying assumption that the TRFs are static. Studies employing current temperature influence models or TRFs to project electricity demand often assume stationary models and fixed TRFs across different time horizons and climate zones. This oversight disregards substantial disparities between countries and the impact of evolving policy interventions. The assumption of static TRFs may increase the risk of inaccurate estimations, posing a considerable challenge for policymakers to adapt future electricity planning. While studies such as those conducted by Hekkenberg et al. [24,48] have aimed to tackle this static nature, their efforts were restricted to a singular case study. They fell short of providing a quantitative analysis of how various social-economic factors influence the TRFs. Consequently, these studies fail to capture the intricate complexities inherent in real-world scenarios.

To comprehend the dynamics of TRFs, it is essential to examine the various factors shaping their form. TRFs depict the correlation between temperature and demand, reflecting a direct influence of temperature on demand levels. It is important to note that while temperature directly influences demand, it does not change the fundamental shape of the TRFs. Instead, the shape of the TRFs is primarily shaped by socio-economic variables [48]. However, the specific socio-economic factors shaping the TRFs and their influences are rarely discussed in existing literature. This study aims to address this gap by conducting an in-depth investigation into the factors influencing electricity demand in residential buildings with a focus on heating and cooling. By analyzing these factors, we aim to enhance our understanding of the dynamic nature of TRFs, and therefore construct future demand time series.

According to the European Commission, buildings within the EU account for 40% of the total energy consumption, representing the highest share of final energy consumption in the EU [49]. This underscores the essential role of the building sector in understanding country-specific electricity demand. In residential buildings, electricity consumption serves multiple purposes, this includes the operation of heating and cooling systems, as well as appliances like refrigerators, freezers, lighting, electric vehicles, and so on [16,50,51]. While certain electric devices may exhibit sensitivity to weather conditions [52], it is noteworthy that the most weather-dependent usages are typically associated with heating and cooling systems. The impact of residential buildings[1] on electricity demand can be observed in the following key aspects.

1.1. Space cooling

Space cooling is the fastest-growing use of energy in buildings [14]. The use of cooling appliances, such as Air Conditioning (AC) in Europe has witnessed a steady increase over the years [53], due to rising temperatures during summers and the occurrence of heatwaves [54]. According to the estimation of the International Environmental Agency (IEA), the utilization of AC is anticipated to increase in the next three decades, emerging as a key driver of global electricity demand [14]. This escalating reliance on cooling appliances raises concerns about a corresponding increase in electricity demand for cooling within buildings, potentially elevating peak electricity demand across Europe, thereby posing the risks of power outages [14,15,55]. Considering the escalating demand for space cooling, it is necessary to incorporate this into projections of electricity demand.

1.2. Passive cooling

Another pivotal factor influencing cooling demand is passive cooling. Passive cooling is a building design approach that works either by removing heat from the building to a natural heat sink or by preventing heat from entering the living space from external heat sources to improve indoor thermal comfort with low or no energy consumption [56,57]. In general, passive cooling can be classified into three categories: solar and heat control, heat exchange reduction, and heat removal [56]. Incorporating passive cooling techniques yields multiple benefits, including peak load reduction and offset, minimizing interior temperature fluctuations, and maintaining indoor air temperatures within a comfortable range, consequently lowering overall cooling demand [56]. A notable example is observed in low-cost housing in southern Spain, where the appropriate use of natural ventilation at night resulted in an average indoor temperature reduction of 5 °C [58]. The application of passive cooling techniques is estimated to reduce energy consumption by a range of 8% to 70%, depending on the specific technique employed [56]. The European Environment Agency (EEA) stresses the significance of passive cooling as a key solution for sustainable cooling [59]. Therefore, integrating passive cooling measures is imperative for future buildings to mitigate the impact of heatwaves and decrease the potential peak load associated with space cooling.[2]

1.3. Electrification of the heating sector

With substantial potential for emission reduction and decarbonization of energy supply chains, electrification is an important strategy to achieve net-zero goals [61]. Within the heating sector, electrification can be implemented by, for example, heat pumps [62,63]. Heat pumps,[3] driven by low-emission electricity, play a central role in the global shift toward secure and sustainable heating. While heat pumps met around 10% of global space heating needs in 2021, the rate of installation is rapidly accelerating [61,64]. In the European Union (EU), heat pump sales increased by 33.8% in 2021 over the previous year, making the EU the fastest-growing market globally for this technology [64]. However, the rise in the electricity share for heating also signifies an increase in electricity demand. It has been shown that if electric heating is employed to electrify the heat demand in EU28 countries, it would more than double the annual electricity demand [13].

1.4. Thermal insulation

The significance of thermal insulation has long been recognized as crucial in shaping the future trajectory of energy consumption in buildings and achieving objectives related to greenhouse gas emissions reduction [49]. Thermal insulation systems and materials are designed to curtail the transmission of heat flow. By enhancing the insulation properties of building envelopes through the use of advanced materials, overall energy efficiency and the sustainability of buildings can be significantly elevated [65]. To evaluate the thermal insulation performance of building materials, thermal transmittance, commonly referred to as U-Value, is frequently used [65]. A consistent reduction in this value over the year has occurred [66], indicating an ongoing improvement in the thermal performance of buildings.

On the European scale, there are regional disparities in the thermal insulation standards of buildings. Northern and Western European countries, with a longstanding tradition of implementing thermal insulation requirements since the 1970s [51], demonstrate relatively high thermal insulation in their building stock [51,67]. In contrast, in southern countries such as Spain and Portugal, where winters are milder, the building inventory is dominated by buildings with little thermal envelope insulation [51,67]. For instance, in Spain, an estimated 90.4% of existing dwellings lack thermal efficiency due to a lack of thermal envelope requirements or a lightweight building code compared to the

[1] In our study, the primary focus is on residential buildings due to the complexity of the non-residential sector, which constitutes a relatively small percentage of the overall buildings, and its less temperature-sensitive characteristics. Specifically, in Europe, residential buildings constitute a significant 75% of the overall building stock, with the remaining 25% comprising non-residential buildings. Compared to residential buildings, non-residential buildings constitute a more complex and heterogeneous sector. Factors such as variations in usage patterns, energy intensity, and construction techniques contribute to the intricate nature of this sector [49].

[2] The impact of passive cooling on heating demand is scarcely addressed in the existing literature. In a specific case study [60], buildings with passive solar shading were found to slightly increase heating demand. However, it is important to note that the passive cooling measure assessed in the study specifically involved an overhang adjustment. Specifically, the overhang angle can be tailored and optimized to ensure sufficient sunshine during the winter months. Additionally, passive cooling encompasses a variety of other measures, such as night ventilation, which, if not activated during winter, does not impact heating demand. Therefore, our perspective is that, in general, passive cooling does not impact heating demand.

[3] The electrification of heating involves the utilization of heat pumps. Although heat pumps can serve cooling purposes, their use in this context categorizes them as cooling appliances, and are already considered in space cooling.

Technical Building Code in force [68]. However, recent years have witnessed a positive trend in Portugal, with a 50% reduction in U-values [51], attributed to the implementation of European regulations in the building sector. Key regulations, such as the Energy Performance of Buildings Directive (EPBD) (Directive 2018/844/EU) [1], require Member States to establish minimum requirements for the energy performance of both newly constructed buildings and existing structures undergoing major renovations. Complemented by other regulations like the Energy Efficiency Directive (EED) (Directive 2018/2002/EU) [69], these directives explicitly focus on enhancing the thermal insulation of buildings. According to the IEA, the global average space heating intensity has decreased by 10% over the past decades, attributed to more widespread and stringent building regulations and higher retrofit rates [70]. Consequently, future analyses of electricity demand should consider the impact of the thermal insulation of the buildings.[4]

Investigating these aforementioned key aspects reveals that while previous studies have explored the potential impact of various residential building factors on electricity demand, their examination seldom extends to the specific influence on TRFs. To the best of our knowledge, no publications have presented a method capturing the dynamics of TRFs within the context of future residential building changes. In response to this gap, we present a comprehensive analysis of electricity demand time series across European regions. Employing a piecewise regression model and investigating four crucial residential building factors, namely space cooling, passive cooling, electrification, and thermal insulation, we aim to understand the correlation between these factors and TRFs across different countries. By delving into the dynamic nature of TRFs, our analysis aims to capture shifts in demand and demand patterns under different climate scenarios, ultimately providing a more realistic projection of future electricity demand.

2. Data

2.1. Electricity demand time series

The electricity demand data is derived from the 'Actual Total Load' data collected by the European Network of Transmission System Operators for Electricity (ENTSO-E) transparency platform. The dataset comprises time series for 38 European countries, with data availability ranging from 2015 to the present day. However, it is worth noting that the available years and temporal resolution of the time series may vary across different countries.

To better investigate the correlation between temperature and electricity demand, we aggregate the time series into daily units by summing the load values for each day. This measurement is taken to mitigate the impact of factors such as sunshine duration and working hours, which strongly influence hourly electricity demand. The daily electricity demand time series for every country in each calendar year are regarded as individual datasets for examination and analysis. However, if an individual dataset exhibits missing values exceeding 5% of its entirety, it is excluded from the total dataset. The final dataset contains 36 countries including Austria, Bosnia and Herzegovina, Belgium, Bulgaria, Switzerland, Cyprus, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Georgia, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Moldova, Montenegro, North Macedonia, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Slovenia, Slovakia, Ukraine, the United Kingdom, and Kosovo. After a thorough screening, the final dataset comprises 254 individual datasets. In Fig. 2, a graphical representation is provided to illustrate the distribution of countries included in the dataset, along with the associated temporal coverage of data availability.

2.2. Country-specific temperature profiles

The temperature data used in our study are collected from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset [72]. ERA5 is a reanalysis dataset that provides a comprehensive global record of climate and weather data with data available from 1940 onwards. For our analysis, we utilize the '2 m temperature' variable.

To obtain country-specific temperature profiles, in contrast to many studies that rely on a general interpolation of temperature data across the country's grid cells, we adopt a more rigorous approach that accounts for the influence of population on electricity demand. Specifically, we begin by identifying the 10 most populated cities in each country and then interpolate the temperature data to the latitude and longitude of the corresponding city to obtain a time series. We then take a population-weighted mean of the temperature to generate a country-specific temperature profile. The population data for each city is derived from GeoNames, a publicly available geographical database maintained by the Open Geospatial Consortium [73]. The latitudinal and longitudinal information for each city is obtained through the Bing Maps REST Services Application Programming Interface (API). Finally, similar to the electricity demand data, we transform the hourly temperature time series into a daily averaged temperature time series by taking the mean value for each day.

2.3. Space cooling penetration rate

To determine the space cooling penetration rate, we utilize the Integrated Database of the European Energy System from the Joint Research Centre (JRC) Data Catalogue [74]. This database meticulously records the installation of AC systems in households across 28 European Union countries from 2000 to 2015. We employ the AC penetration rate as a proxy for the space cooling penetration rate, given that AC systems constitute approximately 99% of the European market for space cooling technologies [75]. We designate the data from the most recent year available, specifically 2015, as the present space cooling penetration rate, representing the percentage of households equipped with cooling appliances. For the future space cooling penetration rate, we refer to the study by Jakubcionis et al. [71]. Their research estimates the potential for space cooling in the EU residential sector, establishing a correlation between cooling demand and the number of cooling degree days in the United States. The estimation is based on the assumption that, over the long term, the space cooling demand potential, characterized by specific cooling demand and space cooling penetration, would be comparable in both American and European dwellings under similar climatic conditions. The current and projected space cooling penetration rates are illustrated in Figs. 3(a) and 3(b), respectively.

2.4. Climate scenarios

To project electricity demand, climate scenario data is essential. In our study, the climate scenario data is obtained from the Coordinated Downscaling Experiment of the European Domain (EURO-CORDEX), the European branch of the international CORDEX initiative. This initiative aims to establish a globally coordinated framework for producing improved regional climate change projections [76]. The specific

[4] While improving thermal insulation can reduce the electric heating demand, its effect on cooling demand is intricate. On one hand, there is a potential for increased cooling demand as improved insulation may lead to a higher probability of overheating due to the greater retention of heat within the building [71]. On the other hand, proper use of ventilation, particularly during nighttime, could counterbalance the potential negative effects of enhanced insulation [71]. Furthermore, a relevant case study comparing buildings with insulation to those without was conducted, revealing that the cooling demand for highly insulated buildings and the base case are similar [60]. Therefore, we posit that thermal insulation is unlikely to significantly alter cooling demand.

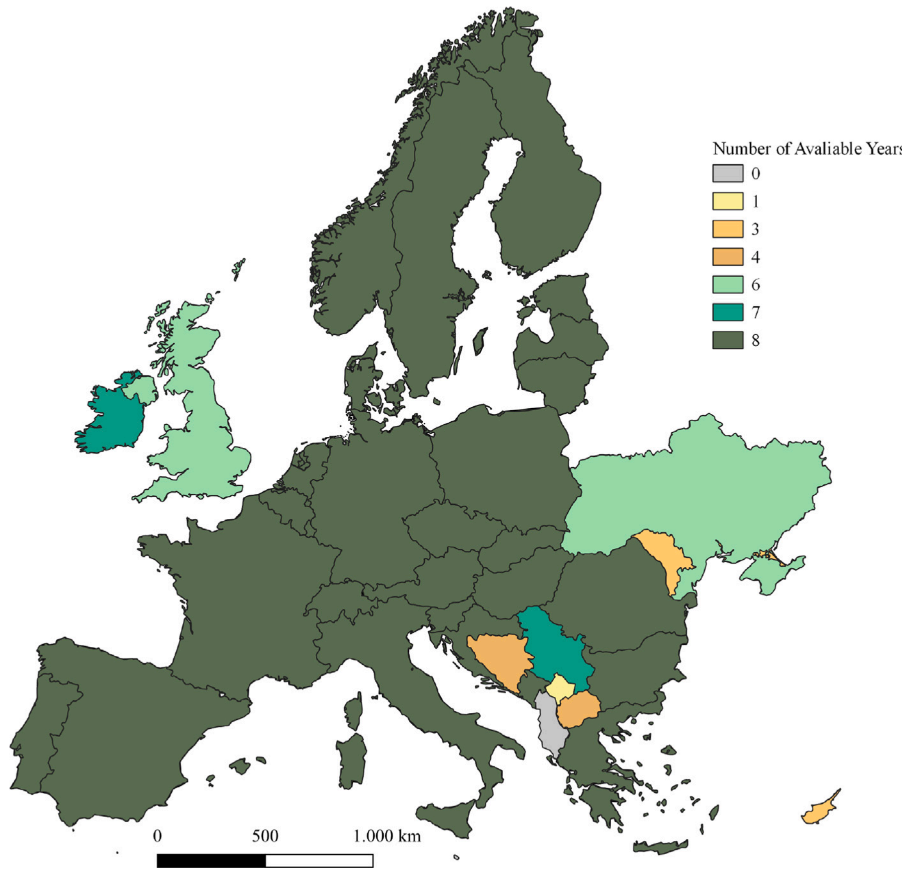
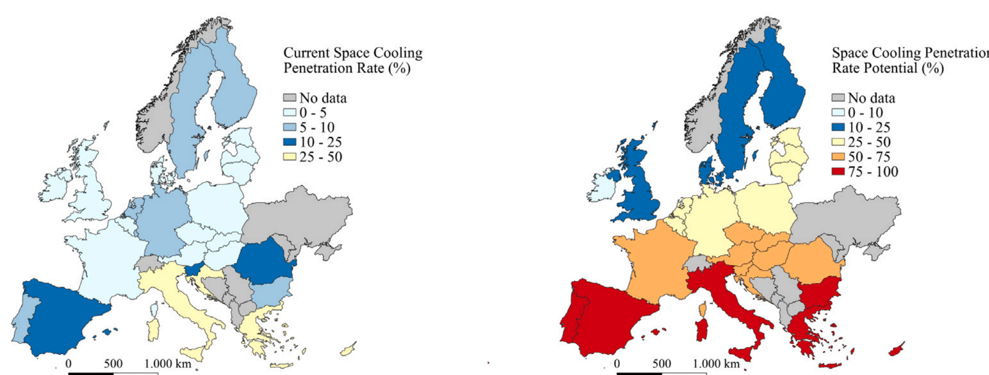


Fig. 2. Number of available years in each study country.



(a) Current space cooling penetration rate

(b) Space cooling penetration rate potential

Fig. 3. Current and future space cooling penetration rate.

data used in our study was derived from the datasets of the fifth phase of the Coupled Model Intercomparison Project (CMIP5) [77]. The Regional Climate Model (RCM) employed is the REgional MOdel (REMO2009), developed by the Climate Service Center Germany (GERICS), and downscaled from the Max Planck Institute Earth System Model at base resolution (MPI-ESM-LR) [78]. Specifically, we utilized realizations r1 and r2 as ensemble members.

In our analysis, we incorporate three different Representative Concentration Pathways (RCPs), which are a set of greenhouse gas concentration trajectories used to model future climate change [79]. Different RCP scenarios assume different levels of greenhouse gas emissions over the next century and result in distinct trajectories of radiative forcing and global warming [79]. RCP2.6 assumes that global greenhouse gas emissions peak around 2020 and then decline rapidly. This scenario represents a future with very stringent climate policies aimed at limiting global warming to below 2 °C by 2100. In comparison, RCP4.5 assumes that greenhouse gas emissions will continue to increase until 2040 and then begin to decline. It is an intermediate scenario that represents a future with moderate climate policies aimed at limiting global warming to 2 °C to 3 °C by 2100. Lastly, RCP8.5 assumes that greenhouse gas emissions will continue to increase throughout the 21st century. It is the highest baseline emissions scenario and is sometimes referred to as the worst-case scenario. Similar to the procedure of obtaining temperature information from ERA5, in our study, we derive the country-specific temperature profiles for these three scenarios till the year 2100.

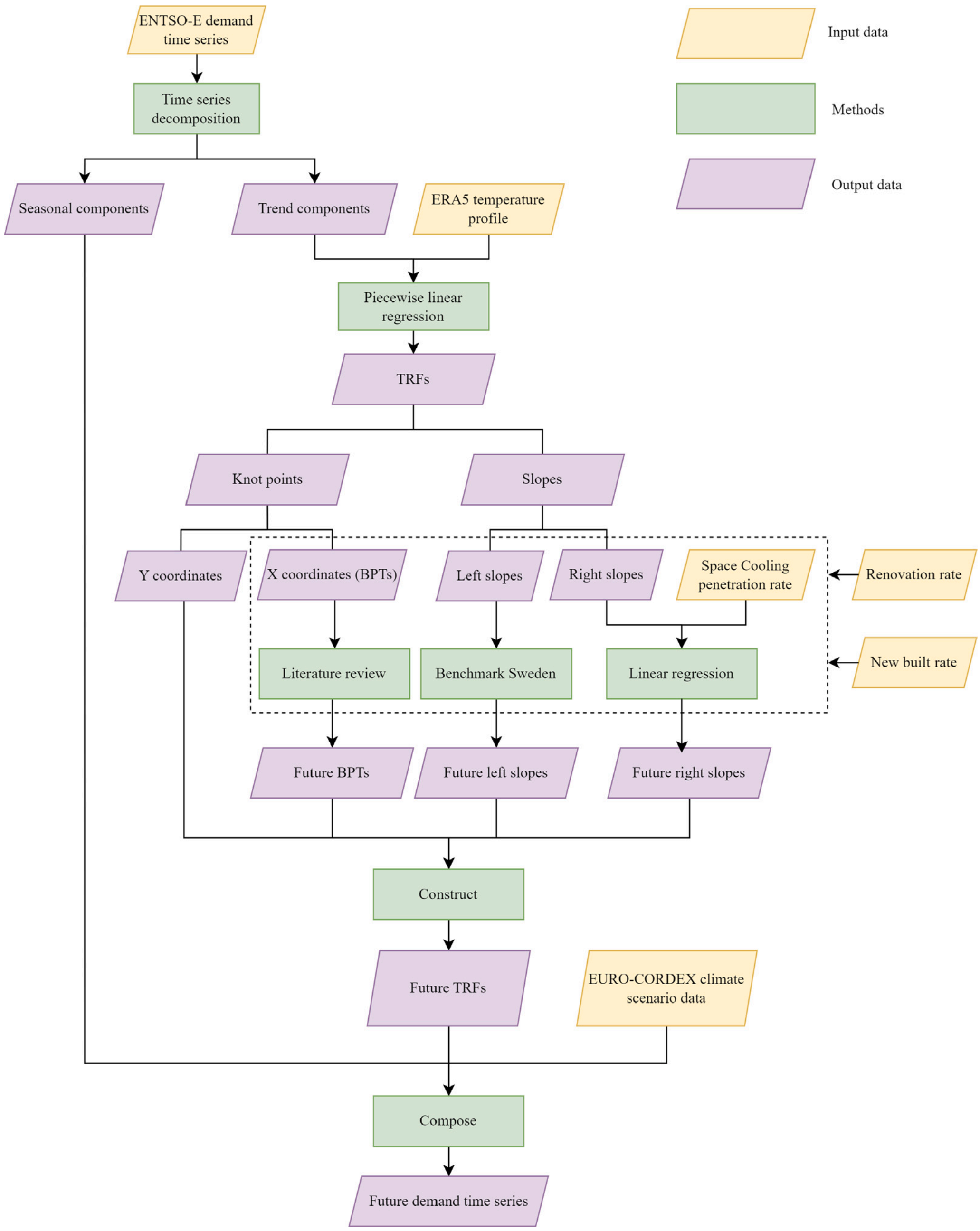


Fig. 4. Flow Chart illustrating the sequential steps for constructing future electricity demand time series.

3. Methods

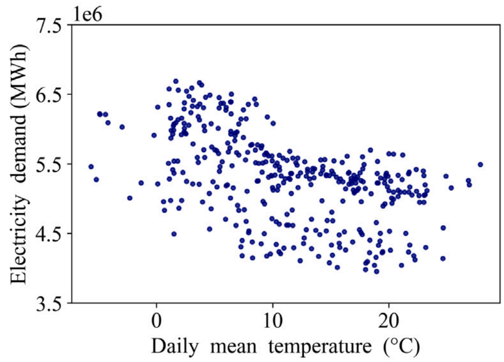
Within the methodological framework of this study, Fig. 4 depicts the approaches and input dataset employed.

3.1. Decomposition of electricity demand time series

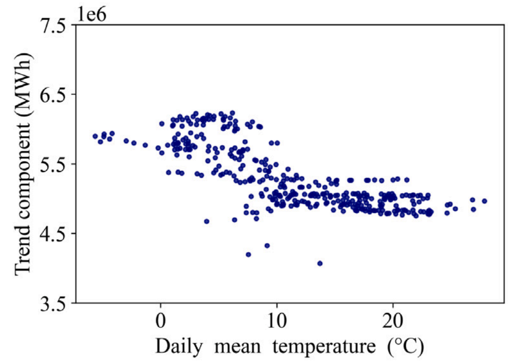
When examining a scatter plot depicting the relationship between temperature and electricity demand in Germany, as shown in Fig. 5(a), two distinct clusters of data points emerge. This occurrence is primarily attributed to the influence of the day of the week and holidays, both of which can significantly impact electricity demand. To mitigate these influences, we employ a time series decomposition technique to decompose the time series into trend, seasonal, and residual components. The seasonal component, which reflects a discernible recurring pattern, can be used to comprehend the weekly fluctuations in electricity demand. The residual component, on the other hand, signifying irregularities, can capture the impact of holidays or other exceptional events. By excluding these components from the time series, the trend component, which represents the overall direction of the time series, can therefore offer a more generalized depiction of the correlation between temperature and electricity demand. Prior to decomposition, we utilize a z-score technique to eliminate significant outliers from our dataset. We set the threshold at 3, which corresponds to the 99.7th percentile of a normal distribution. This step ensures that our analysis is not disproportionately influenced by rare or potentially anomalous data points.

The time series decomposition is conducted via the statsmodel Python package. Specifically, we apply an additive model and specify the period as seven to establish the recurring pattern over a week, thereby capturing the effect of weekdays.

Here, we showcase the electricity demand data for the year 2022 from Germany, to demonstrate our decomposition analysis as depicted



(a) Total electricity demand



(b) Trend component

Fig. 5. Scatter plots of daily mean temperature versus electricity demand and its trend component.

in Fig. 6(a). From Fig. 6(b), we can see that the trend component characterizes the overall long-term behavior of the electricity demand. On the other hand, the seasonal component, depicted in Fig. 6(c), captures the repeating patterns associated with weekdays. After closer investigation of a single calendar week, it becomes evident that the seasonal components exhibit a specific pattern of fluctuations, thus reflecting the effects of weekdays. Holidays, on the other hand, can be well captured in the residual components, as depicted in Fig. 6(d), where the peak residuals are clearly observable during the holiday seasons. More specifically, all major holiday periods in Germany, except for Labor Day[5] exhibit a distinguishable overlapping with the peak residuals observed.

To visualize the effectiveness of the decomposition analysis, Fig. 5(b) compares the scatter plot between the daily temperature and the trend components. A comparison with Fig. 5(a) shows that the data points in Fig. 5(b) are more tightly clustered, which makes it easier to identify and distinguish temperature influences, resulting in a more reliable and accurate TRF. Statistically, the coefficient of variation is reduced from 14.73% to 9.26%, and the absolute value of the Pearson correlation coefficient is increased from 0.39 to 0.67. These findings provide strong evidence of the effectiveness of the decomposition analysis in improving the accuracy and reliability of derived TRFs.

3.2. Construction of TRFs using piecewise regression

To formulate TRFs, we utilize the 'minimize' function in the Python package Scipy for regression in a piecewise form. However, it is important to note that the TRFs exhibit different shapes across different regions. In general, it can be categorized into three distinct forms as depicted in Fig. 7: a linear decreasing curve, a linear decreasing curve followed by a horizontal segment, and two discernible linear components separated by a horizontal line. To model these diverse TRF shapes, we employ different objective functions tailored to each. The linear decreasing curve, as represented in Fig. 7(a) and Eq. (1), is frequently observed in Northern European countries, reflecting the TRF's response to cold weather primarily associated with heating demand. The linear curve with a horizontal segment, as indicated in Fig. 7(b) and Eq. (2), is prevalent in countries with cold and intermediate climates. In these regions, the TRF captures the heating demand and the comfort zone following the heating BPT. Lastly, the V-shaped curve with a 'comfort zone' in between, illustrated in Fig. 7(c) and Eq. (3), is prevalent in intermediate or warm countries, where the TRF reflects both heating and cooling demands.

[5] The reason that Labor Day is not identified as a peak is that Labor Day in the year 2022 happens to be a Sunday, which is already reflected in the seasonal components.

$$D = Slope_1 \times T + b_0 \tag{1}$$

$$D = \begin{cases} Slope_1 \times T + b_1, & \text{if } T \leq BPT_{\mathrm{H}} \\ D_0, & \text{if } T > BPT_{\mathrm{H}} \end{cases} \tag{2}$$

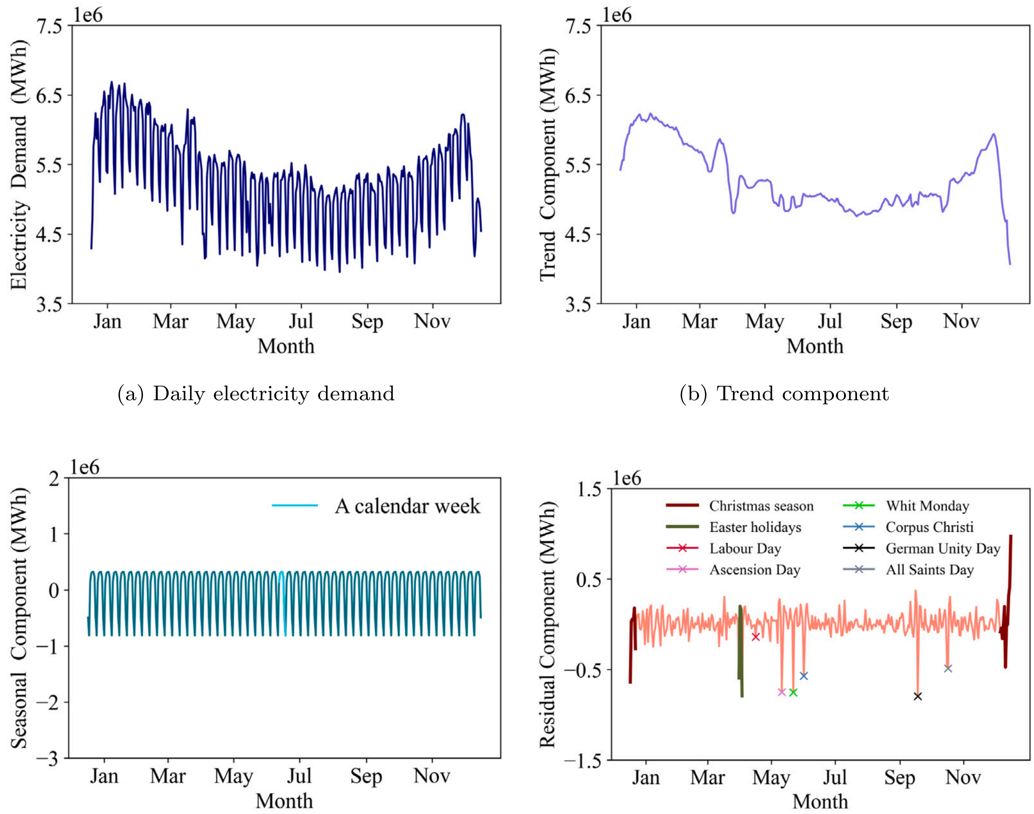
$$D = \begin{cases} Slope_1 \times T + b_2, & \text{if } T \leq BPT_{\mathrm{H}} \\ D_0, & \text{if } BPT_{\mathrm{H}} < T \leq BPT_{\mathrm{C}} \\ Slope_2 \times T + b_3, & \text{if } T > BPT_{\mathrm{C}} \end{cases} \tag{3}$$

where:

$$\begin{aligned} D &= \text{Electricity demand} \\ T &= \text{Temperature} \\ \text{Slope}_1 &= \text{Left slope indicating heating demand} \\ \text{Slope}_2 &= \text{Right slope indicating cooling demand} \\ \text{BPT}_{\mathrm{H}} &= \text{Heating Balance Point Temperature} \\ \text{BPT}_{\mathrm{C}} &= \text{Cooling Balance Point Temperature} \\ b_0, b_1, b_2, b_3 &= \text{Intercepts} \\ D_0 &= \text{Comfort zone demand (non-weather sensitive demand)} \end{aligned}$$

Prior to the model fitting, we first normalize the trend components from 0 to 1 to set the trend components of different countries on a common scale. Additionally, we employ Huber loss during the model fitting process to identify outliers and assign less weight to them, thereby mitigating their impact on our analysis. In the regression process for Eq. (3), it is necessary to assign appropriate boundary conditions for the two BPTs to ensure the reliability of our results. While the most widely adopted BPT value in literature is 18.3 °C or 18 °C, retrieved from the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Handbooks [80], it is acknowledged that BPT values can vary by region. To ascertain proper boundary conditions for BPT values, we conducted a literature review as summarized in Table 1. From Table 1, it is evident that the range of heating BPT typically falls between 12 °C[6] and 18 °C, while the range of cooling BPT is between

[6] While the heating BPT values mentioned in two studies [81,82] for Switzerland and Germany can reach 8 °C or 10 °C, it is worth mentioning that these values are not measured but are rather applied in their respective scenarios. Consequently, they may not accurately represent real-world conditions. Therefore, we opt for 12 °C as a conservative lower bound for our analysis.



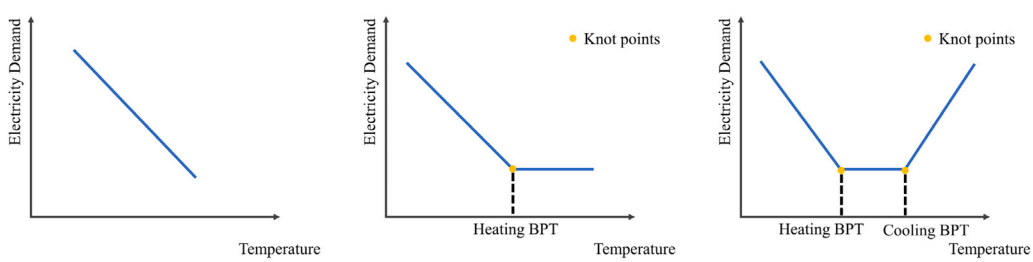
(a) Daily electricity demand

(b) Trend component

(c) Seasonal component

(d) Residual component

Fig. 6. Decomposition analysis for the daily electricity demand of Germany.



(a)

(b)

(c)

Fig. 7. Different shapes of TRFs across Europe.

18 °C and 25 °C.[7] Therefore, we use these values as boundary conditions in the regression process in addition to the objective function. This method is implemented independently for each study region and year to derive the TRFs for the normalized trend components.

3.3. Scenario assumptions

To thoroughly grasp the dynamics of TRFs and integrate the development of residential buildings into our analysis, we delve into the impact of varying levels of space cooling penetration rate, passive cooling, electrification, and thermal insulation within our scenario assumptions. In total, we define five scenarios that represent distinct levels of policy intervention and residential building development until year 2100. The influences of the scenario settings on the BPTs, left and right slopes of the TRFs are quantified in Section 3.4.

- Scenario 0 (S0), Static TRFs: This scenario serves as a baseline scenario, employing historical averaged TRFs to calculate future demand. The TRFs remain static over time, assuming no changes in space cooling penetration rate, passive cooling, electrification, or thermal insulation
- Scenario 1 (S1), Moderate Policy: In this scenario, the space cooling penetration rate remains constant, with renovations of existing buildings focusing primarily on limited thermal insulation improvements. Newly constructed buildings exhibit bigger improvements in thermal insulation. Electrification is introduced in the heating sector of these new buildings, accompanied by a set of limited passive cooling measurements. Both the renovation

[7] While a maximum value of 27 °C is found in literature, it is important to note that this pertains to Saudi Arabia, a region known for extremely hot summers. Given that our research focuses on Europe, we opt for a more appropriate value of 25 °C.

Table 1
Overview of BPT (°C) across literature.

Literatures	Region	BPT (°C)[a]	Heating BPT (°C)	Cooling BPT (°C)
ASHRAE [80]	US	18.3	–	–
Eurostat [83]	Europe	–	15	24
Carbon trust [84]	UK and Germany	–	15.08[b], 15.58[c]	–
SIA 380:2015	Switzerland	–	12	–
Jakubcionis et al. [71]	Europe	18	–	–
Hao et al. [85]	China	–	7.08–12.71	–
Comert et al. [86]	Turkey	15.42	–	–
Ruth et al. [30]	Maryland, US	–	15.56	15.56
A. Dubin [87]	US	11.11–13.89	–	–
Verbai et al. [88]	Hungary	–	12	–
Huang et al. [89]	US	11–21	–	–
Sailor et al. [28]	US	14–21[d]	–	–
Lindelöf et al. [90]	Switzerland	17.4 ± 1.9	–	–
Christenson et al. [81]	Switzerland	–	8, 10, 12	18.3, 20, 22
Giannakopoulos and Psiloglou [91]	Athens, Greece	22	–	–
Olonscheck et al. [82]	Germany	–	10, 12	22
Andrade et al. [92]	Portugal	–	18	25
Psiloglou et al. [93]	Athens, Greece and London, UK	16[e], 20[f]	–	–
Papakostas et al. [94]	Greece	–	15	24
Tsikaloudaki et al. [95]	South Europe	–	–	23
Alhuwayil et al. [60]	Saudi Arabia	–	19	27

[a] For literature that does not specify heating or cooling BPT. If the type of BPTs is specified, this column will be empty.
[b] UK.
[c] Germany.
[d] Florida.
[e] Athens, Greece.
[f] London, UK.

rate and new build rate are kept low, set at 1%[8] and 0.5%[9] respectively.

- Scenario 2 (S2), Strict Policy: In this scenario, a stringent policy and regulatory framework aimed at enhancing building energy performance is enforced. Building renovation leads to improved thermal insulation, consideration of electrification in the heating sector, and the incorporation of limited passive cooling measures. Newly constructed buildings have significant enhancements in thermal insulation, along with the consideration of electrification in the heating sector and effective passive cooling measures. The renovation and new build rates are set optimistically at 3%[10] and 1%,[11] respectively. The second stage of renovation begins once all existing building blocks have undergone renovation. This subsequent phase aims to elevate the energy performance of renovated buildings to the same level as newly constructed ones.
- Scenario 3 (S3), Moderate Policy with boosted space cooling penetration: In this scenario, the Moderate policy is maintained, but boosted space cooling demand is considered in the future. The level of thermal insulation, passive cooling, electrification rate, renovation rate, and new build rate for renovated and newly built buildings remain consistent with S1.
- Scenario 4 (S4), Strict Policy with boosted space cooling penetration: This scenario assumes a combination of strict policy and boosted space cooling penetration in the future.

3.4. Projecting future TRFs for different scenarios

TRFs consist of four crucial components: two-knot points that represent the heating and cooling BPTs, and two linear components that capture the incremental impact on demand due to additional exposure to heat or cold. Therefore, understanding the changes of these crucial components is necessary for projecting future TRFs. Among these components, the y coordinate of knot points represents the non-weather sensitive energy demand and is not influenced by temperature [34]. Consequently, it is treated as a constant in our analysis. The detailed methodologies for projecting other TRF components are introduced in the subsequent sections.

3.4.1. Future BPT

The x-coordinates of the knot points correspond to BPTs, presumed to be predominantly influenced by thermal performance of the buildings, as they represent a shift in electricity demand patterns caused by temperature fluctuations. However, the relationship between BPTs and thermal performance of the buildings is complicated, posing a significant challenge in establishing a statistical relationship between BPTs and other variables associated with residential buildings. To address this complexity, we conducted a thorough literature review. Through this literature review, our goal is to identify appropriate BPT values for both new and renovated buildings and to incorporate these values into our scenarios.

The literature review findings are presented in Table 1, providing a comprehensive overview of the potential range of heating and cooling BPT values. It is noteworthy that a lower heating BPT typically indicates a better-insulated building, while a higher cooling BPT suggests a building with better ventilation. For our scenarios, distinct values are assigned to renovated and newly constructed houses. The minimum heating BPT value extracted from literature is 7 °C. Consequently, this value is assigned to newly constructed houses in S2 and S4. For cooling BPTs, a maximum value of 27 °C is allocated to the newly constructed

[8] This percentage is derived from the report by Buildings Performance Institute Europe (BIEP) [51], which indicates that the current average renovation rate in Europe stands at approximately 1%.
[9] Regarding the new build rate, the BIEP report [51] also indicates an annual growth rate of approximately 1% in the residential sector. However, it is noteworthy that the same report highlights a recent decrease in the new build rate across many countries. Consequently, for this scenario, we adopt a conservative value of 0.5%.
[10] This value is retrieved from the Energy Efficiency plan by the European Commission [96], where the renovation rate of at least 3% is recommended.
[11] This value is obtained from the BIEP report [51], where an observed new build rate of 1% is documented. We presume that the new build rate will persist at the current level, under the assumption that effective policy incentives will drive the construction of new buildings with a focus on energy savings.

Table 2
Future BPT (°C) value for renovated and new houses for different scenarios.

	Building categories	S0	S1	S2	S3	S4
Heating BPT (°C)	Renovated	–	11	8	11	8
	New built	–	10	7	10	7
Cooling BPT (°C)	Renovated	–	24	26	24	26
	New built	–	25	27	25	27

Table 3
Future left slope value for renovated and new houses for different scenarios.

Building categories	S0	S1 and S3	S2 and S4
Renovated	–	Reduction scaled according to ODYSSEE score	−0.049
New built	–	−0.049	−0.030

houses in S2 and S4. A summary of the BPT values used in different scenarios is presented in Table 2. To obtain future BPT values, Eq. (4) is applied. This equation incorporates the renovation and new build rates to calculate the percentage of current, renovated, and newly constructed buildings. The current BPT value[12] is computed as the average BPT value[13] across the years.

$$BPT_f = Pc \times BPT_c + Pr \times BPT_r + Pn \times BPT_n \tag{4}$$

$$LSlope_f = Pc \times LSlope_c + Pr \times LSlope_r + Pn \times LSlope_n \tag{5}$$

where:

$BPTf$ = BPT for future buildings
Pc = Percentage of current buildings
$BPTc$ = BPT for current buildings
Pr = Percentage of buildings that has been renovated
$BPTr$ = BPT for renovated buildings
Pn = Percentage of buildings that is new built
$BPTn$ = BPT for new built buildings
$LSlope_f$ = Left slope value for future buildings
$LSlope_c$ = Left slope value for current buildings
$LSlope_r$ = Left slope value for renovated buildings
$LSlope_n$ = Left slope value for new built buildings

3.4.2. Future left slope

In the overall energy demand for buildings, the left slope corresponds to the heat loss coefficient of the building, commonly denoted as the K value, as indicated in studies by Lindelöf et al. [90,97]. However, when it comes to electricity demand, the situation is more complex due to the additional influence of the electrification rate. To simplify this process, we take Sweden as a benchmark,[14] considering its high share of electricity use [74] and generally good thermal insulation in residential buildings [51].

Currently, the electrification rate in Sweden is 44%, ranking among one of the highest electrification rates in European countries. Meanwhile, this percentage also corresponds with future electrification rate projections from a study by the European Commission, which assumes the residential sector electricity share in heating will grow to between 22% and 44% by 2050 [49]. Additionally, the thermal insulation of Swedish residential buildings ranks among one of the best in Europe [51,101]. Therefore, we choose the left slope value of Sweden (−0.49) as a benchmark for scenarios that involve both increased electrification rates and improved thermal insulation.[15] The left slope is determined in Eq. (5). Specifically, for renovated buildings in Scenarios S2 and S4, and new buildings in S1 and S3, we assign the left slope value of −0.49. For newly constructed houses in S2 and S4, where a more significant thermal insulation improvement is assumed, we assume a slope value of −0.30.

For the renovated buildings in Scenarios S1 and S3, where we assume no changes in the electrification rate, the focus is solely on improving thermal insulation. Consequently, the absolute value of the slope is likely to decrease due to improved thermal insulation. However, this reduction is expected to vary across countries based on their respective policies. Countries with more stringent regulations on residential buildings are anticipated to experience a more significant decrease in the absolute value of the left slope.

According to a study by Lindelöf et al. [90], where a case study in Switzerland was conducted, it was observed that the heat loss coefficient (K value) of post-retrofit buildings decreased by 30% compared to pre-retrofit buildings, indicating a 30% reduction in the slope value. To extrapolate this reduction value for other countries, we use 30% in Switzerland as a benchmark and scale it proportionally according to the ODYSSEE Overall Energy Efficiency Score [101]. This score documents the policy intervention level for various European countries, considering factors like energy efficiency level, progress, and policies, as depicted in Fig. 8. Additionally, Table 3 summarizes the left slope reduction in renovated and newly constructed buildings for different scenarios.

3.4.3. Future right slope

Concerning the right slope, our objective is to establish a statistical relationship between the right slope value and the space cooling penetration rate. This is achieved through a linear regression analysis, as illustrated in Fig. 9, which presents a scatter plot and the results of the linear regression between the space cooling penetration rate and the right slope.[16] Our results yield a p-value of 0.000002, and a coefficient of determination (R^2) of 0.645, indicating a satisfactory fit given the limited sample size. The linear function is represented by Eq. (6). This function is subsequently used to obtain future right slope values once the future space cooling penetration rate is determined. In our scenarios with boosted space cooling usage, we assume a linear increase in the space cooling penetration rate, reaching its full potential as defined in Section 2.3 and illustrated in Fig. 3(b) until the year 2050. Subsequently, the rate remains constant.

$$Slope_{right} = 0.149 \times Rate_{SC} + 0.016 \tag{6}$$

[12] The current cooling BPT values in Sweden, Norway, Ireland, and the Czech Republic are unavailable since the TRFs in these regions do not manifest cooling demand, as illustrated in Fig. 7(b) and Eq. (2). Consequently, we assign a cooling BPT value of 25 °C to these countries, representing the upper bound within our boundary conditions for cooling BPT.

[13] We opted for the averaged value instead of the value in 2022 to aim for a more representative figure.

[14] In calculating the future left slope, the left slope value of Sweden is used as a benchmark. This implies that parameters such as the coefficient of performance (COP) value of heat pumps and the share of air and ground source heat pumps are presumed to align with Sweden. Comprehensive analyses of heat pump use in Sweden can be found in existing studies, such as [98–100].

[15] We also present an alternative method that considers the electrification rate and U value in Supplementary Material 2. This method establishes a linear relationship between the electrification rate, U value, and the left slope, enabling the extrapolation of future left slope values. However, due to the data availability and the complexity of finding a representative U value for all building inventories in each study country, this method is not presented here.

[16] The correlation is showcased for countries within the available dataset due to data availability in space cooling penetration rates.

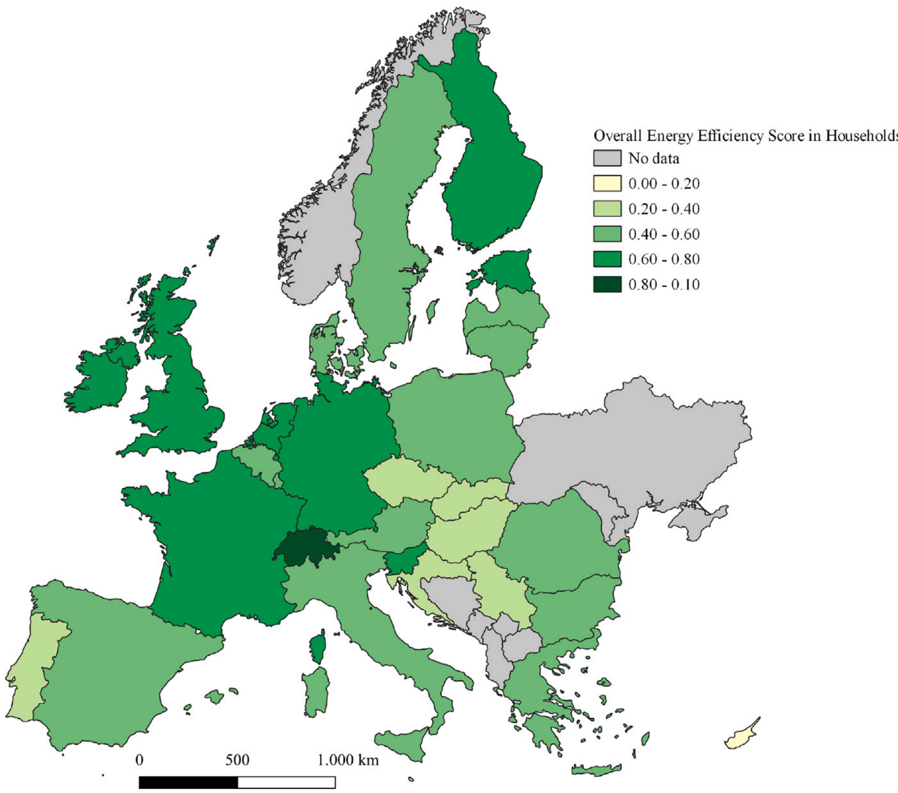


Fig. 8. ODYSSEE energy efficiency score.

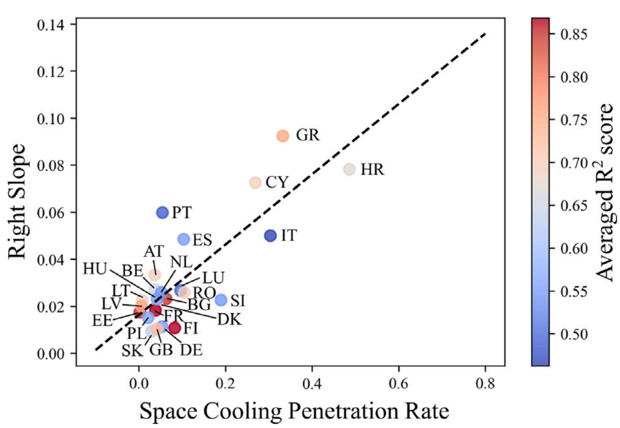


Fig. 9. Linear regression between space cooling penetration rate and right slope.

where:

$Slope_{\text{right}}$ = Right Slope

$Rate_{\text{SC}}$ = Space cooling Penetration Rate

Meanwhile, it is also important to account for the impact of passive cooling. However, capturing its influence can be intricate. On one hand, research, such as [60], highlights that passive cooling is significantly more effective in warmer regions. On the other hand, while numerous studies focus on energy saving through passive cooling, there is a gap in research investigating how passive cooling influences the slope value in TRFs. To address these complexities, we utilize Italy as a benchmark.[17]

We assume that in strict policy scenarios, passive cooling in new and renovated buildings in Italy can reduce the right slope value by 30%[18] and 15%,[19] respectively, while for the moderate policy scenarios, a reduction of 15%[20] is assumed for new buildings. Given the regional variation in the effectiveness of passive cooling, to explore its impact on different countries, the values we assumed for Italy are then scaled

[17] We choose Italy as our benchmark due to its distinction of having the highest average summertime temperature across the years and regions under our research scope. This information is derived from temperature reanalysis data obtained from ERA5, as introduced in Section 2.2 and illustrated in Fig. 10.

[18] We base our assumption of a 30% reduction in right slope value on a review study conducted by Song et al. [56]. Their comprehensive literature review assessed the energy-saving potential of various passive cooling measures. According to their findings, the reduction in energy consumption varies depending on the specific passive cooling method employed. For instance, energy consumption decreased by 8% to 70% with the use of external shading, by 37% with cool-colored paint roofs, by 25% with the creation of green spaces, by 7.88% with the construction of prismatic buildings, by 32% to 100% with vegetation-based walls, by 50% with Phase change material (PCM) based walls, by 33% with insulation incorporation into walls, by 10% to 20% with buildings equipped with solar chimneys, and by 25% with radiative cooling systems. Given the significant variations among different passive cooling strategies, we have opted to use an average value derived from this study, which approximates to 30%. However, it is important to note that a 30% reduction in energy consumption does not equate to a 30% reduction in slope. Due to the lack of research on how passive cooling impacts slope values, we have adopted the 30% reduction as an assumption in our analysis.

[19] Our assumption is that the level of energy savings achieved through passive cooling is lower in renovated buildings. Therefore, we assume a 15% reduction of the right slope value for renovated buildings.

[20] In our scenario assumptions, we posit that the effectiveness of passive cooling measurements in the moderate policy scenario is inferior to that in the strict policy scenario. Hence, we assume a 15% reduction of the right slope value for moderate policy scenarios.

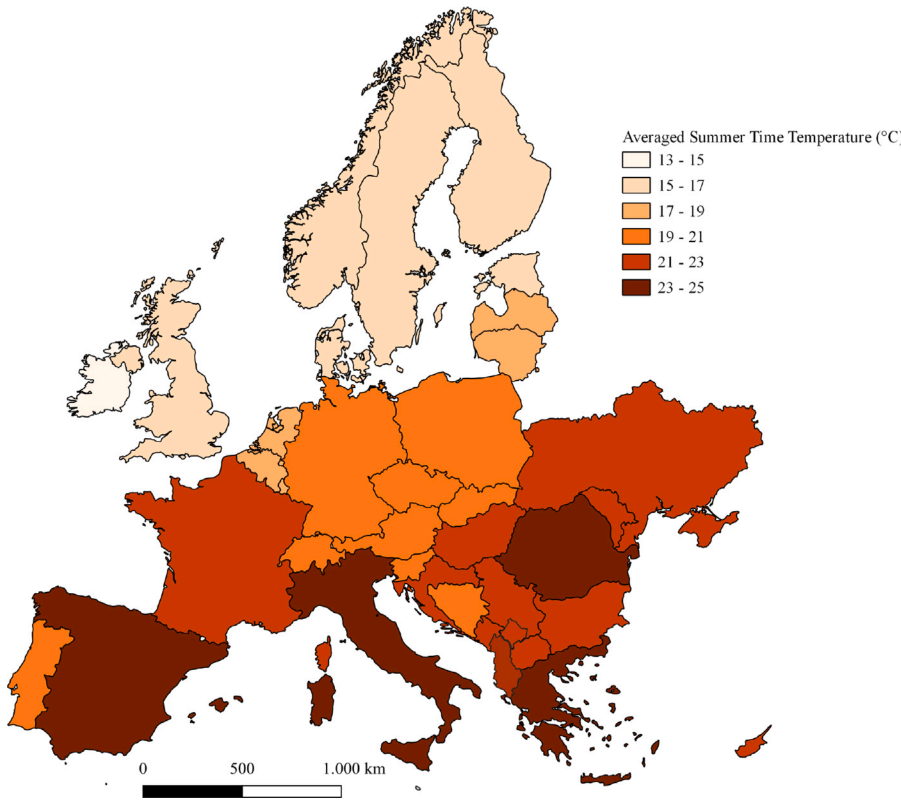


Fig. 10. Summertime temperature map.

Table 4
Future right slope reduction due to passive cooling for different scenarios for Italy.

Building categories	S0	S1 and S3	S2 and S4
Renovated	–	–	Reduction of 15%
New built	–	Reduction of 15%	Reduction of 30%

for other countries based on the historically averaged summertime temperatures, as depicted in Fig. 10, showcasing the average summertime temperatures in the research countries. In summary, the calculation of the right slope is outlined in Table 4 using Italy as an example.

4. Results

4.1. Simulating TRFs using piecewise regression

To evaluate the performance of our piecewise regression model, we employ two statistical indicators: Root Mean Squared Error (RMSE) and coefficient of determination (R^2). Detailed RMSE and R^2 values for each region and year are provided in Supplementary Material 1. We exclude data with R^2 values smaller than 0.4 as indicated in Appendix A. This exclusion is performed because, in such cases, the correlation between temperature and electricity demand is not predominant, and excluding these data can enhance the accuracy of our analysis. In this section, we present the aggregated results for these evaluation indicators. Table 5 lists the mean RMSE and R^2 scores across multiple years for each country. Similarly, Table 6 presents the mean RMSE and R^2 scores across all countries for each year.

Meanwhile, Fig. 11 displays our piecewise regression results for selected countries in the year 2022. These selected regions are distributed across various geographical locations in Europe. It is apparent that their TRFs exhibit different shapes. For example, in countries with cold or intermediate winters, such as Norway and Germany, heating is dominant. The electricity cooling, however, is not obvious in the plot. In countries with warmer summers such as Bulgaria and Serbia,

Table 5
Summary of the average RMSE and R^2 for each country.

Region	RMSE	R^2	Region	RMSE	R^2
AT	0.143	0.690	IT	0.113	0.462
BA	0.145	0.634	LT	0.139	0.680
BE	0.138	0.652	LU	0.130	0.496
BG	0.105	0.848	LV	0.121	0.758
CH	0.120	0.775	MD	0.146	0.577
CY	0.141	0.693	ME	0.145	0.711
CZ	0.119	0.700	MK	0.113	0.824
DE	0.141	0.545	NL	0.183	0.531
DK	0.139	0.681	NO	0.087	0.918
EE	0.100	0.849	PL	0.121	0.559
ES	0.126	0.551	PT	0.157	0.487
FI	0.092	0.868	RO	0.127	0.697
FR	0.977	0.868	RS	0.104	0.874
GB	0.147	0.728	SE	0.094	0.885
GR	0.117	0.757	SI	0.129	0.544
HR	0.139	0.672	SK	0.133	0.631
HU	0.131	0.556	UA	0.110	0.858
IE	0.153	0.613	XK	0.102	0.883

Table 6
Summary of the average RMSE and R^2 for each year.

Year	RMSE	R^2
2015	0.133	0.700
2016	0.123	0.697
2017	0.120	0.714
2018	0.111	0.751
2019	0.123	0.704
2020	0.160	0.637
2021	0.122	0.722
2022	0.119	0.716

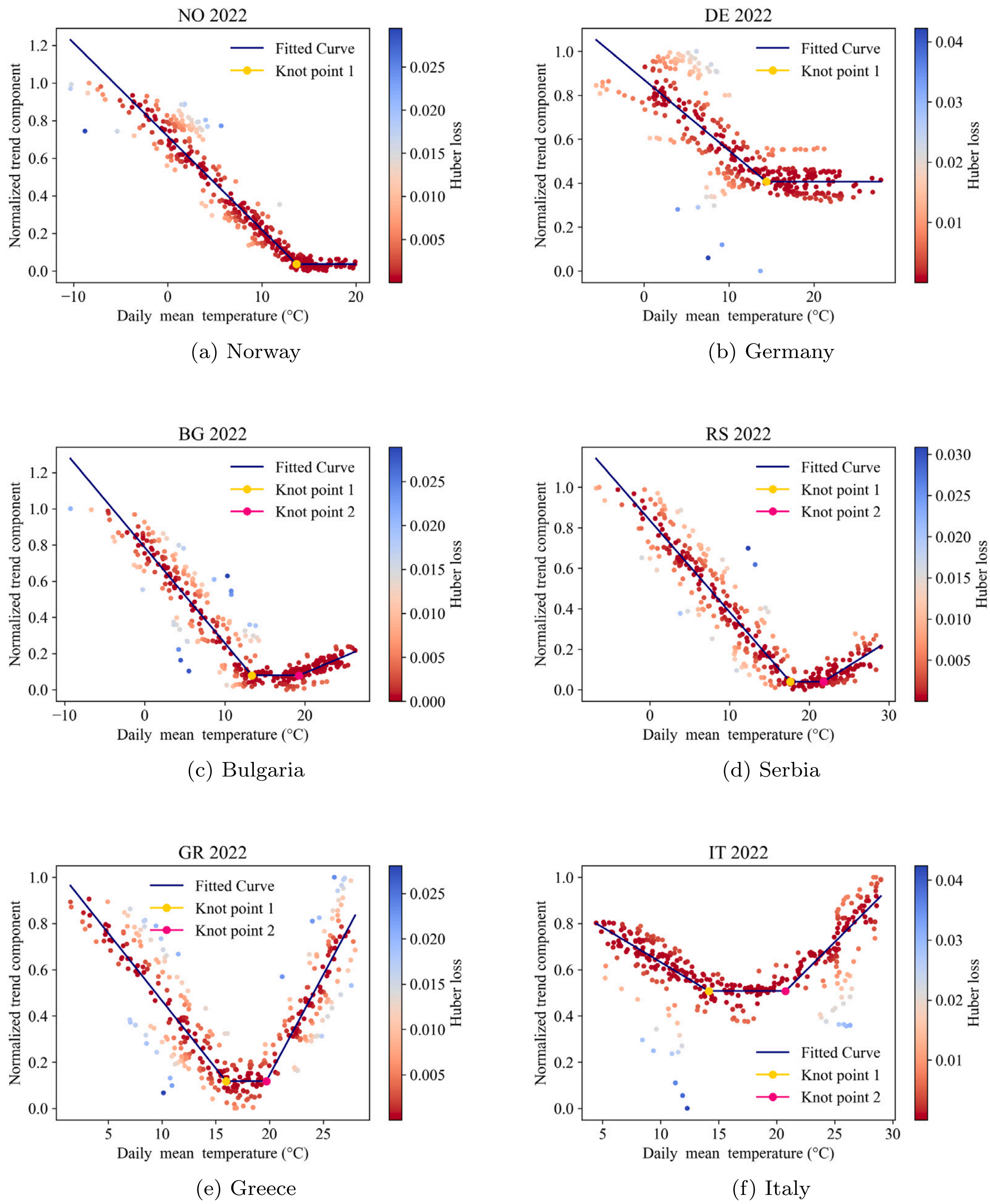


Fig. 11. Piecewise regression results for selected countries.

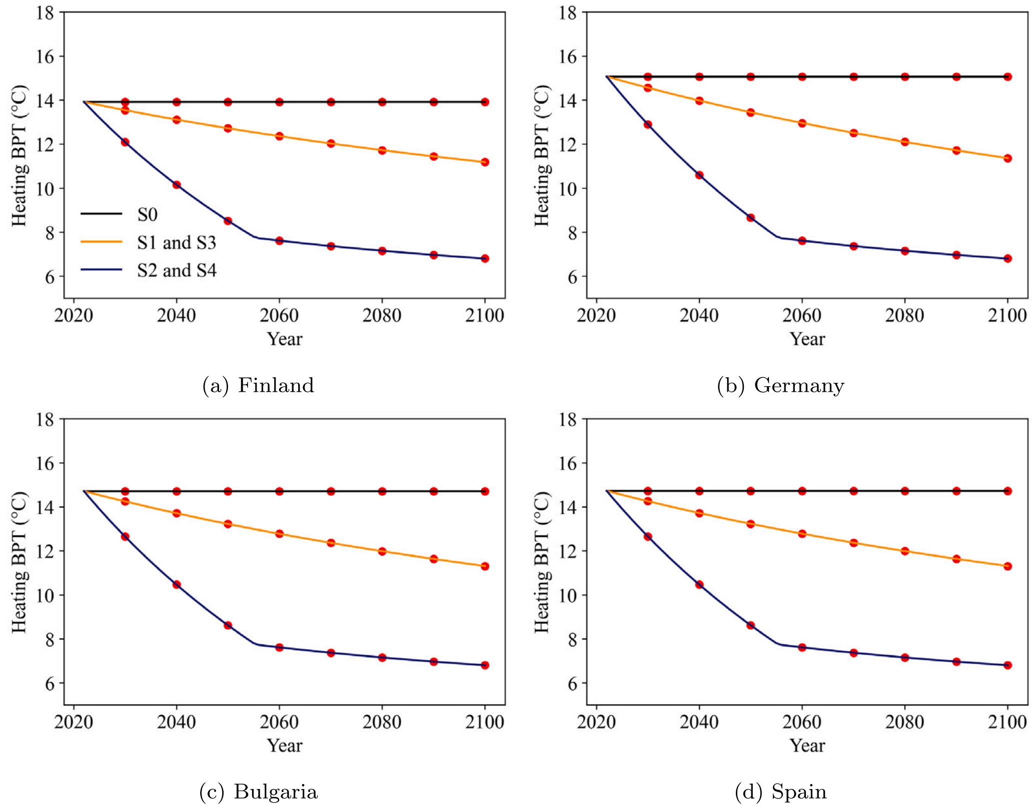
although the cooling demand is obvious, the heating effect is still more pronounced. In comparison, in countries with hot summers such as Greece, the cooling effect is as dominant as heating, and in Italy, the cooling is even more dominant.

4.2. Future TRFs and demand time series

With the methodology for projecting future BPTs and slopes established, we proceed to construct future TRFs. The dynamics of the various TRF components over time are visualized. In this context, we showcase results for four representative countries: Finland (FI), Germany (DE), Bulgaria (BG), and Spain (ES). Figs. 12, 13, 14, and 15 illustrate the evolving patterns of heating BPTs, cooling BPTs, left slopes, and right slopes over time respectively. Meanwhile, Fig. 16 presents the future TRFs for these countries in the years 2025, 2050, and 2100.

After constructing the future TRFs, the relationship between temperature and electricity demand can be determined. Consequently, TRFs can be employed to derive time series of electricity demand for future years using the climate scenario data introduced in Section 2.4. However, to accurately reconstruct the electricity demand time series, two additional steps are necessary. Firstly, the normalized trend components need to be denormalized by rescaling the data back to the minimum and maximum values of the historically averaged trend components. Subsequently, the historical averaged seasonal components are added to these denormalized trend components.[21] The resulting daily electricity demand time series under various scenarios for the years 2050 and 2100 are illustrated in Figs. 17 and 18. For clarity, we only showcase the results from ensemble realization r1 of the climate

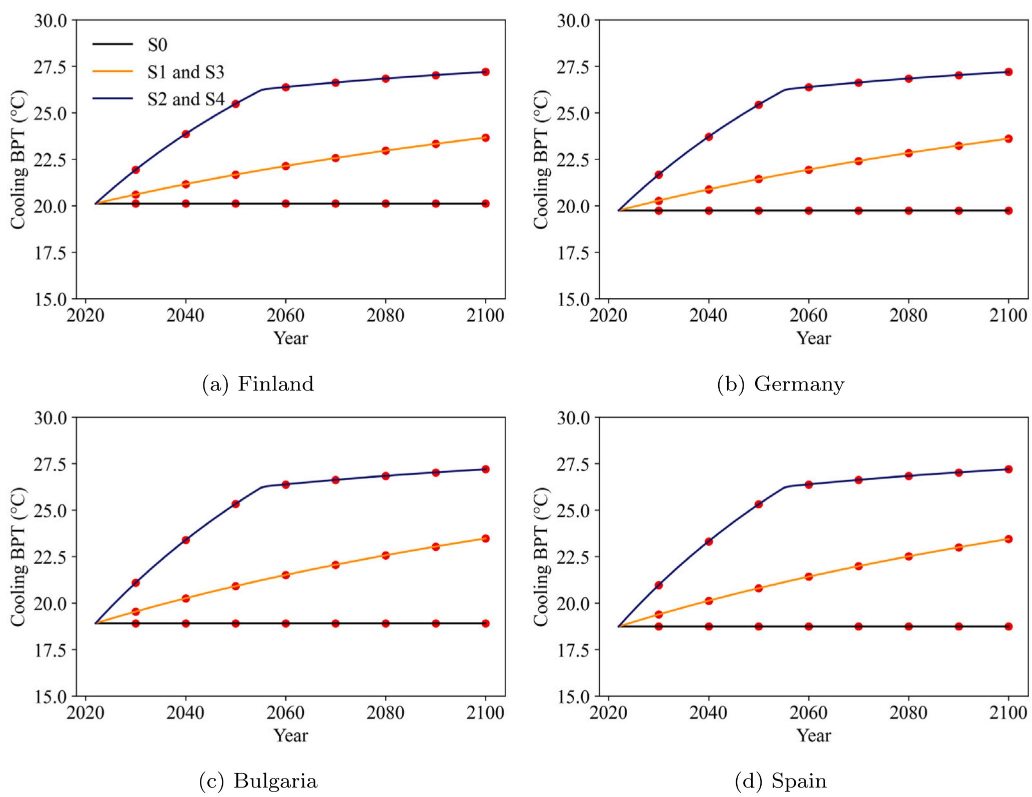
[21] The reason for not adding the residual component stems from its role as an anomaly indicator. The residual component captures deviations from the expected patterns and can include noise or irregularities that are not necessarily representative of the underlying structure.



(a) Finland (b) Germany

(c) Bulgaria (d) Spain

Fig. 12. Change of heating BPT over time for representative countries.



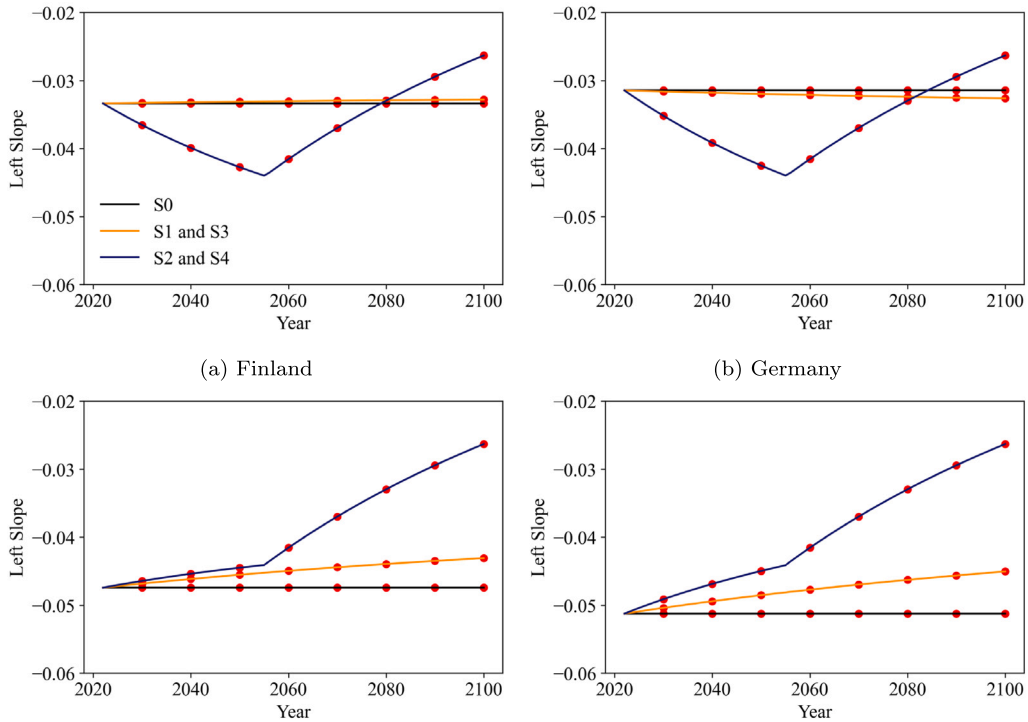
(a) Finland (b) Germany

(c) Bulgaria (d) Spain

Fig. 13. Change of cooling BPT over time for representative countries.

scenario data. The electricity demand time series corresponding to ensemble realization r2 is provided in Supplementary Material 4.

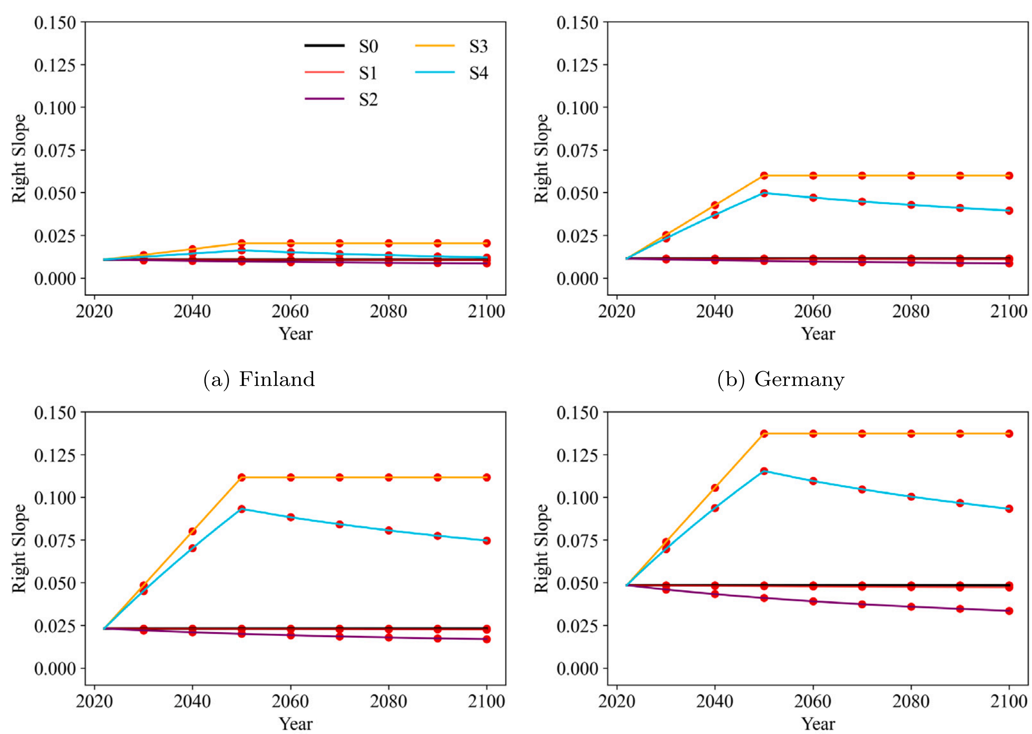
Examining the variations in BPTs and slopes across different climate scenarios and years for four key countries provides insights into how



(a) Finland (b) Germany

(c) Bulgaria (d) Spain

Fig. 14. Change of left slope over time for representative countries.

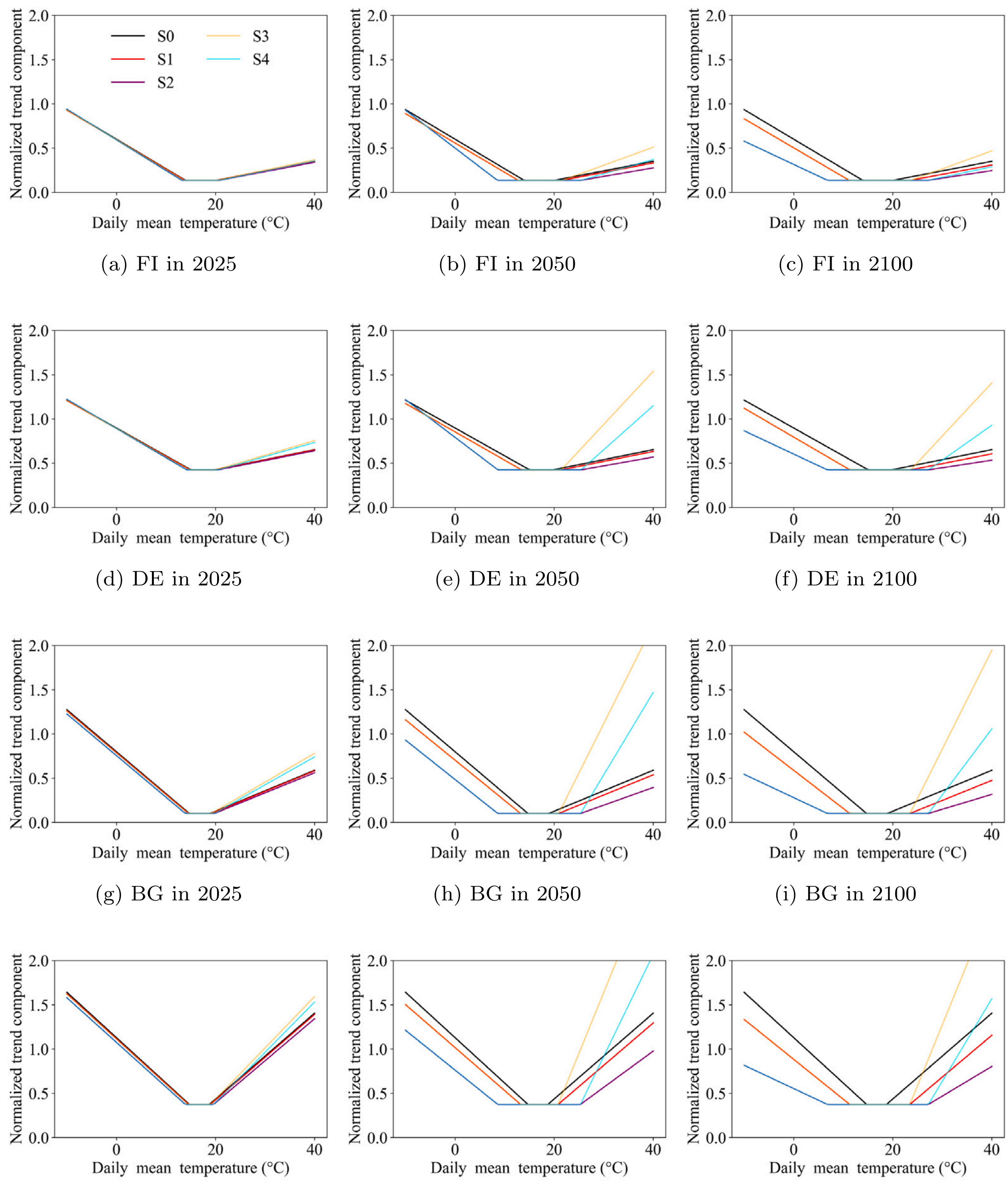


(a) Finland (b) Germany

(c) Bulgaria (d) Spain

Fig. 15. Change of right slope over time for representative countries.

these components of TRFs are influenced. In terms of the heating BPT, a consistent decline is observed in all scenarios compared to our baseline scenario (S0). The strict policy scenarios (S2 and S4) exhibit a notably greater decrease than the moderate policy scenarios (S1 and S3). Taking Germany as an example, the moderate policy scenario decreases the heating BPT from the current approximately 15 °C to around 12 °C by 2100. In contrast, the strict policy scenario demonstrates a more pronounced decrease, reaching around 8 °C before 2055 in the initial



(a) FI in 2025 (b) FI in 2050 (c) FI in 2100

(d) DE in 2025 (e) DE in 2050 (f) DE in 2100

(g) BG in 2025 (h) BG in 2050 (i) BG in 2100

(j) ES in 2025 (k) ES in 2050 (l) ES in 2100

Fig. 16. TRFs in years 2025, 2050, and 2100 for representative countries.

renovation stage. The reduction then stabilizes in the second renovation stage, reaching around 7 °C, resulting in substantial electricity savings. Conversely, for the cooling BPT, the opposite trend is observed. In Germany, the cooling BPT increases from 20 °C to around 23 °C in the moderate policy scenario and experiences a significant rise under the strict policy scenario. In the first renovation stage, it elevates to around 26 °C and can further reach 27 °C by 2100.

Additionally, considering the left slope, the moderate policy scenario reveals a general decrease in the absolute value of slopes across all countries. This suggests that electricity demand becomes less sensitive to cold temperatures, primarily due to improvements in the thermal insulation of buildings. However, a distinct trend emerges in the strict policy scenario. In Finland and Germany, the slope initially decreases until 2055, followed by an upward trajectory. In Bulgaria and Spain, on the other hand, the slope experiences a slight increase until 2055, followed by a more pronounced rise until 2100. This pattern underscores the impact of electrification on different countries. In Germany and Finland, where the current absolute slope value is modest due to efficient thermal building performance, the implementation of strict policies, despite the improvement in thermal insulation, can result in higher winter electricity demand due to increased electrification rate. Conversely, in countries like Spain and Bulgaria, where thermal insulation is less effective, the impact of thermal improvement on the left slope value is more pronounced. In the long run, the collective enhancement of thermal insulation results in a substantial increase in the absolute value of the left slope for all countries.

Regarding the right slope, in scenarios where the space cooling penetration rate remains at the current level (S1 and S2), passive cooling demonstrates its ability to decrease the right slope value. This effect is particularly pronounced in the strict policy scenario (S2), where passive cooling is applied to both renovated and new buildings. This reduction is more pronounced in warmer countries like Bulgaria and Spain. This suggests that, in the long run, the right slope will exhibit less sensitivity to temperature, potentially reducing electricity demand during the summer. However, when considering scenarios with boosted space cooling penetration rates (S3 and S4), there is a notable increase

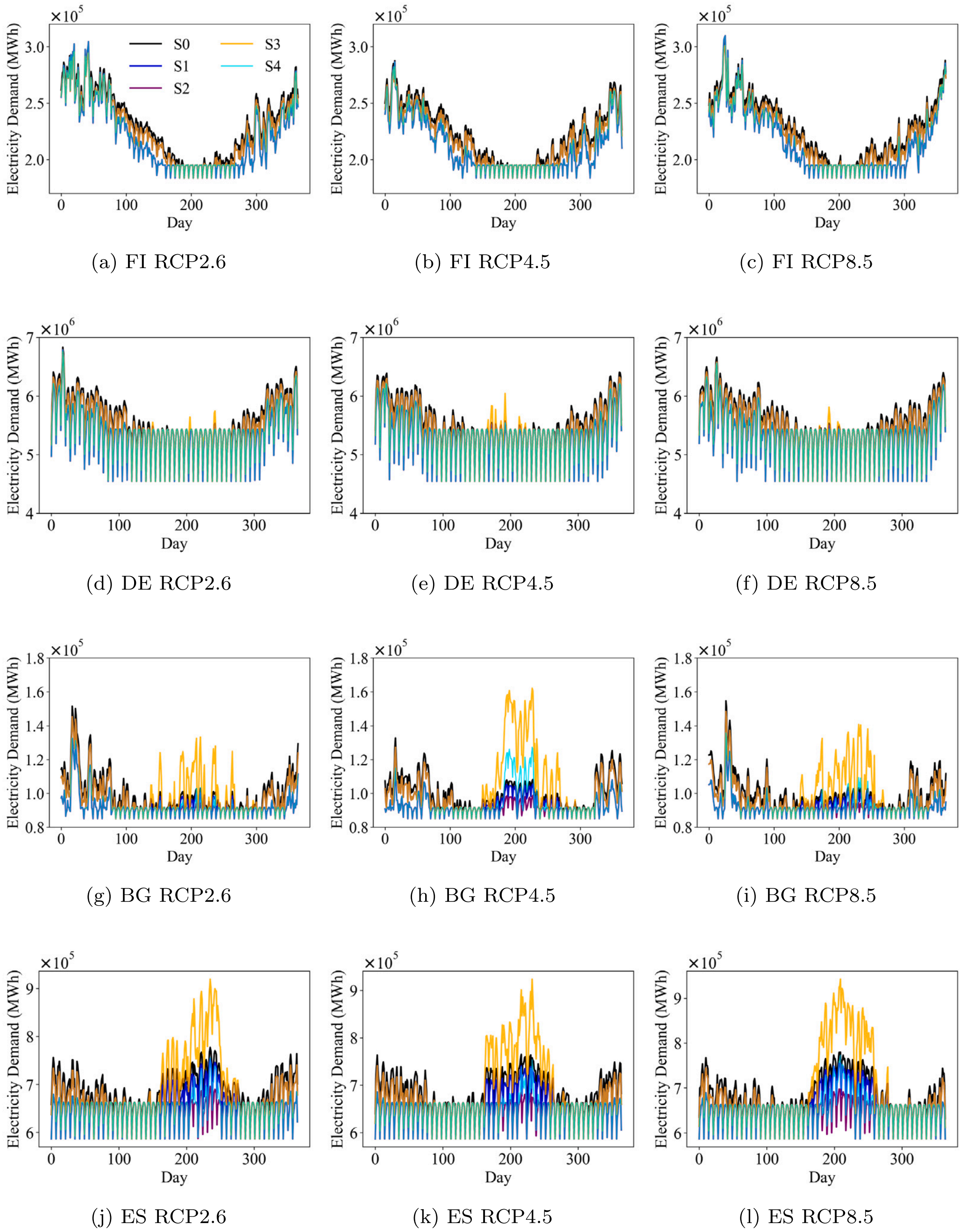


Fig. 17. Daily time series plot under different climate scenarios in the year 2050 for representative countries.

in the right slope value, especially in warmer countries. For Bulgaria and Spain, the increase is substantial in both scenarios. Notably, in Scenario S4, where passive cooling is implemented alongside boosted space cooling, the right slope value begins to decrease after 2050. This is attributed to the space cooling penetration rate reaching its full potential in 2050, and the subsequent impact of passive cooling measures.

By comparing current and future TRFs across various climate scenarios, substantial changes in the TRF shapes become apparent. The future TRFs and time series for all countries are provided in Supplementary Material 3. The most pronounced changes are observed in Bulgaria and Spain, attributed to a substantial increase in space cooling usage. Simultaneously, the enhancement of building thermal insulation, facilitated by both moderate and strict policies, leads to considerably larger comfort zones compared to the present TRF. This underscores the effectiveness of policy interventions, particularly building code regulations, in reducing the overall electricity demand.

After constructing the time series, the impact of dynamic TRFs becomes evident, showcasing notable differences in the electricity demand patterns. In the case of Finland, the most significant variance appears in the winter months.[22] In 2050, the differences between scenarios are insignificant for both summer and winter months; however, by 2100, under RCP 8.5, a substantial 13.7% reduction is observed in the strict policy scenarios (S2 and S4). This phenomenon is attributed to the combined effects of electrification rates and improved thermal insulation. While the thermal insulation effects are in place in 2050, the impact on electricity demand reduction in scenarios S2 and S4 is

[22] Defined as January, February, and December.

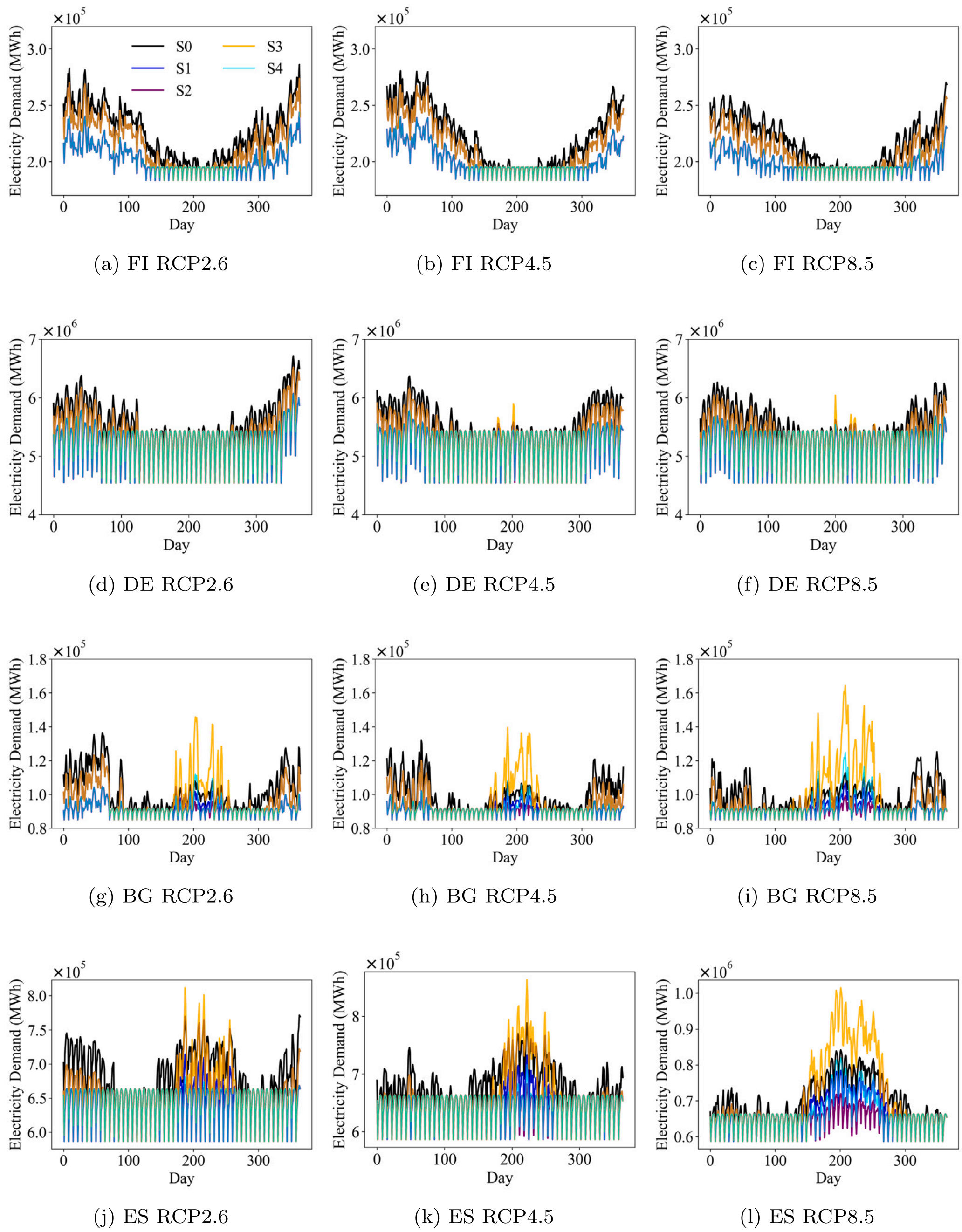


Fig. 18. Daily time series plot under different climate scenarios in the year 2100 for representative countries.

less pronounced due to increased electrification rates. A similar trend in the winter months is noted in Germany. However, in the summer months.[23] Germany exhibits a significant increase of the peak demand in 2050 under RCP 4.5 for S3, yet this significant increase is balanced in S4, where passive cooling is implemented. In comparison to Finland and Germany, warmer countries experience more substantial changes in both the summer and winter months. For example, In winter, under RCP 2.6 in 2050, moderate and strict policy scenarios can reduce electricity demand in Bulgaria by 4.1% and 12.8%, respectively. However, for the summer months, a significant increase in total electricity demand and peak demand can be observed. Under RCP 4.5 in 2050, compared to S0, Scenarios S3 and S4 increase total summer demand in Bulgaria by 24.8% and 2.2%. Specifically, in Bulgaria, under the RCP 8.5 scenario, when compared to S3, our projections indicate that the implementation of effective passive cooling measurements in S4 is expected to reduce the electricity demand during the summer months of 2100 by around 1.1 TWh. In Spain, this reduction is notably higher at 3.7 TWh. This underscores the long-term effectiveness of passive cooling, particularly in warmer regions.

5. Discussion and limitations

In our piecewise regression analysis, we observe variations in the shape of the TRFs across different regions. From the mean RMSE and R^2 score across different regions, on average our RMSE is 0.114 and our R^2 score is 0.671, suggesting our piecewise model performs well in accurately estimating the TRFs. However, it is noteworthy that certain

[23] Defined as June, July, and August.

regions, such as Italy, Luxembourg, and Portugal, have lower R^2 scores, indicating that the temperature influences on demand may not be strong in these areas. These findings suggest the need for more detailed and region-specific analyses to better understand the factors driving electricity demand patterns in these regions. Meanwhile, from the mean R^2 score across different years, we can also observe that the R^2 score is around 0.7, except for the year 2020, which has a lower R^2 score of 0.637. This suggests that the temperature influence on electricity demand in 2020 was weaker compared to other years and may have been obscured by other influential factors. Notably, the COVID-19 pandemic occurred in 2020, and previous studies, such as [102–104] have documented significant changes in people's behavior and demand patterns during the pandemic. These changes likely contributed to the reduced influence of temperature on electricity demand observed in 2020.

Upon projecting future electricity demand, we design five scenarios that not only take into account the enforcement of moderate and strict building regulations but also factor in the escalating use of space cooling. Our results indicate the profound impacts of these variables on the shape of TRFs, and consequently on the time series. Our findings demonstrate a noteworthy difference in policy development across various countries. In colder countries where heating predominates, stringent policies are likely to lead to increased electricity demand until around 2050, driven by the increase in the electrification rate. Nevertheless, this increase is anticipated to be offset by a subsequent reduction in electricity demand, attributable to enhanced thermal insulation in buildings and an optimistic renovation and new built rate. Meanwhile, in regions where cooling demand is pronounced, the effect of moderate policy is limited. Under the moderate policy framework, a substantial increase in electricity demand and peak loads during summer can still be observed due to the significant increase in space cooling use. Under a strict policy framework, however, the electricity demand is projected to witness a considerable reduction, potentially even returning to current levels despite a significant increase in space cooling penetration, thanks to the implementation of passive cooling measures. These interventions, such as the improvement of thermal insulation and the implementation of effective passive cooling methods, play a major role in reducing future residential electricity demand. Other measures, such as Demand Side Management (DSM) with heat (e.g., heat pumps) and non-heat applications (e.g., electric vehicles), the enhancement of energy storage solutions and further grid flexibility, as well as the expansion of the electricity grid to facilitate cross-border electricity exchange, lead to a reliable and stable electricity system of the future.

In spite of our findings, it is important to acknowledge the uncertainties presented in our study. One significant limitation of our research lies in assuming a constant y value for the knot point, which is unlikely to be sustained in the future given the evolving economy and population dynamics. While this introduces uncertainties into our study, it falls beyond the specific scope focused on understanding how policy interventions in residential buildings influence the shape of TRFs.

Another limitation involves the assumptions in our scenarios where we have only accounted for four factors related to residential buildings. Yet the complexities shaping a country's overall electricity demand are far-reaching. Variables such as human behavior, perceptions of comfortable temperatures, electricity prices, and a country's socioeconomic progress could potentially wield influence over the TRFs. Future research can delve deeper into exploring these influences on TRF shapes. In the meantime, a noticeable research gap exists concerning the investigation of how thermal insulation, the use of heat pumps, and passive cooling affect the slope value of TRFs. Given the scarcity of existing literature on this matter, particularly regarding the impact of passive cooling, our scenario assumptions necessitate assuming changes in the slope value based on our assumptions. Consequently, this introduces uncertainties into our results. However, once studies are available to address these issues, more realistic assumptions can be incorporated.

Furthermore, our study solely focused on aggregated electricity demand, yet examining demand disaggregated by sector might yield further insights, as the influence of climate is different for different sectors [105–107]. Unfortunately, comprehensive, sector-specific electricity demand data for our study regions is unavailable. Nonetheless, once such data is available, disaggregating demand by sector may help improve both our piecewise linear regression and future electricity demand projections. In addition, our study exclusively investigates daily electricity demand. To increase the temporal resolution of our demand time series, we could include an intra-day variation as a typical demand pattern, as demonstrated in [47].

6. Conclusion

Our study presents a comprehensive method that incorporates dynamic changes in Temperature Response Functions (TRFs) to project electricity demand. The results indicate that compared to using stationary TRFs, incorporating dynamic changes can lead to significant differences in future electricity demand patterns. Our analysis reveals that the impact of policy intervention on electricity demand differs across regions. In northern and intermediate European countries, an increase in winter demand until around 2050 is anticipated due to the increase in electrification rates. However, improving the thermal insulation for buildings could potentially lead to decreased winter demand in the long run. Conversely, in Southern European countries, increased space cooling usage is projected to significantly increase summertime electricity demand. Addressing this increase may necessitate investments in more flexible power systems to manage peak demands. Our proposed solution involves implementing effective passive cooling measures in residential buildings which can significantly reduce summer electricity demand. Additionally, strategies such as enhancing energy storage in power systems and promoting energy-efficient meters could also effectively manage energy usage during peak periods and ensure supply security. Overall, our study provides a valuable foundation for future research to better understand the complex correlation between temperature, residential buildings, and electricity demand. By projecting potential future electricity demand under various scenarios, our findings can support policymakers and energy system modelers in making informed decisions to ensure a sustainable energy future.

CRediT authorship contribution statement

Wenxuan Hu: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation. **Yvonne Scholz:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Madhura Yeligeti:** Writing – review & editing, Validation, Resources, Investigation. **Ying Deng:** Writing – review & editing, Methodology, Investigation. **Patrick Jochem:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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.

Data availability

All the data used in this study are publicly accessible, as outlined in Section 2. The future electricity demand time series for each study country under ensemble realizations r1 and r2, and across three RCPs from 2023 to 2100, are provided in Zenodo at the following URL/DOI: https://doi.org/10.5281/zenodo.10678016.

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Appendix A

After conducting piecewise regression to simulate the TRFs, we opt to exclude data with R^2 values less than 0.4 to enhance the accuracy of our further analysis. The excluded data, along with corresponding statistical indicators, is detailed in Table A.7.

Table A.7
Overview of the excluded dataset and corresponding RMSE and R^2.

Region	Year	RMSE	R^2	Region	Year	RMSE	R^2
BA	2021	0.168	0.313	SI	2015	0.161	0.388
HU	2015	0.155	0.311	SI	2019	0.152	0.273
LU	2015	0.131	0.192	ES	2020	0.178	0.372
LU	2016	0.137	0.186	IT	2016	0.171	0.057
LU	2017	0.119	0.347	IT	2017	0.143	0.175
LU	2018	0.214	0.148	IT	2018	0.135	0.167
LU	2020	0.225	0.270	IT	2019	0.135	0.296
PL	2015	0.143	0.364	IT	2020	0.217	0.126
PL	2020	0.200	0.296	IT	2021	0.147	0.295
PT	2019	0.161	0.377	DE	2015	0.133	0.398
PT	2020	0.218	0.245	DE	2019	0.136	0.399

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123387. In Supplementary Material 1, we present our findings from piecewise regression analysis, providing plots alongside corresponding RMSE and R^2 scores for each country and year. Supplementary Material 2 offers an alternative method for estimating left slope values. In Supplementary Material 3, we provide future TRFs and electricity demand time series for each study countries based on our scenarios. To compare different climate ensemble realizations, Supplementary Material 4 presents the electricity demand time series for each study countries based on our scenario assumptions for the year 2050 and 2100 under ensemble realizations r1 and r2.

References

[1] Parliament TE, the Council of the European Union. Directive 2010/31/EU of the European parliament and of the council of 19 may 2010 on the energy performance of buildings (recast). Off J Eur Union 2010.
[2] Hor C-L, Watson SJ, Majithia S. Analyzing the impact of weather variables on monthly electricity demand. IEEE Trans Power Syst 2005;20(4):2078–85.
[3] Fan J-L, Hu J-W, Zhang X. Impacts of climate change on electricity demand in China: An empirical estimation based on panel data. Energy 2019;170:880–8.
[4] Apadula F, Bassini A, Elli A, Scapin S. Relationships between meteorological variables and monthly electricity demand. Appl Energy 2012;98:346–56.
[5] Hou R, Li S, Wu M, Ren G, Gao W, Khayatnezhad M, et al. Assessing of impact climate parameters on the gap between hydropower supply and electricity demand by RCPs scenarios and optimized ANN by the improved pathfinder (IPF) algorithm. Energy 2021;237:121621.
[6] Fotis P, Karkalakos S, Asteriou D. The relationship between energy demand and real GDP growth rate: The role of price asymmetries and spatial externalities within 34 countries across the globe. Energy Econ 2017;66:69–84.
[7] Szustak G, Dąbrowski P, Gradoń W, Szewczyk Ł. The relationship between energy production and GDP: Evidence from selected European economies. Energies 2022;15(1):50.
[8] Hirsh RF, Koomey JG. Electricity consumption and economic growth: a new relationship with significant consequences? Electr J 2015;28(9):72–84.
[9] Günay ME. Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey. Energy Policy 2016;90:92–101.
[10] Jamil F, Ahmad E. Income and price elasticities of electricity demand: Aggregate and sector-wise analyses. Energy Policy 2011;39(9):5519–27.
[11] Dai Y, Zhao P. A hybrid load forecasting model based on support vector machine with intelligent methods for feature selection and parameter optimization. Appl Energy 2020;279:115332.
[12] Toktarova A, Gruber L, Hlusiak M, Bogdanov D, Breyer C. Long term load projection in high resolution for all countries globally. Int J Electr Power Energy Syst 2019;111:160–81.
[13] Connolly D. Heat roadmap Europe: Quantitative comparison between the electricity, heating, and cooling sectors for different European countries. Energy 2017;139:580–93.
[14] International Energy Agency. The future of cooling. 2018, https://www.iea.org/reports/the-future-of-cooling. [Accessed 10 October 2023].
[15] UNEP DTU Partnership. Climate technologies in an urban context. 2021, https://tech-action.unepccc.org/wp-content/uploads/sites/2/2021/10/2021-06-tna-cities-guidebook-web.pdf. [Accessed 10 October 2023].
[16] Jochem P, Whitehead J, Dütschke E. The impact of electric vehicles on energy systems. Int. encycl. transp., 1, 560–565. Tech. rep., 2021, http://dx.doi.org/10.1016/B978-0-08-102671-7.10515-9.
[17] Crozier C, Morstyn T, McCulloch M. The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. Appl Energy 2020;268:114973.
[18] Brouwer AS, Kuramochi T, van den Broek M, Faaij A. Fulfilling the electricity demand of electric vehicles in the long term future: An evaluation of centralized and decentralized power supply systems. Appl Energy 2013;107:33–51.
[19] Zainal BS, Ker PJ, Mohamed H, Ong HC, Fattah I, Rahman SA, Nghiem LD, Mahlia TI. Recent advancement and assessment of green hydrogen production technologies. Renew Sustain Energy Rev 2024;189:113941.
[20] Bouckaert S, Pales AF, McGlade C, Remme U, Wanner B, Varro L, D'Ambrosio D, Spencer T. Net zero by 2050: A roadmap for the global energy sector. 2021.
[21] Palacios-Garcia E, Moreno-Munoz A, Santiago I, Flores-Arias J, Bellido-Outeirino F, Moreno-Garcia I. A stochastic modelling and simulation approach to heating and cooling electricity consumption in the residential sector. Energy 2018;144:1080–91.
[22] Mattsson N, Verendel V, Hedenus F, Reichenberg L. An autopilot for energy models–automatic generation of renewable supply curves, hourly capacity factors and hourly synthetic electricity demand for arbitrary world regions. Energy Strategy Rev 2021;33:100606.
[23] Trull O, García-Díaz JC, Troncoso A. One-day-ahead electricity demand forecasting in holidays using discrete-interval moving seasonalities. Energy 2021;231:120966.
[24] Hekkenberg M, Benders R, Moll H, Uiterkamp AS. Indications for a changing electricity demand pattern: The temperature dependence of electricity demand in the Netherlands. Energy Policy 2009;37(4):1542–51.
[25] Yildiz B, Bilbao JI, Sproul AB. A review and analysis of regression and machine learning models on commercial building electricity load forecasting. Renew Sustain Energy Rev 2017;73:1104–22.
[26] Henley A, Peirson J. Non-linearities in electricity demand and temperature: parametric versus non-parametric methods. Oxford Bull Econom Statist 1997;59(1):149–62.
[27] Li X, Sailor D. Electricity use sensitivity to climate and climate change. World Resour Rev 1995;7(3).
[28] Sailor DJ, Muñoz JR. Sensitivity of electricity and natural gas consumption to climate in the USA—Methodology and results for eight states. Energy 1997;22(10):987–98.
[29] Amato AD, Ruth M, Kirshen P, Horwitz J. Regional energy demand responses to climate change: methodology and application to the commonwealth of Massachusetts. Clim Change 2005;71(1–2):175–201.
[30] Ruth M, Lin A-C. Regional energy demand and adaptations to climate change: methodology and application to the state of Maryland, USA. Energy Policy 2006;34(17):2820–33.
[31] Hiruta Y, Gao L, Ashina S. A novel method for acquiring rigorous temperature response functions for electricity demand at a regional scale. Sci Total Environ 2022;819:152893.
[32] Woods J, Fuller C. Estimating base temperatures in econometric models that include degree days. Energy Econ 2014;45:166–71.
[33] Krese G, Lampret Ž, Butala V, Prek M. Determination of a building's balance point temperature as an energy characteristic. Energy 2018;165:1034–49.
[34] Fazeli R, Ruth M, Davidsdottir B. Temperature response functions for residential energy demand–a review of models. Urban Clim 2016;15:45–59.
[35] Miller NL, Hayhoe K, Jin J, Auffhammer M. Climate, extreme heat, and electricity demand in California. J Appl Meteorol Climatol 2008;47(6):1834–44.
[36] Auffhammer M, Aroonruengsawat A. Simulating the impacts of climate change, prices and population on california's residential electricity consumption. Clim Change 2011;109:191–210.

[37] Mukherjee S, Nateghi R. Climate sensitivity of end-use electricity consumption in the built environment: an application to the state of Florida, United States. Energy 2017;128:688–700.
[38] Li Y, Pizer WA, Wu L. Climate change and residential electricity consumption in the Yangtze River Delta, China. Proc Natl Acad Sci 2019;116(2):472–7.
[39] Ihara T, Genchi Y, Sato T, Yamaguchi K, Endo Y. City-block-scale sensitivity of electricity consumption to air temperature and air humidity in business districts of Tokyo, Japan. Energy 2008;33(11):1634–45.
[40] Wang Y, Bielicki JM. Acclimation and the response of hourly electricity loads to meteorological variables. Energy 2018;142:473–85.
[41] Moral-Carcedo J, Vicéns-Otero J. Modelling the non-linear response of Spanish electricity demand to temperature variations. Energy Econom 2005;27(3):477–94.
[42] Hashimoto Y, Ohashi Y, Nabeshima M, Shigeta Y, Kikegawa Y, Ihara T. Sensitivity of electricity consumption to air temperature, air humidity and solar radiation at the city-block scale in Osaka, Japan. Sustain Cities Soc 2019;45:38–47.
[43] Moral-Carcedo J, Pérez-García J. Temperature effects on firms' electricity demand: An analysis of sectorial differences in Spain. Appl Energy 2015;142:407–25.
[44] Brown MA, Cox M, Staver B, Baer P. Modeling climate-driven changes in US buildings energy demand. Clim Change 2016;134:29–44.
[45] Alberini A, Prettico G, Shen C, Torriti J. Hot weather and residential hourly electricity demand in Italy. Energy 2019;177:44–56.
[46] Bessec M, Fouquau J. The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach. Energy Econ 2008;30(5):2705–21.
[47] Castillo VZ, De Boer H-S, Muñoz RM, Gernaat DE, Benders R, van Vuuren D. Future global electricity demand load curves. Energy 2022;258:124741.
[48] Hekkenberg M, Moll H, Uiterkamp AS. Dynamic temperature dependence patterns in future energy demand models in the context of climate change. Energy 2009;34(11):1797–806.
[49] European Commision. In-depth analysis in support of the commisssion comminication COM(2018) 773. 2018, https://climate.ec.europa.eu/system/files/2018-11/com_2018_733_analysis_in_support_en.pdf. [Accessed 10 October 2023].
[50] Nishimwe AMR, Reiter S. Estimation, analysis and mapping of electricity consumption of a regional building stock in a temperate climate in Europe. Energy Build 2021;253:111535.
[51] Economidou M, Atanasiu B, Despret C, Maio J, Nolte I, Rapf O, Laustsen J, Ruyssevelt P, Staniaszek D, Strong D, et al. Europe's buildings under the microscope. A country-by-country review of the energy performance of buildings. 2011.
[52] Hart M, De Dear R. Weather sensitivity in household appliance energy end-use. Energy Build 2004;36(2):161–74.
[53] Pezzutto S, Fazeli R, De Felice M, Sparber W. Future development of the air-conditioning market in Europe: an outlook until 2020. Wiley Interdiscip Rev Energy Environ 2016;5(6):649–69.
[54] Füssel H-M, Jol A, et al. Climate change, impacts and vulnerability in Europe 2012 an indicator-based report. 2012.
[55] European Environment Agency. Adaptation challenges and opportunities for the European energy system. 2021, https://www.eea.europa.eu/publications/adaptation-in-energy-system. [Accessed 10 October 2023].
[56] Song Y-l, Darani KS, Khdair AI, Abu-Rumman G, Kalbasi R. A review on conventional passive cooling methods applicable to arid and warm climates considering economic cost and efficiency analysis in resource-based cities. Energy Rep 2021;7:2784–820.
[57] Samuel DL, Nagendra SS, Maiya M. Passive alternatives to mechanical air conditioning of building: A review. Build Environ 2013;66:54–64.
[58] Escandón R, Suárez R, Sendra JJ. Field assessment of thermal comfort conditions and energy performance of social housing: The case of hot summers in the Mediterranean climate. Energy Policy 2019;128:377–92.
[59] European Environment Agency. Cooling buildings sustainably in Europe: exploring the links between climate change mitigation and adaptation, and their social impacts. 2022, https://www.eea.europa.eu/publications/cooling-buildings-sustainably-in-europe. [Accessed 10 October 2023]. Published in 10.11.2022/ Last Updated 26.04.2023.
[60] Alhuwayil WK, Almaziad FA, Mujeebu MA. Energy performance of passive shading and thermal insulation in multistory hotel building under different outdoor climates and geographic locations. Case Stud Therm Eng 2023;45:102940.
[61] International Energy Agency. Electrification. 2023, https://www.iea.org/energy-system/electricity/electrification. [Accessed 10 October 2023].
[62] Hedegaard K, Mathiesen BV, Lund H, Heiselberg P. Wind power integration using individual heat pumps–analysis of different heat storage options. Energy 2012;47(1):284–93.
[63] Waite M, Modi V. Potential for increased wind-generated electricity utilization using heat pumps in urban areas. Appl Energy 2014;135:634–42.
[64] International Energy Agency. The future of heat pumps. 2022, https://iea.blob.core.windows.net/assets/4713780d-c0ae-4686-8c9b-29e782452695/TheFutureofHeatPumps.pdf. [Accessed 10 October 2023].
[65] Asdrubali F, D'Alessandro F, Schiavoni S. A review of unconventional sustainable building insulation materials. Sustain Mater Technol 2015;4:1–17.
[66] Lechtenböhmer S, Schüring A. The potential for large-scale savings from insulating residential buildings in the EU. Energy Eff 2011;4:257–70.
[67] Enerdata. Floor U-values (weighted average based on stock). 2023, https://entranze.enerdata.net/floor-u-values.html. [Accessed 10 October 2023].
[68] Palma RM, Ramos JS, Delgado MG, Amores TRP, D'Angelo G, Domínguez SÁ. Extending the concept of high-performance buildings to existing dwellings. Energy Build 2023;296:113431.
[69] Parliament TE, the Council of the European Union. Directive 2012/27/EU of the European parliament and of the council of 25 october 2012 on energy efficiency, amending directives 2009/125/EC and 2010/30/EU and repealing directives 2004/8/EC and 2006/32/EC text with EEA relevance. Off J Eur Union 2012.
[70] International Energy Agency. Building envelopes. 2023, https://www.iea.org/energy-system/buildings/building-envelopes. [Accessed 10 October 2023].
[71] Jakubcionis M, Carlsson J. Estimation of European union residential sector space cooling potential. Energy Policy 2017;101:225–35.
[72] Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, Nicolas J, Peubey C, Radu R, Schepers D, et al. The ERA5 global reanalysis. Q J R Meteorol Soc 2020;146(730):1999–2049.
[73] Geonames. GeoNames. 2023, URL http://geonames.org/. [Accessed 10 October 2023].
[74] Mantzos L, Matei N-A, Mulholland E, Rózsai M, Tamba M, Wiesenthal T, et al. The JRC integrated database of the European energy system. 2018.
[75] Brown JS, Domanski PA. Review of alternative cooling technologies. Appl Therm Eng 2014;64(1–2):252–62.
[76] EURO-CORDEX. EURO-CORDEX - coordinated downscaling experiment - European domain. 2023, URL https://www.euro-cordex.net/. [Accessed 10 October 2023].
[77] Taylor KE, Stouffer RJ, Meehl GA. An overview of CMIP5 and the experiment design. Bull Am Meteorol Soc 2012;93(4):485–98.
[78] Giorgetta M, Jungclaus J, Reick C, Legutke S, Brovkin V, Crueger T, Esch M, Fieg K, Glushak K, Gayler V, et al. Climate change from 1850 to 2100 in MPI-esm simulations for the coupled model intercomparison project 5. J Adv Model Earth Syst 2012.
[79] Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, Van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, et al. The next generation of scenarios for climate change research and assessment. Nature 2010;463(7282):747–56.
[80] American Society of Heating R, Engineers A-C, Ashrae, Bagheri H, Owen M. 2013 ASHRAE handbook-fundamentals. ASHRAE handbook: fundamentals, ASHRAE; 2013, URL https://books.google.de/books?id=1K75nAEACAAJ.
[81] Christenson M, Manz H, Gyalistras D. Climate warming impact on degree-days and building energy demand in Switzerland. Energy Convers Manage 2006;47(6):671–86.
[82] Olonscheck M, Holsten A, Kropp JP. Heating and cooling energy demand and related emissions of the German residential building stock under climate change. Energy Policy 2011;39(9):4795–806.
[83] Eurostat. Energy statistics - cooling and heating degree days. 2019–2020, https://ec.europa.eu/eurostat/cache/metadata/en/nrg_chdd_esms.htm. [Accessed 10 October 2023].
[84] Carbon Trust. Degree days for energy management. 2012, https://www.sustainabilityexchange.ac.uk/files/degree_days_for_energy_management_carbon_trust.pdf. [Accessed 10 October 2023].
[85] Hao Z, Zhang X, Xie J, Yin K, Liu J. Balance point temperature and heating degree-days in different climate conditions for building energy efficiency applications. Build Environ 2022;216:109013.
[86] Cömert M, Yildiz A. Climate change impacts on electricity demand in Turkey. In: 2019 international artificial intelligence and data processing symposium. IDAP, IEEE; 2019, p. 1–5.
[87] Dubin JA. An integrated engineering–econometric analysis of residential balance point temperatures. Energy Econom 2008;30(5):2537–51.
[88] Verbai Z, Lakatos Á, Kalmár F. Prediction of energy demand for heating of residential buildings using variable degree day. Energy 2014;76:780–7.
[89] Huang J, Gurney KR. Impact of climate change on US building energy demand: sensitivity to spatiotemporal scales, balance point temperature, and population distribution. Clim Change 2016;137:171–85.
[90] Lindelöf D. Bayesian estimation of a building's base temperature for the calculation of heating degree-days. Energy Build 2017;134:154–61.
[91] Giannakopoulos C, Psiloglou BE. Trends in energy load demand for Athens, Greece: weather and non-weather related factors. Clim Res 2006;31(1):97–108.
[92] Andrade C, Mourato S, Ramos J. Heating and cooling degree-days climate change projections for Portugal. Atmosphere 2021;12(6):715.
[93] Psiloglou B, Giannakopoulos C, Majithia S, Petrakis M. Factors affecting electricity demand in Athens, Greece and London, UK: A comparative assessment. Energy 2009;34(11):1855–63.
[94] Papakostas K, Mavromatis T, Kyriakis N. Impact of the ambient temperature rise on the energy consumption for heating and cooling in residential buildings of Greece. Renew Energy 2010;35(7):1376–9.
[95] Tsikaloudaki K, Laskos K, Bikas D. On the establishment of climatic zones in Europe with regard to the energy performance of buildings. Energies 2011;5(1):32–44.

[96] European Commision. Energy efficiency plan 2011, com(2011) 109 final. 2011, https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0109:FIN:EN:PDF. [Accessed 10 October 2023].
[97] Lindelöf D, Alisafaee M, Borsò P, Grigis C, Viaene J. Bayesian verification of an energy conservation measure. Energy Build 2018;171:1–10.
[98] Johansson P. Heat pumps in Sweden–A historical review. Energy 2021;229:120683.
[99] Sandvall A, Karlsson KB. Energy system and cost impacts of heat supply to low-energy buildings in Sweden. Energy 2023;268:126743.
[100] Ministry of Infrastructure (Sweden). Sweden's report under article 14(1) of directive 2012/27/EU on energy efficiency – promotion of efficiency in heating and cooling. 2021, https://energy.ec.europa.eu/system/files/2021-10/se_ca_2020_en.pdf. [Accessed 12 February 2024].
[101] Odyssee Energy. 2021 EU energy efficiency scoreboard. 2021, [Accessed 10 October 2023].
[102] Covid I. Impact of electricity–statistical report may 2020. International energy agency. 2020, (19).
[103] Krarti M, Aldubyan M. Review analysis of COVID-19 impact on electricity demand for residential buildings. Renew Sustain Energy Rev 2021;143:110888.
[104] Santiago I, Moreno-Munoz A, Quintero-Jiménez P, Garcia-Torres F, Gonzalez-Redondo M. Electricity demand during pandemic times: The case of the COVID-19 in Spain. Energy Policy 2021;148:111964.
[105] Zamanipour B, Ghadaksaz H, Keppo I, Saboohi Y. Electricity supply and demand dynamics in Iran considering climate change-induced stresses. Energy 2023;263:126118.
[106] MacMackin N, Miller L, Carriveau R. Modeling and disaggregating hourly effects of weather on sectoral electricity demand. Energy 2019;188:115956.
[107] Chang Y, Kim CS, Miller JI, Park JY, Park S. A new approach to modeling the effects of temperature fluctuations on monthly electricity demand. Energy Econ 2016;60:206–16.