

Article

Forecasting UK Electricity and Gas Demand Under RCP Scenarios for Net-Zero Energy Security Using ML

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Abstract

Climate change is altering energy-demand patterns through changing temperatures and heating and cooling requirements. Long-term energy-demand projections are essential for energy security, infrastructure planning, and preparing net-zero energy systems. However, integrated assessments of climate-sensitive electricity and gas demand trajectories in the UK under long-term climate-forcing pathways and net-zero transition assumptions remains limited. To address this gap, this study develops a scenario-based machine-learning framework to jointly project electricity and gas demand in the UK up to 2050 under climate-forcing pathways. CMIP6 daily temperature projections at 0.25° resolution are used to calculate Heating Degree Days and Cooling Degree Days under low-, intermediate-, and high-forcing pathways, labelled RCP2.6, RCP4.5, and RCP8.5. These indicators are used as inputs to Random Forest models for electricity and gas demand. By 2050, electricity demand under RCP8.5 is 4.1% higher than under RCP2.6, while gas demand is 6.8% lower. Under the net-zero adjustment, gas demand declines because of the assumed 75% reduction in gas use, while electricity demand rises as part of displaced gas demand shifts to electricity. Adjusted electricity demand differs by 2–3 TWh between the highest- and lowest-warming pathways, while adjusted gas demand differs by 7–8 TWh. The framework jointly assesses climate-sensitive electricity and gas demand and links these projections to net-zero gas-reduction and electrification assumptions. The results support electricity-capacity and storage planning, electrification strategies, hydrogen infrastructure investment, and decisions on the future role of gas networks in UK energy-security planning under changing climate and transition conditions across Britain.

Keywords: electricity and gas demand forecasting; climate change impacts; net-zero energy systems; RCP scenarios; Random Forest; electrification; UK energy system



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1. Introduction

Climate change has become one of the most pressing challenges facing energy systems, infrastructure planning, and long-term policy design [1]. The IPCC Sixth Assessment Report states that human-induced greenhouse gas emissions have already increased global surface temperature by approximately 1.1 °C above pre-industrial levels during 2011–2020 [2]. Continued emissions are expected to intensify global warming, with the 1.5 °C threshold likely to be reached in the near term under most assessed scenarios [3]. Each additional increment of warming is projected to increase the frequency and severity of

climate-related hazards, including heatwaves, heavy precipitation, droughts, and flooding [4].

In the UK, these changes are already evident. The Met Office reports that the UK has warmed by around 1 °C since the 1950s, accompanied by more frequent hot spells, fewer cold spells, and increasing rainfall intensity [5]. By the 2070s, UK summers are projected to be 1–6 °C warmer than the 1990s, with the average hottest summer day becoming 4–7 °C warmer and the likelihood of prolonged temperatures above 30 °C increasing substantially, particularly in southern England [5]. Rainfall intensity is also expected to rise, with summer rainfall intensity increasing by up to 20% and winter rainfall intensity by up to 25%, increasing the risk of surface-water flooding [6]. These projections suggest that the UK will face growing risks from overheating, flooding, drought, and pressure on infrastructure [7].

These climatic changes are expected to affect a wide range of sectors, including public health, water resources, agriculture, and energy infrastructure [8]. Among these, the power sector is particularly sensitive to changes in climate patterns, as variations in temperature, precipitation, and extreme weather events can affect both electricity demand and supply [9]. Rising temperatures are likely to alter seasonal electricity demand by reducing heating requirements in milder winters while increasing cooling demand during hotter summers [10]. In particular, the growing use of air conditioning and other cooling technologies is expected to increase peak electricity demand during heatwaves and prolonged periods of high temperatures [11]. Such changes may create new challenges for electricity system planning and security, as shifts in demand profiles can lead to mismatches between electricity supply and demand, especially during extreme weather events when generation, transmission, and distribution infrastructure may also be under stress [9,12]. As climate warming intensifies, policymakers, system operators, and energy planners need to consider climate-driven shifts in electricity demand when developing long-term plans and energy models. This is crucial to ensure that future electricity systems stay adequate, reliable, and adaptable amidst changing climate conditions [12].

Therefore, assessing how energy demand may change under different climate scenarios has become a key priority for energy planning in many countries. Examining these changes is essential for understanding how future demand profiles may evolve and for identifying potential risks to the supply-demand balance and long-term energy security. Accordingly, this study aims to forecast electricity and gas demand in the UK under different climate scenarios through 2050. The analysis focuses on the climate-sensitive component of demand reflected in changes in heating and cooling requirements. Therefore, the results should be understood as climate-related demand projections, rather than as a complete forecast of future energy demand. To represent these alternative climate futures in a consistent and internationally recognised way, this study uses Representative Concentration Pathways (RCPs), which provide standardised scenarios of future greenhouse gas concentrations and associated warming levels.

1.1. Climate Scenarios and Forecasting Approaches

Future energy demand forecasting under climate change requires a clear representation of alternative warming pathways, because different climate futures can lead to different temperature patterns, heating and cooling requirements, and consequently different energy-demand outcomes. In this context, Representative Concentration Pathways (RCPs) provide a useful framework for linking climate projections with long-term energy demand analysis. RCPs are standardised climate scenarios developed to describe possible future trajectories of greenhouse gas concentrations and their resulting effects on Earth's energy balance. They provide alternative pathways that allow researchers to compare climate impacts under

different levels of future warming [12,13]. The four commonly used RCPs are RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The numbers refer to the approximate radiative forcing level reached by 2100, measured in watts per square metre (W/m^2), relative to pre-industrial conditions [13]. Radiative forcing can be understood as the additional heat energy retained in the climate system because of increased greenhouse gas concentrations [14]. This retained energy is directly linked to global warming: as radiative forcing increases, more heat is trapped within the atmosphere–ocean system, leading to higher global mean surface temperatures [15]. Therefore, lower RCP values, such as RCP2.6, are associated with lower levels of warming, whereas higher RCP values, such as RCP8.5, represent futures with higher greenhouse gas concentrations, stronger radiative forcing, and greater warming impacts. Figure 1 illustrates the historical and projected changes in global annual mean surface temperature under selected RCP scenarios in this study.

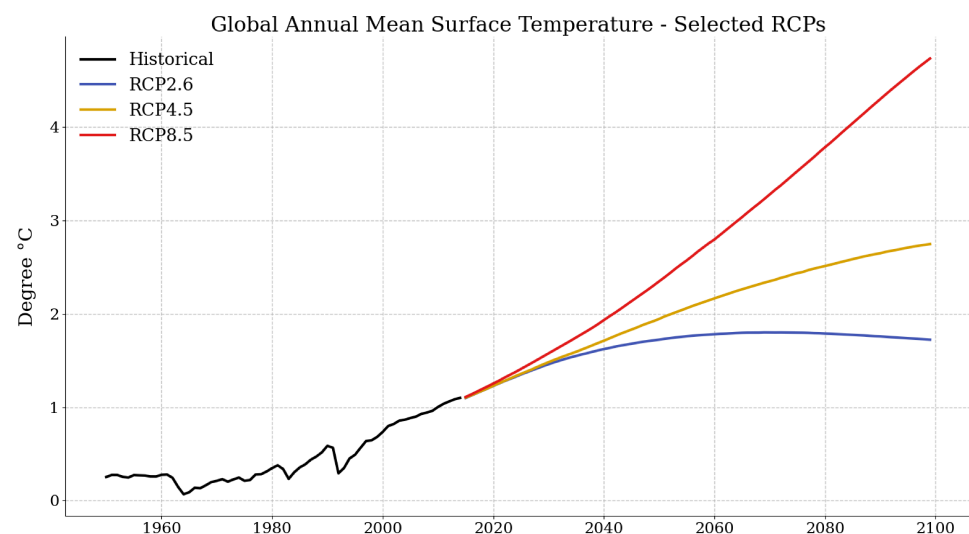


Figure 1. Global annual mean surface temperature projections under RCP2.6, RCP4.5, and RCP8.5 with the historical temperature trend.

After defining the climate scenarios, the next step is to translate these pathways into future energy demand projections. Since electricity and gas demand are strongly influenced by weather conditions, particularly temperature, each RCP scenario can be used to generate a different set of future weather inputs [16–18]. These inputs are then combined with historical energy-consumption data to estimate how demand may change under alternative warming pathways. Several methodological approaches can be used for this purpose. Traditional statistical methods, such as regression-based models and time-series analysis, are commonly used to quantify the relationship between energy demand and climatic variables [19–22]. These methods are useful because they provide interpretable results and can identify how temperature changes affect heating and cooling demand. In contrast, physical or bottom-up demand models explicitly represent energy-service requirements, technologies, and end-use characteristics, and are therefore well suited to examining structural changes such as electrification, technology substitution, and efficiency improvements. However, they typically require substantially more detailed technological, behavioural, and sector-specific input data than statistical approaches [23]. Energy demand may also be affected by non-linear interactions between climate, seasonality, socio-economic conditions, and behavioural patterns [18]. For this reason, machine learning methods have increasingly been applied to energy demand forecasting [24,25]. Algorithms such as Random Forests, Gradient Boosting, Support Vector Regression, and Artificial Neural Networks can capture complex and non-linear relationships between historical demand and explanatory variables, making them suitable for forecasting under changing

climate conditions [26]. More advanced artificial-intelligence frameworks have also been developed to learn multiple related energy-system tasks simultaneously. For example, Liang et al. [27] proposed a scenario-oriented dual-task learning framework that integrates non-intrusive load monitoring with robust energy management in hybrid microgrids. By jointly learning the related load-monitoring and energy-management tasks, the framework exploits shared information between the two tasks and improves robustness under different operating scenarios. This approach demonstrates the potential of multi-task learning for addressing interconnected prediction and decision-making problems in energy systems. However, such frameworks are primarily suited to high-resolution operational settings involving multiple interdependent tasks and detailed appliance- or asset-level data, whereas long-term national demand forecasting typically relies on lower-frequency aggregated explanatory variables.

1.2. Gap in Existing Literature and Contribution of This Work

Many studies that have used climate projections to estimate future changes in heating and cooling requirements show a decline in winter heating demand and an increase in summer cooling demand as temperatures rise. These changes are particularly important for energy systems because they can alter not only annual consumption, but also seasonal demand patterns and peak-load conditions. While regression and time-series models have been widely used for their transparency, more recent studies have employed machine learning methods to capture non-linear relationships among demand, weather, and temporal variables. Table 1 summarises selected studies that have forecasted electricity or gas demand while explicitly considering climate-related variables.

Table 1. Summary of selected studies on energy demand forecasting under climate-related variables.

Paper	Region	Period	Models	Demand Type
[28]	Ireland	Hourly projections to 2060	Artificial Neural Network (ANN)	Electricity
[29]	Poland	Daily, day-ahead	ML algorithms, including Random Forest and kernel-based approaches	Gas
[30]	United States	Hourly/day-ahead	Data-driven temperature-sensitivity modelling	Electricity
[31]	Thailand	Hourly/day-ahead	Feedforward Artificial Neural Network (FF-ANN)	Electricity
[32]	South Korea	Monthly residential electricity	Long Short-Term Memory (LSTM)	Electricity
[33]	Italy	Daily, day-ahead	Random Forest; Support Vector Regression	Gas
[34]	Nepal	Daily, day-ahead	Artificial Neural Network (ANN)	Electricity
[35]	Turkey	Annual; long-term	Artificial Neural Network (ANN)	Electricity
[36]	India	Annual; long-term	Long Short-Term Memory, Recurrent Neural Networks	Electricity & Gas
[37]	Germany	Hourly profiles; annual load-profile generation	Dense Artificial Neural Network	Electricity
[38]	Portugal	168-h ahead	XGBoost, Random Forest	Electricity
[39]	UK	Daily, Day-ahead	Multivariate Gaussian, Gaussian Baseline	Electricity & Gas
[40]	UK	Monthly data (January 1995–March 2022)	Neural Network, Support Vector Regression	Electricity & Gas
[41]	UK	Annual; long-term (1993–2019)	Multiple Linear Regression, Support Vector Machine, Neural Network	Electricity & Gas
This Paper	UK	Annual; long-term up to 2050	Random Forest (RF)	Electricity & Gas

As shown in the table, previous studies have covered a wide range of geographical contexts and methods. For example, Huang and Iglesias [28] projected Ireland's hourly electricity demand up to 2060 using an Artificial Neural Network (ANN) model and showed that future climate and socioeconomic changes can significantly affect long-term electricity demand patterns. Panek and Wlodek [29] examined natural gas demand in Poland using neural networks, Multiple Linear Regression (MLR), and Random Forest, and found that meteorological conditions and historical consumption are important drivers of gas consumption. Similarly, Marziali et al. [33] studied one-day-ahead gas demand forecasting in Italy using several base forecasters and ensemble predictors, showing that combining different predictors can improve forecasting accuracy and outperform system-operator predictions. In the electricity sector, Madrid and Antonio [38] developed 168 h-ahead load forecasts for Portugal using XGBoost and Random Forest, and found that historical load and weather variables can improve short-term electricity demand prediction. Across these studies, Random Forest is one of the frequently applied machine-learning models identified in this literature review, particularly because it can capture nonlinear relationships and can be effectively applied to relatively limited datasets [26,42]. This provides further support for its application in the long-term forecasting framework adopted in this study.

In the UK context, previous studies have mainly focused on historical or short-term demand forecasting. For example, Bala and Shuaibu [40] modelled monthly UK electricity and gas consumption using neural-network, support-vector, and hybrid approaches based on historical data up to 2022, while Liu and Li [41] investigated annual UK electricity and energy consumption using neural-network, multiple linear regression and support-vector methods using data up to 2019. More recently, Gioia et al. [39] developed an advanced statistical framework for regional electricity net-demand forecasting across Great Britain. These studies primarily focus on historical model development and validation, rather than long-term joint projections of electricity and gas demand under alternative climate scenarios and net-zero transition assumptions [39].

Analysing electricity and gas demand is particularly important for countries such as the UK, because net-zero and decarbonisation policies are likely to change both the level and timing of energy demand across regions [43]. The electrification of heating and transport is expected to increase electricity demand and alter peak-load patterns, particularly in regions with high heat demand, dense populations, or rapid uptake of electric vehicles and heat pumps [44,45]. At the same time, the development of low-carbon hydrogen and the gradual reduction in fossil gas use may change the future role of gas networks, including where gas demand declines, where hydrogen blending or network conversion may be required, and where additional electricity and gas inputs may be needed for hydrogen production [46,47].

To address these gaps, this study develops a long-term climate-sensitive forecasting framework for UK electricity and gas demand up to 2050 under selected RCP scenarios. The modelling scope centres on the relationship between aggregate energy demand and temperature-related heating and cooling requirements, while recognising that broader socioeconomic and technological developments are not modelled explicitly. The main contribution of this work is its joint assessment of both energy carriers within a single scenario-based framework, which enables the impacts of alternative warming pathways on electricity and gas demand to be compared consistently. This is important because climate change may simultaneously increase cooling-related electricity demand and reduce heating-related gas demand, creating new challenges for energy-system planning, infrastructure investment, and supply-demand balancing. The projections consequently provide a climate-sensitive reference point rather than attempting to represent every determinant of future energy consumption. The results can support integrated energy-system modelling by providing climate-adjusted demand inputs for long-term planning. These inputs are

important for estimating future generation, storage, and network requirements. They can also help identify peak-demand risks, particularly where cooling-related electricity demand increases during hotter periods or where heating demand remains high in colder regions. For electrification pathways, the projections provide a baseline for assessing how much additional electricity may be required as heating and transport shift away from fossil fuels. In addition, they can inform decisions on whether gas networks should be maintained, repurposed, or gradually reduced in different regions. Therefore, the study contributes not only to the demand-forecasting literature, but also to broader discussions on how climate change and net-zero transitions may jointly reshape future electricity and gas systems.

2. Methodology

2.1. Energy Inputs

National domestic and non-domestic electricity and gas consumption data for the UK over the period 1970–2024 are obtained from [48,49]. Figure 2 presents the historical evolution of total UK electricity and gas demand during this period. As shown in the figure, total electricity demand increased by about 79.5% from 1970 to its peak in 2005, followed by a decline of about 22.5% by 2024. The initial increase reflects the expansion of electricity use across domestic, commercial, and industrial activities, while the subsequent decline can be linked to improvements in energy efficiency, changes in industrial structure, higher efficiency of appliances and equipment, and broader shifts in consumption patterns. Despite this reduction in recent years, electricity demand in 2024 remains around 39.1% higher than its 1970 level, showing that electricity still plays a larger role in the UK energy system than at the beginning of the study period.

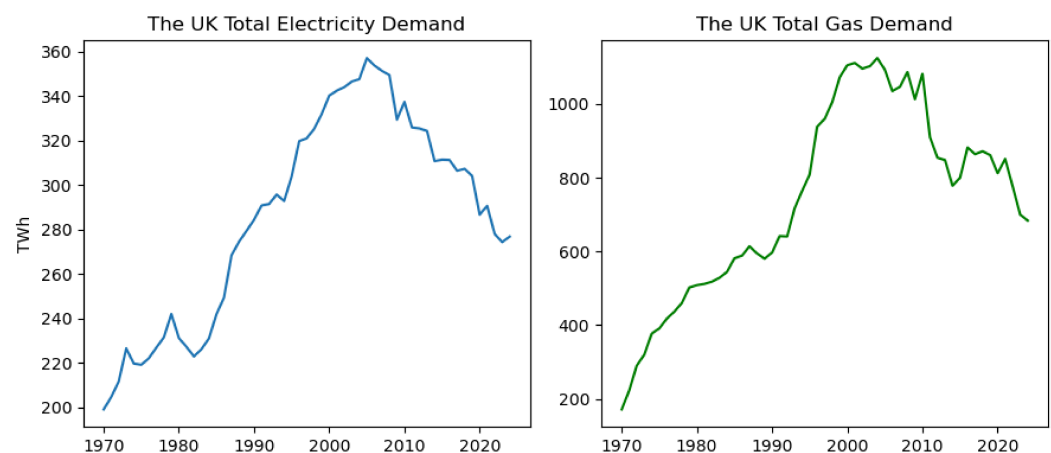


Figure 2. Historical trends in total UK electricity and gas demand from 1970 to 2024.

Gas demand shows a more pronounced long-term variation. It increased sharply by about 500.7% from 1970 to its peak in 2004, reflecting the expansion of gas use in the UK energy system, particularly for space heating and, from the 1990s onward, gas-fired electricity generation. This growth is consistent with the wider shift towards natural gas in the UK energy sector during the “dash for gas” period [50]. After reaching its maximum level, gas demand declined by about 39.2% by 2024. This decline can be attributed to a combination of improved energy efficiency, changes in industrial demand, warmer years reducing heating requirements, and the increasing contribution of low-carbon electricity sources, which reduced the role of gas in power generation. Nevertheless, total gas demand in 2024 remains higher than in 1970.

2.2. Weather Inputs

Temperature is one of the most important climate-related drivers of electricity and gas demand, because it directly affects the need for space heating and cooling [51]. In general, lower outdoor temperatures increase heating requirements, which mainly raises gas demand and, in some cases, electricity demand. Conversely, higher outdoor temperatures can reduce heating demand but increase electricity consumption for cooling [52]. Therefore, temperature directly influences both the level and seasonal pattern of energy demand. The relationship between energy demand and temperature can be expressed generally as Equation (1).

$$D_t = f(\theta_t) + \varepsilon_t \quad (1)$$

where D_t is the electricity or gas demand at time t , θ_t is the outdoor temperature, $f(\theta_t)$ represents the relationship between temperature and demand, and ε_t is the error term. However, raw temperature alone is limited because its effect on energy demand is neither linear nor symmetric. A change in temperature does not always lead to the same change in demand. Similarly, temperatures near a comfort threshold may have little effect on either heating or cooling demand. For this reason, this study uses Heating Degree Days (HDD) and Cooling Degree Days (CDD) instead of raw temperature. HDD and CDD transform temperature into indicators that are more directly related to energy use. This approach is consistent with recent regional and multi-regional studies that use temperature-derived or degree-day indicators as the principal climate-sensitive variables for assessing changes in electricity, gas, heating, and cooling demand under future climate pathways [51,53–57]. HDD measures the extent to which outdoor temperature falls below a base temperature and therefore represents heating requirements. CDD measures the extent to which outdoor temperature rises above the base temperature and therefore represents cooling requirements. This allows the model to distinguish between cold-driven and heat-driven demand effects. In this study, a heating base temperature of 15.5 °C and a cooling base temperature of 22 °C are used for calculating HDD and CDD, respectively [58]. HDD and CDD are calculated using the daily minimum temperature (θ_L), daily maximum temperature (θ_H), daily average temperature ($\bar{\theta}$), and the relevant heating or cooling base temperature (θ_b). This approach is more detailed than using only the daily average temperature because it captures within-day temperature variation. Heating or cooling may be required during part of the day even when the daily average temperature is close to the base temperature.

The HDD indicator is calculated using Equation (2).

$$HDD = \begin{cases} 0, & \theta_b \leq \theta_L \\ 0.25(\theta_b - \theta_L), & \theta_L < \theta_b < \bar{\theta} \\ 0.5(\theta_b - \theta_L) - 0.25(\theta_H - \theta_b), & \bar{\theta} \leq \theta_b < \theta_H \\ \theta_b - \bar{\theta}, & \theta_H \leq \theta_b \end{cases} \quad (2)$$

The CDD indicator is calculated using Equation (3).

$$CDD = \begin{cases} \bar{\theta} - \theta_b, & \theta_b \leq \theta_L \\ 0.5(\theta_H - \theta_b) - 0.25(\theta_b - \theta_L), & \theta_L < \theta_b < \bar{\theta} \\ 0.25(\theta_H - \theta_b), & \bar{\theta} \leq \theta_b < \theta_H \\ 0, & \theta_H \leq \theta_b \end{cases} \quad (3)$$

When the temperature is below the heating base temperature, HDD becomes positive because additional heating is required to maintain indoor comfort. A higher HDD value means that the outdoor temperature is further below the heating base temperature, or remains below it for a longer period, indicating stronger heating demand. In contrast, when the temperature exceeds the cooling base temperature, CDD becomes positive, indicating

that cooling may be needed. A higher CDD value means that the temperature is further above the cooling base temperature, or remains above it for longer, indicating greater cooling demand.

Accordingly, the demand relationship can be rewritten as Equation (4).

$$D_t = f(HDD_t, CDD_t) + \varepsilon_t \quad (4)$$

where HDD_t and CDD_t represent heating and cooling requirements at the time t . By using HDD and CDD, the model can better capture the non-linear relationship between climate conditions and energy demand. The HDD and CDD values used as model inputs are derived from climate projection pathways. Under the CMIP6/ScenarioMIP convention, the underlying temperature projections correspond to SSP1-2.6, SSP2-4.5, and SSP5-8.5. For consistency with the forcing-based terminology adopted throughout this study, these pathways are subsequently referred to as RCP2.6, RCP4.5, and RCP8.5, representing low-, intermediate-, and high-forcing temperature pathways, respectively. These labels are used solely to distinguish the magnitude of the projected temperature changes and do not indicate the incorporation of SSP-based assumptions regarding population, economic growth, technological development, land use, or energy-system transformation into the forecasting model.

The temperature projections representing the 4.5 and 8.5 forcing pathways were extracted through the Google Earth Engine CMIP6 Explorer (GEECE) [59]. As the 2.6 forcing pathway was not available through the selected GEECE interface, the corresponding temperature projections were obtained directly from the NASA Earth Exchange Global Daily Downscaled Projections for CMIP6 archive (NEX-GDDP-CMIP6) [60]. The climate models selected for the three forcing pathways were CanESM5, HadGEM3-GC31-MM, and UKESM1-0-LL. The extracted daily variables were minimum near-surface air temperature (tasmin), maximum near-surface air temperature (tasmax), and mean near-surface air temperature (tas). The data were extracted at a daily temporal resolution and a spatial resolution of $0.25^\circ \times 0.25^\circ$.

Historical and future temperature simulations were processed separately and then combined to form continuous daily series covering the period 1970–2050. Scenario-based simulations were available from 2015 onwards, and data up to 2050 were used. The historical and future series were joined at the common transition year of 2015 without interpolation.

The UK boundary was defined as the region of interest. For each climate-model simulation, the gridded temperature values were spatially aggregated by calculating a weighted mean across the grid cells associated with the UK region of interest. This procedure produced nationally aggregated daily minimum, maximum, and mean temperature series for each climate model and forcing pathway.

No additional bias correction was applied by the authors after the temperature data were extracted. Therefore, any residual biases remaining in the underlying downscaled climate projections may also be present in the temperature series and are acknowledged as a limitation of the analysis.

To reduce dependence on an individual climate model, the daily temperature series from CanESM5, HadGEM3-GC31-MM, and UKESM1-0-LL were combined to produce a multi-model mean for each forcing pathway. For the 4.5 and 8.5 forcing pathways, the GEECE ensemble-mean option was used to calculate the mean of the selected simulations. For the 2.6 forcing pathway obtained directly from NEX-GDDP-CMIP6, the corresponding model simulations were combined using the same multi-model averaging procedure. The resulting multi-model mean daily minimum, maximum, and mean temperatures

were subsequently used to calculate HDD and CDD for the full 1970–2050 period using Equations (2) and (3), respectively.

2.3. Random Forest Forecasting Model

To model the relationship between HDD CDD and energy demand, this study applies the Random Forest (RF) ML algorithm. The literature has shown that this model often achieves strong predictive performance across standard forecasting evaluation criteria and has been successfully applied in a wide range of energy-demand studies [61–63]. Its suitability is mainly due to its ability to capture non-linear relationships, account for interactions between variables, and produce robust predictions without requiring strict assumptions about the underlying data structure [29,64]. Therefore, the model is used in this study to estimate future electricity and gas demand. In a single decision tree, the dataset is divided into several terminal regions or leaves [65]. For each leaf, the predicted demand is calculated as the average observed demand of the training samples that fall within that region Equation (5).

$$\hat{D}_{R_m} = \frac{1}{N_m} \sum_{i \in R_m} D_i \quad (5)$$

where $\hat{D}_{R_m}$ is the predicted demand in terminal region R_m , N_m is the number of observations in that region, and D_i is the observed electricity or gas demand for observation i . However, because a single tree can be sensitive to the training data, RF improves robustness by averaging the predictions of many trees, Equation (6).

$$\hat{D}_t = \frac{1}{B} \sum_{b=1}^B T_b(X_t) \quad (6)$$

where $\hat{D}_t$ is the predicted demand at time t , B is the total number of trees, and $T_b(X_t)$ is the prediction of the b -th tree using the input vector X_t .

In this study, the input vector includes HDD, CDD, and time-related variables. The model is first trained using historical electricity and gas demand data together with historical HDD and CDD values. Then, future HDD and CDD values are calculated from temperature projections under each RCP scenario and introduced into the trained model. Since each RCP represents a different future warming condition, the corresponding HDD and CDD values differ across scenarios, leading to different electricity and gas demand forecasts. The main forecasting relationship used in this study can therefore be written as Equation (7).

$$\hat{D}_{t,s}^{e/g} = RF(HDD_{t,s}, CDD_{t,s}) \quad (7)$$

where $\hat{D}_{t,s}^{e/g}$ represents the forecasted electricity or gas demand at time t under RCP scenario s , $HDD_{t,s}$ and $CDD_{t,s}$ are the heating and cooling degree-day values calculated from the temperature projections of scenario s . This formulation enables the study to estimate and compare future electricity and gas demand in the UK under alternative climate scenarios through 2050.

2.4. Model Training and Hyperparameter Tuning

Before applying the RF model for forecasting, its hyperparameters are specified and tuned. Hyperparameters are predefined settings that control the training process and determine how the forest is constructed [66]. In an RF model, these include the number of decision trees, the maximum depth of each tree, the minimum number of samples required to split an internal node, and the minimum number of samples required in a leaf node.

These choices can strongly affect the model's forecasting accuracy, robustness, and ability to generalise to unseen data [42].

In this study, hyperparameter tuning is carried out using a grid search strategy, in which predefined combinations of hyperparameter values are tested systematically. The range of values considered for each RF hyperparameter is presented in Table 2. The best-performing combination is selected according to the evaluation metrics described in the following section.

Table 2. Candidate hyperparameter values for the grid search procedure for tuning the RF models.

Hyperparameter	Candidate Values
Number of trees (n_estimators)	200, 300, 400, 500, 600
Maximum tree depth (max_depth)	2, 5, 8, 10, 12, 15, 20
Minimum samples required to split an internal node (min_samples_split)	2, 5, 10
Minimum samples required in a leaf node (min_samples_leaf)	1, 2, 4

Because the dataset is time-dependent, a random train–test split is not appropriate [67]. Random splitting could mix earlier and later years, allowing information from future periods to influence model training and causing information leakage. This could lead to overly optimistic forecasting results [68]. Therefore, chronological data splitting is used, in which the model is always trained on past observations and evaluated on a later period. In this study, each hyperparameter combination is evaluated using an expanding-window TimeSeriesSplit framework with two sequential train-validation periods: 1970–2018 for training and 2019–2020 for validation, followed by 1970–2020 for training and 2021–2022 for validation. The final hyperparameter configuration is selected based on its overall performance across these validation periods. After hyperparameter selection, the model is retrained using all available data from 1970 to 2022 and evaluated on the held-out test period of 2023–2024.

2.5. Model Validation and Performance Metrics

Following the hyperparameter tuning process, the predictive accuracy of the selected RF model is assessed using standard performance metrics. In the scope of this study, model performance is evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), as presented in Equations (8)–(10), respectively [69]. The R^2 metric measures the proportion of variance in the observed data explained by the model, while MAE and RMSE quantify the prediction error between observed and predicted values. Higher R^2 values and lower MAE and RMSE values indicate improved predictive performance.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (8)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2} \quad (10)$$

where y_i represents the observed electricity or gas demand value for observation i , $\hat{y}_i$ is the corresponding predicted demand value generated by the RF model, $\bar{y}$ is the mean of the observed demand values, and N is the total number of observations in the validation period. For MAE and RMSE, N is the number of predicted observations used to calculate the average prediction error. For each hyperparameter combination, the RF model was

evaluated across two chronological validation folds by training on the corresponding historical period and predicting demand during the subsequent two-year validation period. MAE and RMSE were calculated separately for each fold by comparing the predicted and observed electricity or gas demand values. Because each individual validation fold contained only two annual observations, fold-specific R^2 values were considered to have limited interpretive value. Therefore, the out-of-sample predictions from the two validation folds were pooled, and a single R^2 value was calculated over the four validation years from 2019 to 2022 for each hyperparameter combination. The final hyperparameter configuration was selected based on its overall validation performance, considering the pooled R^2 together with the fold-specific MAE and RMSE values. After hyperparameter selection, the final model was retrained using all available data from 1970 to 2022 and independently evaluated on the held-out test period of 2023–2024. The final test performance was then reported using R^2 , MAE, and RMSE.

The methodological framework described in this section provides the basis for forecasting future electricity and gas demand under alternative climate scenarios. Historical demand data and climate-related variables are first used to train and validate the RF model. Subsequently, future HDD and CDD values, based on RCP temperature projections, are incorporated into the trained model to produce demand forecasts through 2050. The following section presents and discusses the model validation results, forecasting performance, and projected changes in electricity and gas demand under the selected climate scenarios.

3. Results and Discussion

After applying the degree-day calculations described in Section 2.2, the annual HDD and CDD trends for the UK under the selected RCP scenarios are shown in Figure 3. Across all scenarios, HDD shows a general decline from 1970 to 2050, indicating a gradual reduction in heating requirements as temperatures rise. This decline is relatively moderate under RCP2.6, with HDD stabilising after the early 2000s, but it becomes more significant under RCP4.5 and RCP8.5, especially after 2020. In contrast, CDD increases over time, although its magnitude remains much smaller than HDD's because the UK has historically been a heating-dominated country. Under RCP2.6, CDD remains low and fluctuates within a narrow range, showing limited growth in cooling requirements. However, under RCP4.5 and RCP8.5, CDD rises more clearly after the 2000s and shows several sharp peaks toward the 2030–2050 period. Overall, Figure 3 indicates a gradual shift in the UK's climate-influenced energy demand factors: heating demand pressure is expected to decrease, while cooling demand is likely to rise. This pattern is consistent with the UK climate projections, indicating warmer future conditions and hotter summers. As a result, gas demand for heating may decrease over time, while electricity demand for cooling could become more important during warmer periods [70].

To better understand the relationship between climate-related variables and energy demand, the calculated HDD and CDD values are first compared with historical UK electricity and gas demand. This provides an initial diagnostic assessment of whether these variables are meaningfully associated with observed demand before being used in the forecasting model. Figures 4 and 5 illustrate these relationships under the selected RCP scenarios for electricity and gas demand, respectively. Since HDD and CDD represent heating- and cooling-related temperature exposure, their association with demand helps justify their inclusion as explanatory variables in the RF model.

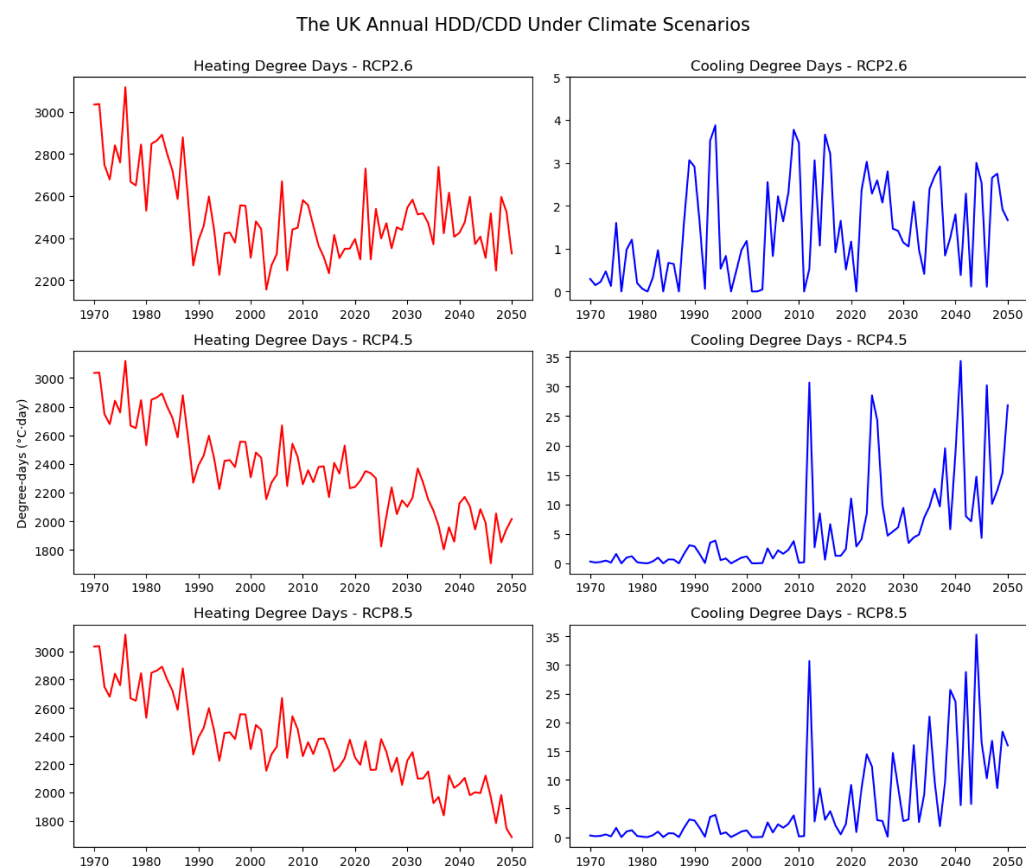


Figure 3. Calculated Annual HDD and CDD in the UK under RCP2.6, RCP4.5, and RCP8.5 scenarios, 1970–2050.

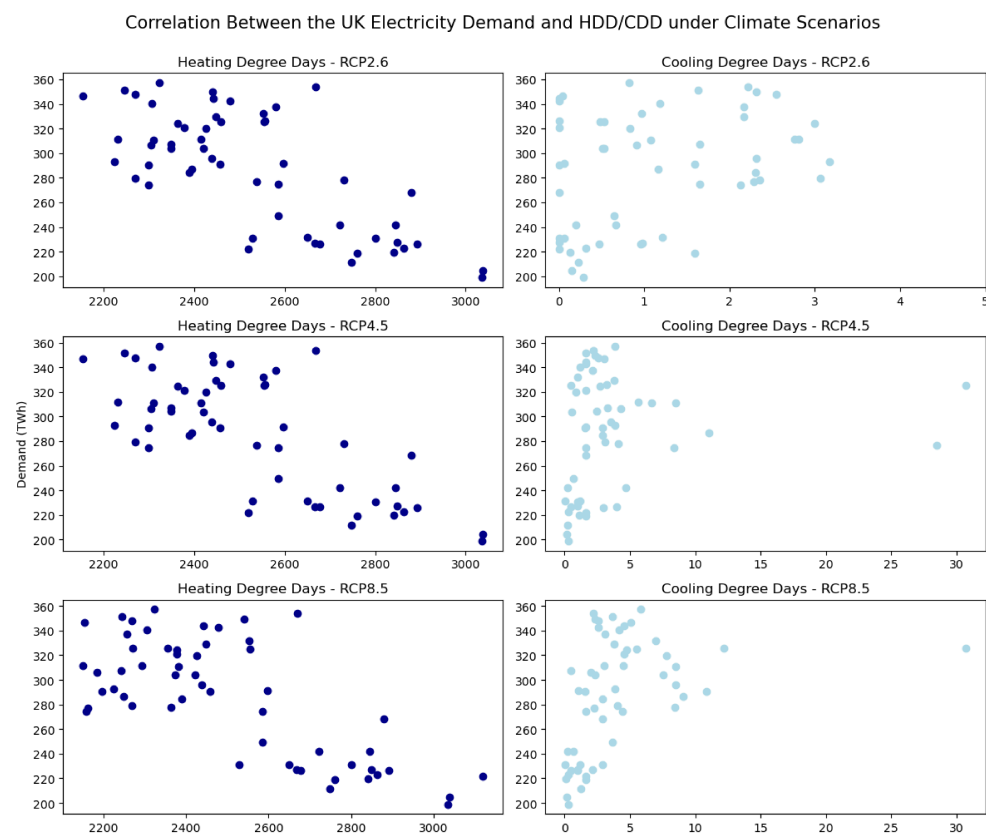


Figure 4. Relationship between annual HDD/CDD and historical UK electricity demand under RCP2.6, RCP4.5, and RCP8.5 scenarios.

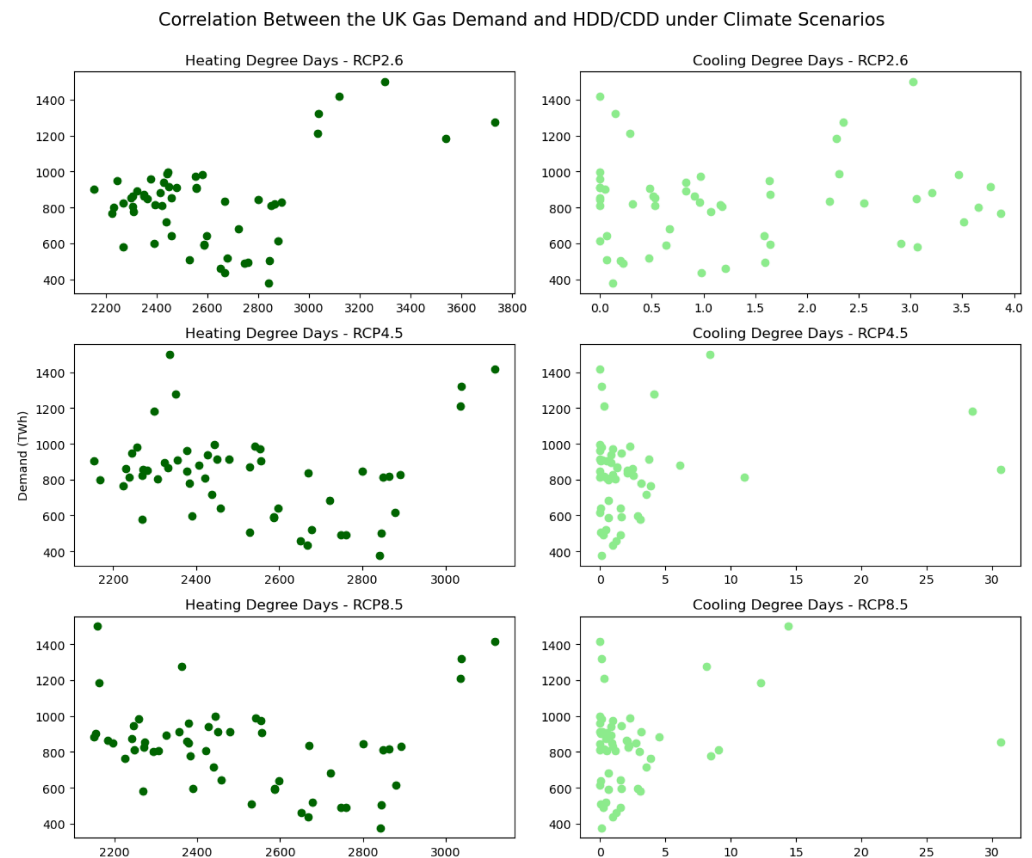


Figure 5. Relationship between annual HDD/CDD and historical UK gas demand under RCP2.6, RCP4.5, and RCP8.5 scenarios.

Figure 4 shows the relationship between HDD/CDD and electricity demand. For HDD, the scatter plots under RCP2.6, RCP4.5, and RCP8.5 show a generally negative association, where higher HDD values are mostly associated with lower historical electricity demand. A higher HDD value indicates a greater number of days with heating requirements. However, in the UK, space heating has traditionally been supplied mainly through gas-based heating systems rather than electricity-based heating. Therefore, years with higher HDD values do not necessarily lead to higher electricity demand, because the heating-related response is more strongly reflected in gas consumption. By contrast, lower HDD values indicate milder or warmer conditions, when heating requirements decline and electricity use for cooling or other temperature-sensitive end uses may become more relevant. This helps explain why electricity demand appears higher at lower HDD values in the scatter plots. The CDD-electricity relationship shows a different pattern. Under RCP2.6, CDD values remain low and the points are widely scattered, suggesting a weak cooling-related signal in electricity demand. Under RCP4.5 and RCP8.5, CDD values extend to much higher levels, and the scatter plots show that higher CDD values tend to occur alongside relatively high electricity demand observations. This indicates that cooling-related electricity demand may become more important under warmer climate scenarios, as cooling demand is mainly supplied by electricity. However, the relationship remains dispersed, reflecting the fact that cooling demand in the UK is still emerging and electricity consumption is also affected by multiple non-weather factors, including economic activity, efficiency improvements, electrification, and changes in end-use behaviour.

Figure 5 presents the corresponding relationships for gas demand. Compared with electricity, gas demand shows a clearer heating-related dependence. Across the RCP scenarios, higher HDD values are generally associated with higher gas demand observations,

particularly at the upper end of the HDD range. This is consistent with the dominant role of gas in space heating, where colder conditions increase heating requirements and therefore gas consumption. In contrast, the relationship between CDD and gas demand is weak across all scenarios. Most observations are concentrated at low CDD values, and high CDD values do not correspond to a consistent increase in gas demand. This is expected because cooling demand is mainly supplied through electricity rather than gas. Therefore, CDD is more relevant to electricity demand than to gas demand, whereas HDD is more directly relevant to gas demand.

Comparing Figures 4 and 5, the climate–demand relationship is stronger and more interpretable for gas than for electricity. Gas demand responds more directly to HDD because it is closely linked to space-heating needs. Electricity demand, by contrast, shows a more mixed relationship: HDD effects are partly masked by broader structural and behavioural drivers, while CDD becomes increasingly relevant under RCP4.5 and RCP8.5 as warmer conditions increase cooling-related demand. Overall, these results support the inclusion of both HDD and CDD in the forecasting framework, as they capture different aspects of climate sensitivity for electricity and gas demand and allow future demand projections to reflect scenario-dependent warming effects.

Following the hyperparameter tuning procedure described in Section 2, the RF models were trained and evaluated using grid search combined with time-series validation. The best-performing hyperparameter combinations for the electricity and gas demand models are presented in Table 3. The final hyperparameters were selected based on their overall performance across the chronological validation stages. To assess the consistency of model performance during the tuning process, the fold-specific MAE and RMSE values for the selected models are reported in Table 4. The pooled R^2 calculated across the four validation years (2019–2022) is 0.97 for electricity demand and 0.95 for gas demand.

Table 3. Selected hyperparameters of the optimised RF models for electricity and gas demand forecasting.

Type	n_estimators	max_depth	min_samples_split	min_samples_leaf
Electricity	500	15	2	2
Gas	600	12	2	2

Table 4. Validation performance of the RF models under different climate scenarios.

Scenario	Type	Validation Stage I (2019–2020)		Validation Stage II (2021–2022)	
		MAE (TWh)	RMSE (TWh)	MAE (TWh)	RMSE (TWh)
RCP2.6	Electricity	5.8	6.6	6.5	7.3
	Gas	24.9	29.5	27.4	31.8
RCP4.5	Electricity	6.3	7.1	7.2	8.0
	Gas	26.1	30.7	29.0	33.8
RCP8.5	Electricity	6.0	6.9	6.7	7.6
	Gas	25.6	31.2	28.3	34.6

After hyperparameter selection, the final models were then evaluated on the test period covering 2023–2024. The resulting test-performance metrics for both electricity and gas demand models under each climate scenario are presented in Table 5.

Table 5. Performance metrics of the optimised RF models on the final test period under different climate scenarios.

Scenario	Type	R^2	MAE (TWh)	RMSE (TWh)
RCP2.6	Electricity	0.98	6.1	7.1
	Gas	0.96	26.8	32.2
RCP4.5	Electricity	0.97	7.0	7.7
	Gas	0.96	28.7	33.5
RCP8.5	Electricity	0.97	6.4	7.8
	Gas	0.95	27.2	36.0

Using the optimised hyperparameters reported in Table 3, the RF models are run to forecast electricity and gas demand under the three climate scenarios. The resulting projections are shown in Figures 6 and 7 for electricity and gas demand, respectively.

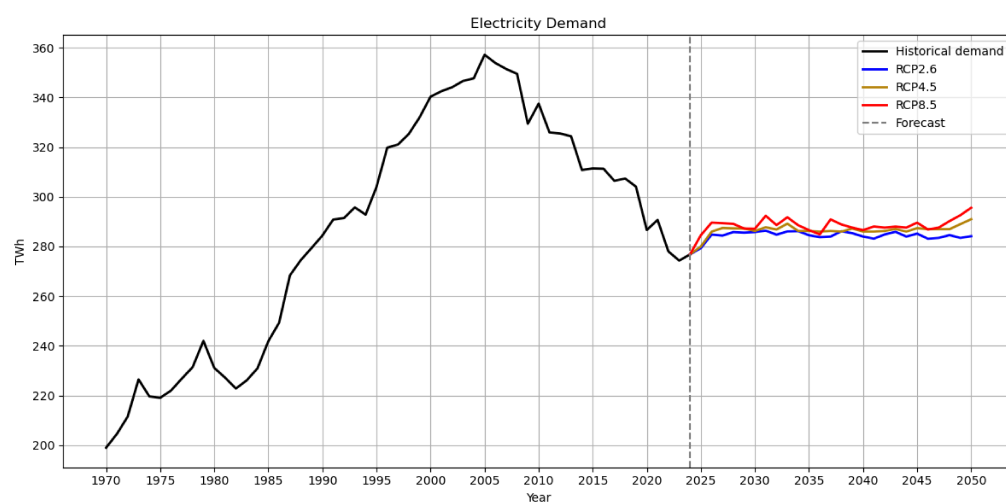
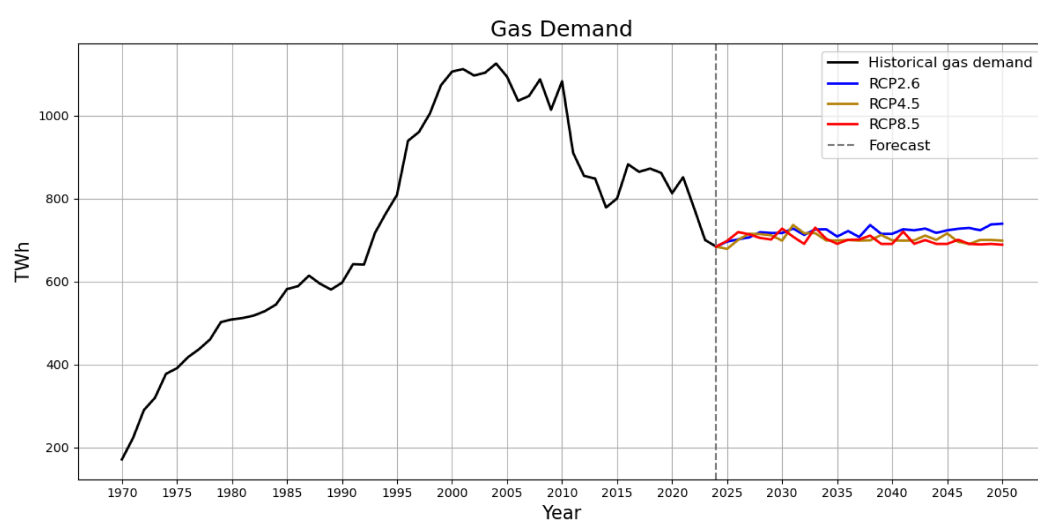
**Figure 6.** Historical and projected electricity demand under RCP2.6, RCP4.5, and RCP8.5 climate scenarios.**Figure 7.** Historical and projected gas demand under RCP2.6, RCP4.5, and RCP8.5 climate scenarios.

Figure 6 shows that the RCP8.5 and RCP4.5 scenarios generally result in higher electricity demand toward the end of the forecasting horizon, while RCP2.6 remains slightly lower and more stable. By 2050, electricity demand is 4.13% higher under RCP8.5 and

2.50% higher under RCP4.5 compared with RCP2.6. In addition, RCP8.5 results in 1.68% higher electricity demand than RCP4.5. This difference can be explained by the stronger warming trends under RCP8.5 and RCP4.5, which increase CDD, as shown in Figure 3. Since Figure 4 indicates a positive relationship between cooling requirements and electricity demand, higher CDD values lead to higher projected electricity consumption. In contrast, the RCP2.6 scenario does not show a substantial increase in electricity demand over the projection period and mainly fluctuates around a relatively stable level, with a slight decline toward the end of the forecasting horizon. This is consistent with the lower temperature increase under RCP2.6 (Figure 1), where global net-zero policies limit future warming.

Figure 7 shows that gas demand remains relatively stable across the forecasting period, but the RCP4.5 and RCP8.5 scenarios generally result in lower gas demand toward the end of the forecasting horizon compared with RCP2.6. By 2050, gas demand is 5.52% lower under RCP4.5 and 6.86% lower under RCP8.5 compared with RCP2.6. In addition, RCP8.5 results in 1.42% lower gas demand than RCP4.5. This difference can be explained by the stronger warming trends under RCP8.5 and RCP4.5, which reduce HDD and therefore lower heating requirements (Figure 3). Since gas demand is strongly associated with heating demand, lower HDD values under warmer climate scenarios lead to lower projected gas consumption. In contrast, RCP2.6 shows comparatively higher gas demand toward the end of the projection period, which is consistent with more limited warming and relatively higher heating requirements. The yearly fluctuations observed in both electricity and gas projections reflect interannual variations in HDD and CDD under the RCP scenarios, and the nature of the RF model, which captures non-linear demand responses.

It should be noted that these projections capture only the influence of climate-driven changes on electricity and gas demand. They do not account for UK policy measures, such as decarbonisation strategies, electrification of heating and transport, energy-efficiency improvements, or broader structural changes in the energy system. However, climate-related changes in heating and cooling requirements are highly likely to occur and should therefore be considered as an essential baseline in energy planning. Ignoring this component can lead to an incomplete understanding of demand conditions and potential risks in the energy system.

To examine how these climate-sensitive projections can be used as a baseline for policy-relevant energy planning, an additional net-zero adjustment is applied to the electricity and gas demand projections. This adjustment shows how the baseline demand projections can be modified when they are aligned with the direction of UK energy and climate policy towards 2050. In this way, the original projections represent the demand impact of climate change and the adjusted projections represent how those demand pathways may change when net-zero policies, particularly gas reduction and electrification, are also considered. For each scenario, the 2050 gas demand target is set at 25% of the scenario's 2025 gas demand, corresponding to a 75% reduction between 2025 and 2050. This assumption is aligned with the scale and direction of fossil-gas reduction envisaged under the Seventh Carbon Budget Balanced Pathway, in which electricity progressively replaces oil and gas across buildings, transport, and industry [43,71]. The resulting adjusted trajectories should therefore be interpreted as conditional net-zero-aligned scenarios.

In this study, the net-zero-aligned gas adjustment is applied to the projected gas demand in each year. Therefore, the adjusted gas demand is calculated as shown in Equation (11).

$$Gas_{adjusted,t,s} = Gas_{projected,s} \left[1 - 0.75 \left(\frac{t - 2025}{25} \right) \right] \quad (11)$$

where $Gas_{adjusted,t,s}$ is the net-zero-adjusted gas demand in year t under climate scenario s and $Gas_{projected,s}$ is the projected gas demand before the net-zero adjustment. This formula-

tion applies a gradual linear reduction from 2025 to 2050, so that gas demand reaches 25% of its 2025 level by 2050.

The annual reduction in gas demand is then calculated as the difference between the original projected gas demand and the adjusted gas demand. This displaced gas demand is partly transferred into additional electricity demand. A one-to-one conversion from gas to electricity is not assumed, because electric technologies are generally more efficient than fossil-fuel-based technologies [72]. Therefore, the amount of additional electricity required is lower than the amount of gas displaced. In this study, a gas-to-electricity conversion factor of 0.3 is used [73], meaning that each 1 TWh of displaced gas demand is assumed to require 0.3 TWh of additional electricity demand. This additional electricity demand is then added to the projected electricity demand to obtain the final net-zero-adjusted electricity demand.

The resulting adjusted trajectories therefore represent electricity and gas demand pathways after applying a net-zero-aligned demand-side transformation (Table 6). In all three scenarios, gas demand declines substantially by 2050, while electricity demand increases to reflect the electrification of energy services previously supplied by gas.

Table 6. Adjusted electricity and gas demand results for the three RCP scenarios from 2025 to 2050, reported in TWh.

Year	RCP8.5 Electricity	RCP4.5 Electricity	RCP2.6 Electricity	RCP8.5 Gas	RCP4.5 Gas	RCP2.6 Gas
2025	284.5	279.9	276.8	697.9	678.4	696.1
2030	323.1	320.8	321.0	618.3	593.8	609.2
2035	354.9	355.4	356.2	483.4	489.0	495.9
2040	389.1	389.8	391.5	379.8	384.6	393.1
2045	426.3	429.1	427.2	276.2	286.3	289.2
2050	466.0	463.8	466.4	172.1	174.6	179.8

As shown in Table 6, the adjusted pathways indicate a consistent long-term shift from gas to electricity between 2025 and 2050. However, the changes are not perfectly linear, because the adjusted electricity values are based on both the original climate-sensitive demand projections and the additional electricity demand associated with displaced gas use. Therefore, year-to-year variations reflect changes in climate-related heating and cooling requirements as well as the gradual electrification adjustment. The net-zero-aligned projections are also presented in Figures 8 and 9 to compare the historical demand trends with the adjusted future pathways under the three RCP scenarios.

In addition to the overall trend, comparing the demand projections across climate scenarios is also important for long-term energy planning. Therefore, Figures 10 and 11 compare the projected differences in electricity and gas demand under the RCP4.5 and RCP8.5 climate scenarios relative to the RCP2.6 scenario, which represents the most favourable low-warming pathway, between 2025 and 2050.

The results show a clear demand-side transition across all three scenarios between 2025 and 2050. The largest gas reduction occurs under RCP8.5, where the decline is 21.9 TWh greater than under RCP4.5 and 9.5 TWh greater than under RCP2.6. This is because stronger warming under RCP8.5 reduces heating requirements more substantially, leading to a larger climate-driven reduction in heating-related gas demand. In addition, the imposed gas-reduction adjustment reduces gas demand across all scenarios. Therefore, the strongest decline occurs under RCP8.5 because it combines the largest warming-related reduction in heating demand with the net-zero gas reduction pathway. At the same time, under RCP2.6, warming is more limited, so heating requirements remain higher than in the

warmer scenarios. As a result, more gas demand remains in RCP2.6 compared with RCP8.5 and RCP4.5, because the climate-driven reduction in heating-related gas use is weaker.

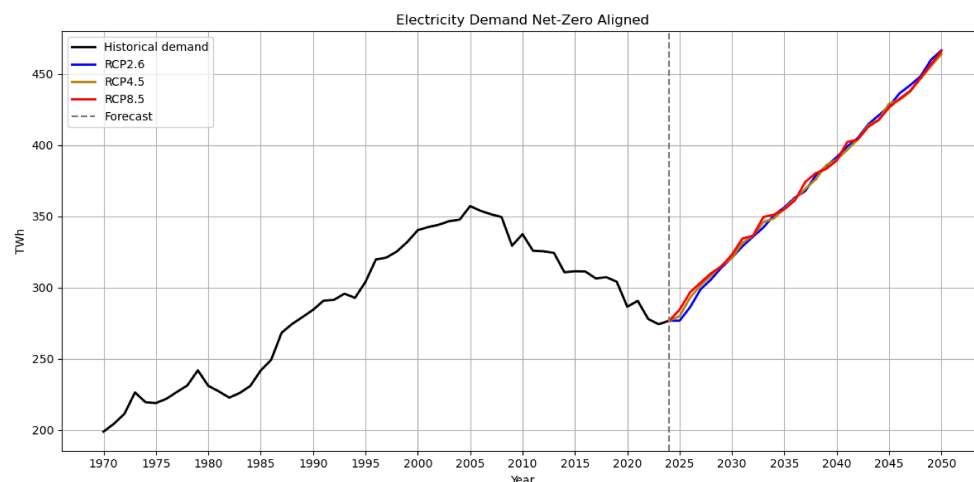


Figure 8. Historical and net-zero-aligned projected electricity demand under RCP2.6, RCP4.5, and RCP8.5 climate scenarios.

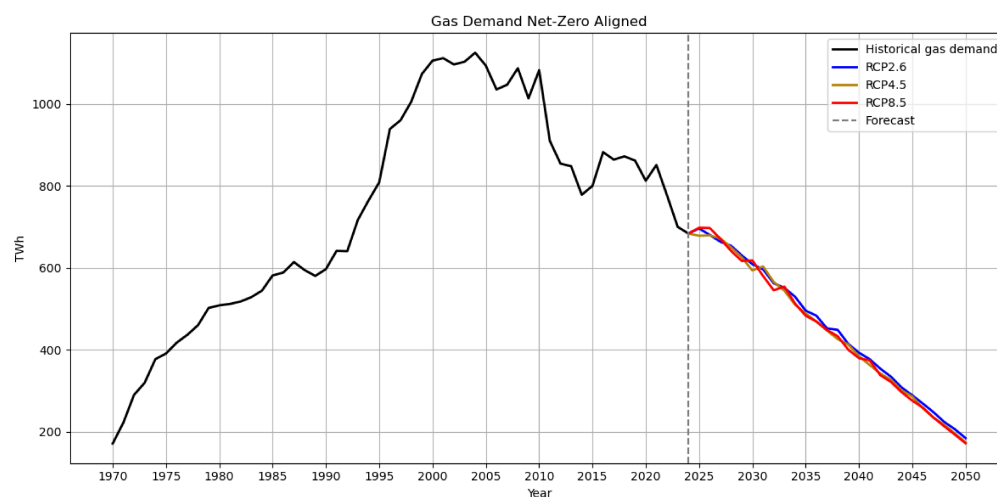


Figure 9. Historical and net-zero-aligned projected gas demand under RCP2.6, RCP4.5, and RCP8.5 climate scenarios.

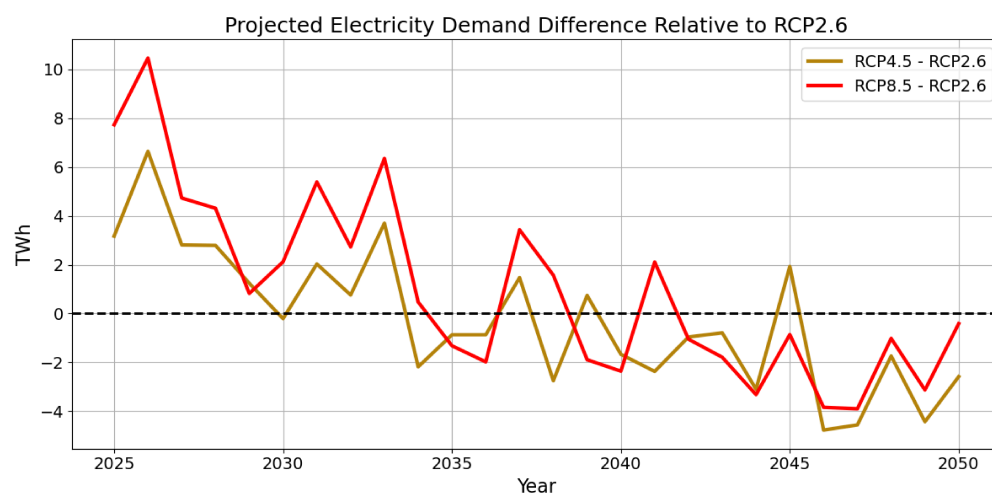


Figure 10. Projected electricity demand differences under the 4.5 and 8.5 climate scenarios relative to the 2.6 scenario between 2025 and 2050.

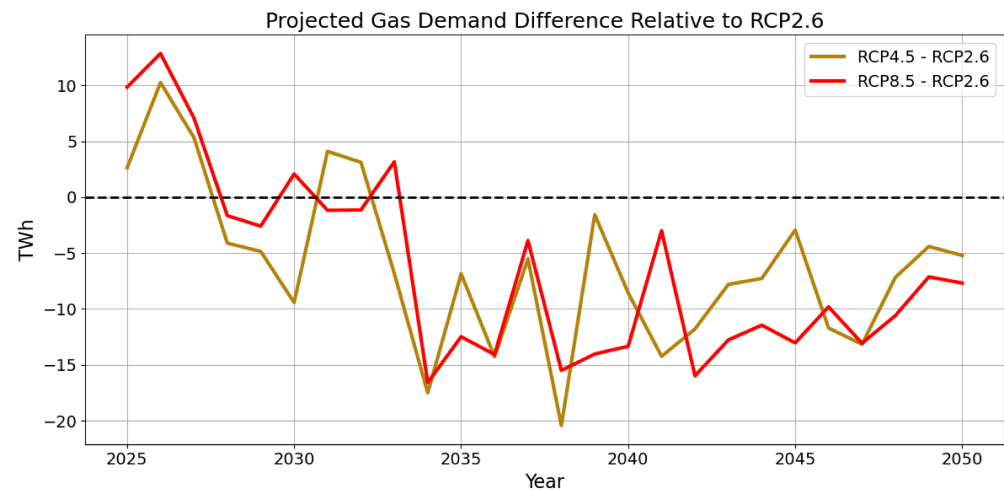


Figure 11. Projected gas demand differences under the 4.5 and 8.5 climate scenarios relative to the 2.6 scenario between 2025 and 2050.

Electricity demand also increases across all scenarios, but the interaction between climate effects and electrification differs between scenarios. Under RCP8.5 and RCP4.5, stronger warming increases cooling-related electricity demand. As a result, electricity demand is generally higher in these warmer scenarios during the earlier part of the projection period. For example, in 2027, electricity demand under RCP2.6 is 298.8 TWh, compared with 303.5 TWh under RCP8.5 and 301.6 TWh under RCP4.5. This indicates that, in the early years, the lower level of warming under RCP2.6 leads to lower cooling-related electricity demand. However, this pattern changes over time. Because warming is weaker under RCP2.6, heating demand remains more important, and gas demand is not reduced as strongly through climate-driven warming alone. This leaves more residual gas demand that must be displaced through the net-zero electrification adjustment. In other words, although RCP2.6 initially has lower electricity demand, the net-zero transition requires a larger amount of remaining gas use to be shifted into electricity. As this gas-to-electricity substitution becomes stronger, the electricity pathway under RCP2.6 catches up with and eventually exceeds the warmer scenarios. This reversal can be seen in the later years of the projection. Between 2025 and 2050, the increase in electricity demand under RCP2.6 is 8.14 TWh higher than under RCP8.5 and 5.75 TWh higher than under RCP4.5. By 2050, electricity demand reaches 466.4 TWh under RCP2.6, compared with 466 TWh under RCP8.5 and 463.8 TWh under RCP4.5. Therefore, by the end of the projection period, the stronger electrification requirement under RCP2.6 more than offsets its lower cooling-related electricity demand.

Overall, the key finding is that all three scenarios follow the same direction of change: electricity demand rises and gas demand falls. However, the reasons for the increase in electricity differ across scenarios. Under RCP8.5 and RCP4.5, stronger warming increases cooling-related electricity demand, which keeps electricity demand higher in the earlier years. Under RCP2.6, electricity demand is initially lower because warming is more limited, but heating demand remains more important and gas demand stays higher. This means that achieving the net-zero pathway requires a larger shift from gas to electricity under RCP2.6. Over time, this electrification effect becomes strong enough for RCP2.6 to reach the highest electricity demand by 2050. These results show that the adjusted pathways move in the expected direction of the UK net-zero transition; however, for these pathways to be fully consistent with net zero, several additional conditions must hold. First, the additional electricity demand must be supplied by low-carbon electricity. If the additional electricity is generated from unabated gas-fired power plants, emissions shift from end-use sectors to the power sector rather than being eliminated. Second, the remaining gas demand in 2050 must either be used in limited applications with carbon capture and storage, replaced

by low-carbon gases such as hydrogen where appropriate, or balanced by greenhouse gas removals. Third, emissions from sectors not directly represented by electricity and gas demand, such as agriculture, aviation, shipping, waste and industrial process emissions, must also be reduced or offset by removals.

4. Conclusions and Policy Implications

This study developed a machine learning-based forecasting framework to estimate national long-term electricity and gas demand in the UK under climate change impacts up to 2050. The main aim was to assess electricity and gas demand together within a single scenario-based framework and to examine how climate-driven demand changes may interact with a net zero electrification pathway. To do this, historical electricity and gas demand data were combined with climate-sensitive variables derived from RCP temperature projections, including Heating Degree Days and Cooling Degree Days. These variables were then used as inputs to Random Forest models to forecast future demand under different climate scenarios.

The results show that climate change affects electricity and gas demand in different directions. By 2050, electricity demand is 2.5% higher under RCP4.5 and 4.1% higher under RCP8.5 compared with RCP2.6, reflecting higher cooling-related electricity use under warmer conditions. In contrast, gas demand is 5.5% lower under RCP4.5 and 6.8% lower under RCP8.5, mainly due to reduced heating requirements. These findings show that stronger warming increases electricity demand while reducing gas demand, highlighting the need to assess both energy carriers together in long-term planning.

The net-zero adjustment further highlights the interaction between climate change and electrification. By 2050, adjusted electricity demand reaches around 464–466 TWh across the three scenarios, showing that electrification becomes a major driver of future electricity demand. At the same time, gas demand declines more strongly under warmer scenarios; for example, the total gas-demand reduction under RCP8.5 is 21.9 TWh greater than under RCP4.5 and 9.5 TWh greater than under RCP2.6. Under the lower-warming RCP2.6 scenario, more heating-related gas demand remains, so more residual gas use needs to shift to electricity under the assumed net-zero-aligned pathway. This explains why adjusted electricity demand in 2050 is slightly higher under RCP2.6 than under RCP4.5, at 466.4 TWh compared with 463.8 TWh. Overall, the results show that climate mitigation pathways and electrification strategies need to be assessed together rather than separately.

These projections provide a comprehensive data-driven baseline for integrated electricity and gas demand planning in the UK's net zero transition, while also showing why climate change needs to be explicitly considered in long-term energy planning. By incorporating climate variables, the framework captures how warmer conditions can simultaneously increase cooling-related electricity demand and reduce heating-related gas demand. For electricity systems, the results can help policymakers and infrastructure planners assess future generation capacity, storage requirements, and network reinforcement needs, particularly as heating, transport, and other energy services become increasingly electrified. This additional electricity demand must be supplied by low-carbon generation to avoid shifting emissions from end-use sectors to the power sector. For gas systems, the projected decline in demand can inform decisions on whether existing networks should be maintained, gradually reduced, or repurposed for low-carbon gases such as hydrogen. Remaining gas demand in 2050 may also need to be addressed through demand reduction, hydrogen where appropriate, carbon capture and storage, or greenhouse gas removals. Therefore, long-term climate-sensitive demand projections such as those developed in this study can support investment decisions, regulatory planning, hydrogen infrastructure

planning, and risk assessment for maintaining energy security, reliability, and affordability across the UK.

Despite these contributions, several aspects of the framework can be further developed in future research. The projections presented in this study are national climate-sensitive baseline trajectories based on historical relationships between aggregate energy demand and selected climatic and temporal variables. Future work can extend the framework by incorporating additional drivers, including GDP, population, and energy prices. In addition, sectoral and end-use decomposition could help distinguish climate-sensitive changes in heating and cooling demand more clearly from secular changes associated with economic restructuring, efficiency improvements, prices, policies, and technology adoption. Because the present analysis is based on annual national demand data, it cannot capture short-duration peak-load shocks or intra-annual demand variability associated with extreme weather events. Future research could use higher-frequency regional demand and weather data to assess peak-demand changes and their implications for system planning. More advanced machine-learning, deep-learning, hybrid, ensemble, and alternative statistical approaches may also be considered in future research. In addition, as a tree-based method, Random Forest has a limited ability to extrapolate beyond the historical ranges of predictor variables. A covariate-shift assessment in this study indicated that, under RCP4.5 and RCP8.5, more than 20% of future HDD values and around 4% of future CDD values fall outside the corresponding historical ranges, whereas future HDD and CDD values remain within the historical range under RCP2.6. Therefore, projections under scenarios with out-of-range predictor values should be interpreted cautiously. Future research could further investigate these effects through response analysis and compare the proposed framework with extrapolative statistical models or hybrid physical–data-driven approaches. The results of the present study are deterministic and do not represent prediction intervals or the full probability distribution of future demand. Future research could therefore develop a comprehensive uncertainty-propagation framework. Bootstrap, Monte Carlo, Bayesian, or related methods could be used to generate prediction intervals and to distinguish the relative contributions of climate, demand-model, and transition uncertainty. These extensions could develop the present national climate-sensitive baseline framework into a broader regional and integrated energy-system planning tool for net-zero and climate-resilient energy security.

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