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Machine learning for subnational residential electricity demand forecasting to 2050 under shared socioeconomic pathways: Comparing tree-based, neural and kernel methods

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ABSTRACT

A scenario-based machine learning framework is presented for long-term, subnational electricity demand forecasting, integrating Shared Socioeconomic Pathways (SSPs) with spatially downscaled demographic, economic, and climatic variables. Using Turkey as a case study, the framework projects residential electricity demand to 2050 across all 81 provinces. The subnational approach enables the use of data-intensive machine learning algorithms by expanding the training dataset through the multiplicative effect of combining spatial and temporal dimensions. Six machine learning models: tree-based (Random Forest, XGBoost), neural networks (Feed-forward Neural Network, Long Short-Term Memory), and kernel-based methods (Support Vector Regression, Gaussian Process Regression), are systematically compared against a traditional linear regression benchmark. Random Forest achieves the highest accuracy (R^2 = 0.9359, MAE = 0.04 TWh), outperforming neural and kernel-based models and substantially improving on the linear baseline. Socioeconomic variables, especially family households, population, and GDP, have a greater influence on electricity demand than climatic indicators such as heating and cooling degree days. Turkey's residential electricity demand is projected to increase by 78% from 65.5 TWh in 2023 to 116.7±2.9 TWh by 2050, with substantial variation across provinces. The spatial variation in demand forecasts highlights the value of subnational modelling for energy planning and the limitations of national-level projections. The use of SSPs enables a consistent and policy-relevant exploration of plausible long-term demand trajectories. By combining subnational resolution, scenario-based inputs, and a structured comparison of algorithm families, the study offers a transferable framework for electricity demand forecasting in regionally diverse or data-scarce contexts, supporting infrastructure planning and decarbonisation strategies.

1. Introduction

Global electricity use has steadily increased, driven primarily by population growth, urbanisation, economic development, and technological advancements. The International Energy Agency (IEA) reported a 2.2% increase in global electricity demand in 2023, accelerating to 4.3% in 2024 with projections of nearly 4% annual growth through 2027 [1,2]. The growing demand for energy highlights the need for accurate and reliable long-term electricity demand forecasts for informing energy system planning and policy, and sustainability energy transitions [3]. Projections extending up to 2050 are crucial for developing robust infrastructure and aligning energy systems with sustainability goals, supporting global efforts to transition to resilient energy systems and reduce emissions to net zero by 2050 [4].

The residential sector plays a significant role in the global energy landscape [5]. In 2019, residential electricity consumption accounted for approximately 27% of total global usage, ranking it the second-largest sector after industry [6] (Fig. 1). The factors contributing to rising electricity demand extend beyond global population growth, with the IEA highlighting economic growth, climate conditions, urbanisation, and increasing access to energy-intensive digital technologies as key drivers [2]. Rapid urbanisation, especially in developing countries, has led to more densely populated buildings, neighbourhoods, and cities, with increased reliance on electricity for cooling and supporting urban lifestyles, resulting in higher residential electricity demand [7,8]. Additionally, urban households typically consume more electricity than their rural counterparts driven by higher income levels and greater access to electrical appliances [9].

Turkey (*Türkiye*) mirrors the global upward trajectory in residential electricity demand, with energy planning increasingly shaped by

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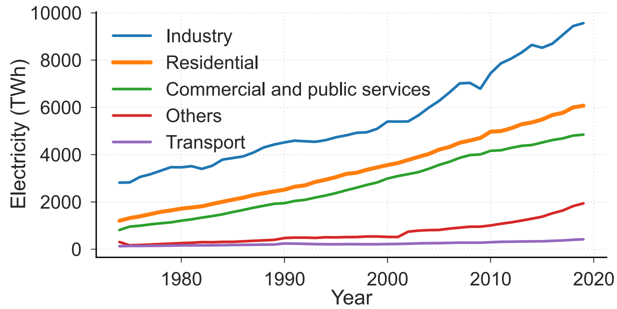


Fig. 1. Global electricity consumption by sector from 1974 to 2019. The residential sector has consistently remained the second-largest electricity consumer after industry, reflecting its significant share in global demand. *Data source:* [6].

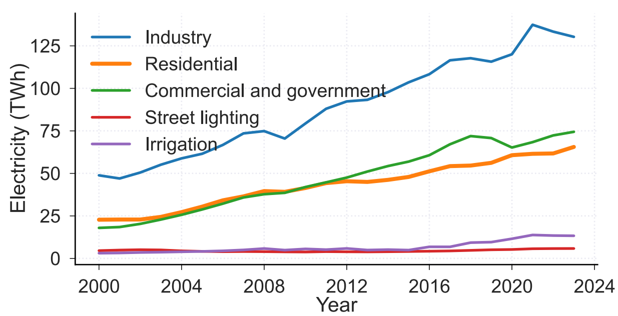


Fig. 2. Electricity consumption by sector in Turkey from 2000 to 2023. The industrial sector has remained the dominant electricity consumer throughout the period. The residential and commercial/government sectors have shown a steady increase over time and are closely aligned in recent years, together accounting for a significant share of national electricity consumption. *Data source:* [11].

climate commitments and the growing role of renewables in national policy frameworks [10]. In 2023, the residential sector accounted for approximately 23% of the country's total electricity usage, reaching 65.5 TWh, as illustrated in Fig. 2 [11]. The country has undergone significant population growth, with an increase of 26% from 2000 to 2023, resulting in a population of 85.4 million. Along with the increased population, rapid urbanisation and economic development have led to a rise in residential electricity demand, but the geographical distribution of the underlying demand growth factors is not even throughout the country [10]. Hence, national estimates often do not account for regional variations in electricity usage, ultimately leading to suboptimal energy planning decisions. Therefore, understanding and forecasting the regional variations in electricity demand is essential for formulating targeted policy interventions, including region-specific energy efficiency programmes and demand-side management strategies [12]. Granular demand forecasts are also instrumental in prioritising and rationalising infrastructure investments across different regions, ensuring equitable development [13]. Additionally, detailed projections enable the optimal siting and sizing of renewable energy projects, considering local demand patterns and resource availability.

Given the significant share of residential electricity consumption and Turkey's diverse geographic, demographic, climatic, and socioeconomic characteristics, accurate demand forecasting is challenging at the sub-national level. Traditional electricity demand forecasting has relied primarily on statistical models, such as time series analysis, regression, and exponential smoothing [14–16]. Techniques such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters smoothing have been widely used due to their ability to capture seasonal patterns and trends. However, these methods often do not fully account for the nonlinear and complex relationships inherent in electricity demand, particularly in contexts where the effects of socioeconomic factors are more pronounced and dynamic.

Recent studies have attempted to address these limitations by incorporating machine learning (ML) approaches, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and tree-based methods such as Random Forest (RF) and Gradient Boosted Regression Trees (GBRT) [17]. These methods can handle large datasets and capture complex interactions between variables, particularly in settings characterised by high data variability and complex, nonlinear patterns. Their flexibility in integrating multiple features contributes to improved forecasting accuracy. However, most ML-based approaches to electricity demand forecasting have focused on national-level or aggregate predictions, often overlooking subnational variations that are important for region-specific planning. Additionally, previous studies limit their models to socioeconomic or climate variables, seldom integrating both to capture their combined impact on electricity demand. Moreover, existing ML models often address short to medium-term horizons, leaving a gap in long-term projections, e.g. those extending to 2050, which are essential for strategic, long-horizon energy planning.

This research developed an ML-based 2050 sub-national residential electricity demand forecasting approach using Turkey as a case study. The novelty lies in the integration of (a) socioeconomic, demographic, and climatic factors for improved accuracy, and (b) Shared Socioeconomic Pathways (SSPs) for aligning projections with broader climate change mitigation and adaptation narratives, enabling consistency in decision-making through the consideration of plausible future scenarios. The SSPs, developed by the international scientific community and utilised by the Intergovernmental Panel on Climate Change (IPCC) in its assessments [18], provide internally consistent narratives and quantitative projections for key drivers such as population, economic development, and technology, which shape long-term electricity demand and are essential inputs for long-term (e.g. 2050) demand forecasting models.

In addition, six widely-used ML algorithms from three different types: tree-based (Random Forest—RF, Extreme Gradient Boosting—XGBoost), neural networks (Feed-forward Neural Network—FFNN, Long Short-Term Memory—LSTM), and kernel-based methods (Support Vector Regression—SVR, Gaussian Process Regression——GPR), are systematically compared against a traditional linear regression benchmark to evaluate their forecasting performance and identify the most suitable model for the study's objectives. This comparison challenges the prevailing assumption that linear models are sufficient for long-term electricity demand forecasting, particularly in heterogeneous sub-national contexts. Electricity demand projections were generated for all 81 Turkish provinces to assess regional variation, offering insights for targeted policy interventions and infrastructure planning.

2. Past works

Electricity demand forecasting plays a crucial role in energy systems operation [19], planning and management across diverse geographical and socio-economic contexts [20]. Countries and regions vary significantly in their priorities, with some focusing on decarbonisation goals and others emphasising economic development, energy security, and operational efficiency [21]. Varying priorities influence the approaches taken in electricity demand forecasting and the selection of methods and variables used in models. Furthermore, the lack of comprehensive data—both for present-day conditions and future projections—poses additional challenges, especially in rapidly evolving energy landscapes [20]. The review of the literature is summarised in Table 1, illustrating trends in methods, variable selection, scope and forecast horizon.

2.1. Forecasting methods

Electricity demand forecasting methods range from conventional statistical models to advanced machine learning techniques. Classical statistical models such as time series analysis, [22] regression [23], and exponential smoothing have been used widely. Techniques such as SARIMA are widely used for long-term forecasting because of their ability to model seasonal consumption trends [24]. Advanced statistical methods such as Holt-Winters Seasonal Smoothing (HSS) [25] consider growth and seasonality in the forecast by incorporating seasonal lift factors in the formulation. HSS has also been found to offer reasonable accuracy in the presence of missing or incomplete data [26]. On the other hand, decomposition techniques such as Fourier Transform [27] and Wavelet Decomposition [28] have improved predictions by capturing multi-scale fluctuations in demand. These approaches provide useful insights into complex electricity consumption patterns.

As data availability continues to expand, various machine learning methods have gained significant popularity in forecasting electricity demand. SVM, which excel at pattern separation in high-dimensional spaces, have emerged as a robust solution [29]. ANNs have proven valuable due to their automatic feature learning capabilities [30]. Deep learning architectures, such as LSTM, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN), have shown strong capability in capturing long-term temporal dependencies [31–33]. Additionally, tree-based methods such as Decision Trees (DT), RF, and GBRT have been widely adopted for their interpretability of feature importance [34]. These techniques have collectively demonstrated their effectiveness in capturing the nonlinear, complex patterns inherent in electricity demand data, offering significant improvements in predictive accuracy and efficiency [35].

A notable trend in the field is the adoption of hybrid models that combine either statistical and ML approaches or multiple ML methods. Such models aim to improve robustness and performance across diverse datasets and forecasting horizons by leveraging the complementary capabilities of different techniques. For example, hybrid approaches often include SARIMA with neural networks [36] to effectively capture both linear/seasonal patterns and complex nonlinear relationships, or combine Adaptive Neuro-Fuzzy Inference System (ANFIS) with LSTM models [37] to harness their respective strengths in handling stable versus variable data patterns, or analyse ANN with Multiple Linear Regression (MLR) [38] to validate and compare different methodological approaches. Some studies integrate several methods or algorithm types into one, often using the outputs of one as inputs to another, others use several methods separately, to improve prediction accuracy.

2.2. Factors affecting electricity demand

The literature highlights the importance of incorporating exogenous variables in electricity demand forecasting models. These variables can be broadly categorised into several key groups: economic variables (GDP, electricity prices, imports/exports), demographic factors (population, household size, number of consumers), weather-related parameters (temperature, humidity, pressure, wind speed, heating/cooling degree days (HDD/CDD)), and historical consumption patterns [39].

Economic and demographic variables are particularly crucial but manifest differently in developing versus developed contexts. Research highlighted that developing countries often exhibit unique energy-economic dynamics between GDP growth and energy consumption and the existence of suppressed demand due to infrastructure limitations [40]. Their analysis revealed that increases in GDP per capita often lead to significantly higher electricity consumption in low and lower-middle-income countries compared to high-income nations, where the relationship is more stable. Additionally, demographic factors such as urbanisation rates and household formation patterns often follow different trajectories in developing contexts [40].

Weather-related variables play a vital role in residential electricity demand as they directly influence household energy consumption patterns. These include direct measurements such as temperature (affecting heating and cooling needs), humidity (with potential effects on cooling demand), atmospheric pressure (correlating with weather systems that affect energy use), and wind speed (influencing heat exchange in buildings and potential renewable energy generation) [41,42]. Additionally, derived indicators such as HDD and CDD serve as standardised measures that capture the cumulative effect of temperature deviations from a predefined base temperature threshold [43], thereby quantifying the energy needed for space conditioning [44]. Historical consumption patterns, form another key category. However, as noted by Sharma et al. [45], the reliability and availability of such historical data can be particularly challenging in developing regions with inadequate data collection infrastructure.

Household size is also a determinant for estimating residential electricity demand as it directly correlates with the number of occupants using electrical appliances, lighting, and energy services simultaneously, alongside less common factors such as household expenditure (reflecting the economic capacity to own and operate multiple electrical devices) and electricity prices (influencing consumer behaviour through price elasticity and potential adoption of energy-efficient alternatives) [46]. In recent years, studies have incorporated the impact of the COVID-19 pandemic, including lockdown measures and curfews, as these restrictions substantially increased residential consumption due to extended home occupancy, widespread adoption of work-from-home arrangements, and increased use of household appliances for daily activities that were previously conducted outside the home [47,48]. This adaptation demonstrates the dynamic nature of variable selection in electricity demand forecasting and the need for models to remain flexible in incorporating new determinants as they become relevant.

2.3. Modelling horizon and scope

The temporal horizon and resolution are key considerations in electricity demand forecasting. Different stakeholders in the energy sector—ranging from utility companies to policymakers—require forecasts with varying prediction horizons and temporal resolutions. For prediction horizons, these range from short-term such as a few hours [51] to long-term extending to two or three decades [54]. Short-term forecasts with typically hourly or daily resolution are essential for operational planning, grid management, economic dispatch, and unit commitment, as they enable real-time balancing of supply and demand [61]. Medium-term forecasts spanning a week to a year, often with monthly resolution are crucial for fuel purchase planning and maintenance scheduling, as they help optimise resource allocation and operational costs [62]. Long-term forecasts extending beyond a year, typically with annual resolution are critical for strategic decision-making, infrastructure development, capital planning, and policy formation, as they guide substantial investments and shape future energy systems [63]. The spatial scope of forecasting studies also varies considerably, ranging from focused analyses of single provinces [52] to nationwide assessments [53,58,60]. This variability in geographical scope serves different planning needs: local-level forecasts help optimise distribution networks and address region-specific demand patterns, while national-level projections support macro-level policy decisions, grid infrastructure planning, and energy security strategies.

3. Methodology

This study develops and validates a structured methodology for long-horizon, province-level electricity demand forecasting, designed to account for evolving socioeconomic and climatic factors through 2050. The methodology is applied to the residential sector in Turkey as a case study to demonstrate its implementation and effectiveness. The integration of SSPs allows for scenario-based analyses, offering

Table 1
Summary of studies on electricity consumption forecasting in Turkey: Methodologies, variables, and forecasting horizon.

Methods	Independent variables	Target variables	Scope	Data period	Forecast horizon	Ref
HSS	Annual income, expenditures, age, education level, marital status, heating, house ownership and appliances	Household consumption	National	2019	NA	[26]
MNN, WOA, SVM	Imports, exports, GDP, population	Demand forecast	National	1980–2019	Up to 2040	[49]
DT, RF, GBRT	Household size, income, heating type, housing Traits	Household consumption	National	2019	NA	[34]
LSTM, SARIMA	Monthly electricity consumption, seasonal changes	Consumption	National	1975–2021	2022–2031	[24]
Novel Approach	HDD, CDD, electricity consumption	Residential consumption	1 district	2017	Real-time	[44]
MRAM	Hourly temperature, time of day	Hourly consumption	1 province	2017	1 week	[42]
ANN, PSO, MLR	Population, imports, exports, cars and passenger numbers	Monthly consumption	1 district	2014–2020	Up to 2040	[38]
ANN	GDP, electricity prices, imports, population, temperature	Consumption	National	1970–2020	2021–2025	[50]
LSTM, ANFIS	Daily energy production	Production from hydro	National	2016–2020	1-day	[31]
LSTM, ANFIS	Daily electricity consumption	Consumption	National	2016–2019	1-day	[32]
CNN	Hourly electricity consumption	Consumption	National	2020–2021	1-2-3 h	[51]
GA, GWO, HHO, SCM	Regional load characteristics, municipality development plan, subscriber profiles	Electricity load	1 province	2004–2018	2019–2024	[52]
NARX ANN, LSTM	Date (day, week, month), temperature, COVID-19 pandemic precautions, last month's daily consumption	Daily consumption	National	2019	2020	[47]
FNN	Average daily - pressure, temperature, wind speed, humidity, day of the week, previous days consumption	Consumption	1 province	2000–2020	Daily	[41]
GPR, SMO, LR, XNV, REP, M5P	Daily consumption and temperature, holidays, curfews during lockdown, time-dependent attributes	Daily demand	National	2020	Daily	[48]
ARIMA, LSSVM	Installed capacity, electricity generation, population, total subscribers, export, import	Consumption	National	1970–2017	2019–2022	[29]
LSTM, ANFIS	Daily electricity generation	Daily renewable generation	National	2016–2019	1-day	[37]
Empirical, LE	Annual electricity demand per capita, population growth	Consumption	National	1975–2016	Up to 2023	[53]
LM, FS	Daily, weekly, seasonal variations	Hourly demand	National	2012–2014	1-year	[27]
DGM, ODGM, NDGM	Annual electricity consumption	Annual consumption	National	1970–2013	2014–2030	[54]
ARIMA, PDM, SPDM	Electricity consumption per capita, regional characteristics, time series data	Regional demand	National	1986–2013	2014–2018	[55]
ANN, MLR	Population, GDP per capita, inflation ratio, average summer and winter temperature, unemployment ratio	Annual demand	National	1975–2013	2014–2028	[56]
SARIMA, NARANN	Electricity production, electricity imports, transmitted electricity, electricity exports	Consumption	National	up to 2010	2010–2020	[36]
LSSVM, ANN, MLR	Electricity generation, installed capacity, total subscribers, population	Annual consumption	National	1970–2009	NA	[30]

(continued on next page)

Table 1 (*continued*).

Methods	Independent variables	Target variables	Scope	Data period	Forecast horizon	Ref
LGCT, NDPC	Total consumption along with sectoral breakdown	Consumption in sectors	National	1945–2006	NA	[57]
OGM(1,1)	Annual electricity consumption	Annual consumption	National	1945–2010	2013–2025	[58]
LR, NLR, ANN	Installed capacity and generation, population, subscribers	Sectoral consumption	National	1990–2007	2008–2015	[23]
SVR	Population, GNP, imports, exports	Annual consumption	National	1975–2006	2007–2026	[59]
STSM	Household expenditure, electricity prices	Residential consumption	National	1960–2008	2009–2020	[46]
STSM	GDP, real average electricity prices,	Demand	National	1960–2008	2009–2020	[22]
GP	Electricity consumption	Consumption	National	1983–2007	2008–2020	[60]

Abbreviations: ARIMA: autoregressive integrated moving average, DGM: discrete grey model, FS: fourier series, GA: genetic algorithm, GP: genetic programming, GWO: grey wolf optimisation, HHO: harris hawk optimisation, HSS: heckman sample selection model, LE: linear extrapolation, LGCT: linear granger causality test, LM: linear model, LR: linear regression, LSSVM: least-square support vector machine, M5P: M5P model tree, MNN: medium neural networks, MRAM: multiple regression analysis method, NARANN: nonlinear autoregressive neural network, NARXANN: nonlinear autoregressive with exogenous inputs neural network, NDGM: nonhomogeneous discrete grey model, NDPC: nonparametric diks and panchenko causality test, NLR: nonlinear regression, ODGM: optimised discrete grey model, OGM: optimised grey model, PDM: panel data models, PSO: particle swarm optimisation, REPTree: reduced error pruning tree, SCM: S-curve model, SMOReg: sequential minimal optimisation regression, SPDM: spatial panel data models, STSM: structural time series model, WOA: whale optimisation algorithm, XNV: correlated Nyström views.

a consistent framework to define key variables such as population and economic activity far into the future, enabling the exploration of electricity demand trajectories under diverse long-term contexts. The methodology comprises several key stages: selection and justification of input variables, data collection and preprocessing, evaluation of machine learning algorithms, and extensive model validation. Each stage is detailed in subsequent sections, providing justifications for methodological choices and highlighting their relevance to long-horizon energy forecasting.

3.1. Shared socioeconomic pathways

The SSP framework, originally developed to explore global socioeconomic and climate futures [18], is applied in this study to assess how long-term demographic and economic developments may influence residential electricity demand. The SSPs offer a set of internally consistent and policy-relevant scenarios that characterise alternative futures based on coherent narratives and quantitative projections of key drivers such as population, economic growth, and technological advancement [64].

While conventional sensitivity analysis—where individual parameters such as population or GDP are perturbed independently—can provide insights into model responsiveness, such approaches often lack the internal consistency and plausibility required for policy-relevant long-term assessments [65,66]. Arbitrary or isolated variations in single parameters may fail to capture the complex interdependencies and socio-political dynamics that shape real-world development trajectories [67]. In contrast, the SSP framework addresses this limitation by offering integrated storylines that are widely used by the climate and energy modelling communities, including by the IPCC, to inform global and national policy analyses [68]. Moreover, the SSPs provide a standardised reference that enables comparability across studies and alignment with national and international policy benchmarks, such as Nationally Determined Contributions [64,69]. This makes the SSP framework not only a scientifically robust but also a practically relevant tool for informing evidence-based decision-making [70]. We implement all five SSP narratives to systematically capture a broad spectrum of plausible futures. SSP1 describes a sustainable development pathway with low challenges to mitigation and adaptation. SSP2 represents a ‘middle of the road’ trajectory with moderate challenges. SSP3 reflects a fragmented world with high socio-political barriers to both mitigation and adaptation. SSP4 highlights an unequal world where adaptation remains difficult despite relatively low mitigation barriers. SSP5 envisions fossil-fuel-driven economic growth with high mitigation challenges but fewer adaptation difficulties. Importantly, the SSPs do not prescribe specific climate outcomes or policies; rather, they offer a socioeconomic baseline that can be combined with climate and policy scenarios to develop comprehensive future assessments [18].

3.2. Variable selection

The variables commonly used to model electricity demand typically include factors such as population [23,29,30,38,49,50,53,56,59,71], GDP [22,49,50,56,71], energy imports [36,38,49,50,59] and exports [36,38,49,59], household data [26,34,46], and weather data [41,42,44,47,48,50] such as HDD and CDD. We used population, GDP, household count (three types of households: single, family, and multi-person), HDD, and CDD as input variables. Initial tests identified the ‘extended family’ household type as inconsistent, leading to its exclusion. The selection process ensured the inclusion of variables that capture Turkey’s socioeconomic and climatic diversity, as well as regional disparities. Initial model performance metrics and feature importance guided our final variable selection. The complete integration of these variables into the modelling framework is illustrated in Fig. 3, highlighting the data sources, input variables, model tuning, and the scenario-based prediction outputs.

3.3. Data sources and preprocessing

Electricity consumption: Province-level residential electricity consumption data were obtained from the Turkish Statistical Institute (TURKSTAT) for 2008–2023 [11].

Heating and cooling degree-days: A gridded temperature dataset, with a spatial resolution of 0.25°—following the Representative Concentration Pathway (RCP) 2.6 [72] scenario, using the ‘r1i1p1’ ensemble member of the HadGEM2-ES global climate model [73]—was obtained from the Copernicus Climate Change Service (C3S) [74] in NetCDF (.nc) format. Data processing was carried out in Python using the xarray, numpy, and pandas libraries. Daily maximum, minimum, and average temperatures were calculated by resampling the original 3-hourly temperature data into daily values. Annual HDD and CDD for each province over the 2008–2050 period were calculated following the UK Met Office methodology [75], as detailed in Eqs. (1) and (2).

$$\mathrm{HDD} = \begin{cases} T_\mathrm{b} - T_\mathrm{avg}, & \text{if } T_\mathrm{max} \le T_\mathrm{b} \\ \frac{T_\mathrm{b}-T_\mathrm{min}}{2} - \frac{T_\mathrm{max}-T_\mathrm{b}}{4}, & \text{if } T_\mathrm{avg} \le T_\mathrm{b} < T_\mathrm{max} \\ \frac{T_\mathrm{b}-T_\mathrm{min}}{4}, & \text{if } T_\mathrm{min} < T_\mathrm{b} < T_\mathrm{avg} \\ 0, & \text{if } T_\mathrm{min} \ge T_\mathrm{b} \end{cases} \tag{1}$$

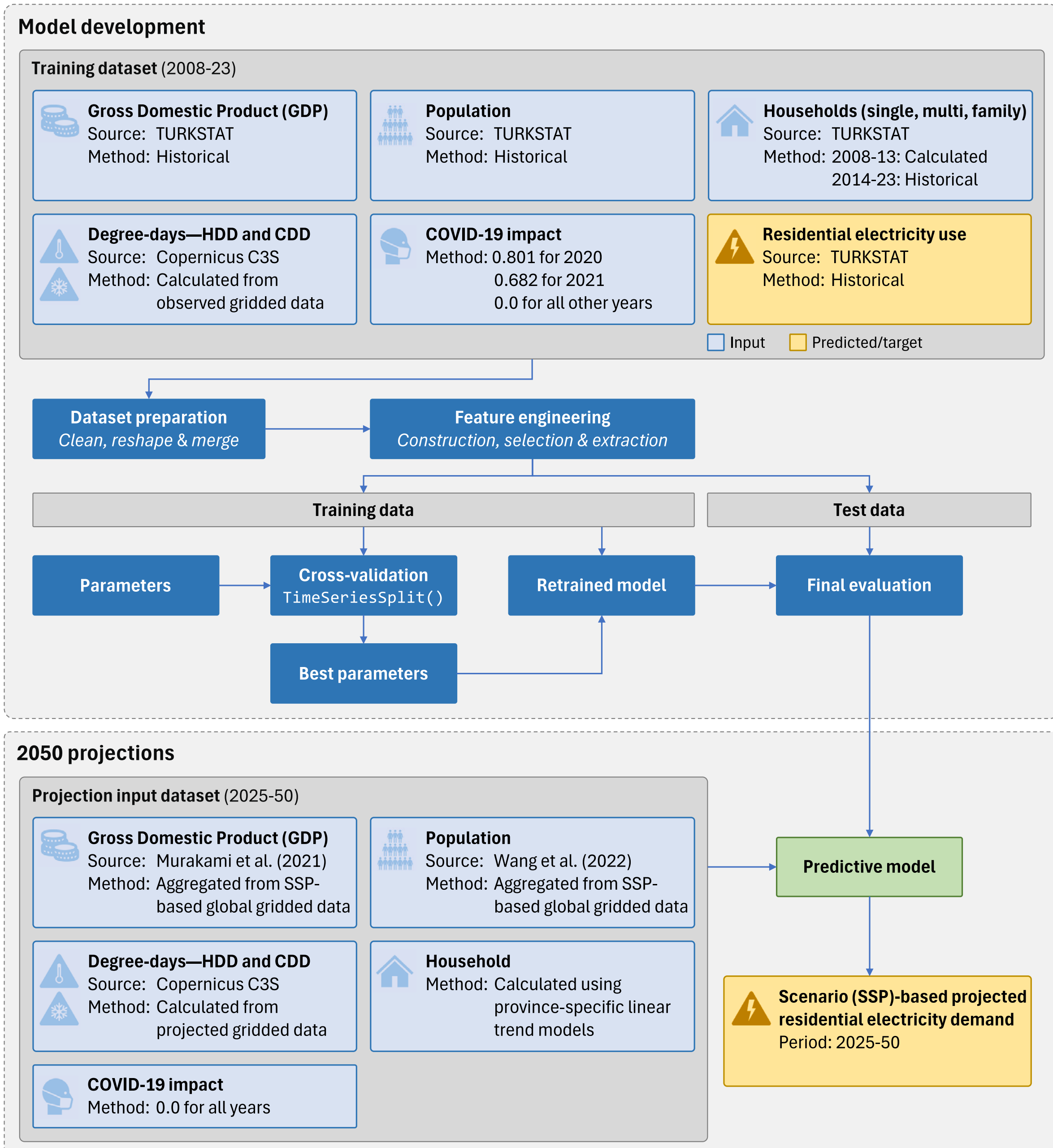


Fig. 3. Overview of the research framework. There are two main components: (a) model development that includes training data collection (2008–23), feature engineering, model training and validation, and final evaluation; and (b) 2050 projections that employ SSP-aligned inputs (2025–50) to generate subnational electricity demand forecasts. The approach integrates observed and scenario-based data to inform long-term energy planning at the provincial level.

$$\mathrm{CDD} = \begin{cases} 0, & \text{if } T_{\max} \le T_{\mathrm{b}} \\ \frac{T_{\max}-T_{\mathrm{b}}}{4}, & \text{if } T_{\max} > T_{\mathrm{b}} \ge T_{\mathrm{avg}} \\ \frac{T_{\max}-T_{\mathrm{b}}}{2} - \frac{T_{\mathrm{b}}-T_{\min}}{4}, & \text{if } T_{\mathrm{avg}} > T_{\mathrm{b}} > T_{\min} \\ T_{\mathrm{avg}} - T_{\mathrm{b}}, & \text{if } T_{\min} \ge T_{\mathrm{b}} \end{cases} \tag{2}$$

Here, T_{avg} denotes the average daily temperature, $T_{\min}$ and $T_{\max}$ represent the daily minimum and maximum temperatures, respectively, and T_{b} is the base temperature used in the calculation (15.5 °C for HDD and 22 °C for CDD).

Population: Historical province-level population data covering the period 2008–2024 were obtained from TURKSTAT [76]. We utilised global gridded population distribution datasets aligned with the SSPs developed by Wang et al. [77], provided at five-year intervals (2020–2100) with a spatial resolution of 1 km (30 arc-seconds). Using Python-based spatial analysis packages: rasterio [78], geopandas [79], and rasterstats [80], we aggregated gridded population data along Turkish provincial administrative boundaries, converting pixel-level population counts to province-level totals for each SSP scenario at five-year intervals. To achieve annual resolution projections for the years 2025 through 2050, we calculated province-specific compound annual growth rates from the five-yearly SSP gridded population data [77]. These growth rates were computed separately for each province and each SSP scenario, ensuring that distinct provincial demographic trends were individually captured. Calculated growth rates were then applied to the latest officially reported population data (2024) from TURKSTAT, enabling consistent annual projections starting from a reliable baseline. Although TURKSTAT provides national-level population

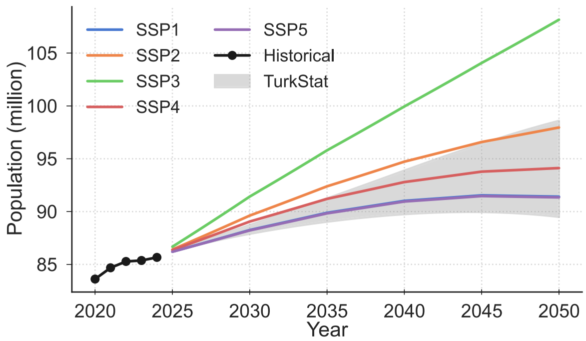


Fig. 4. Comparison of population projections for Turkey (2025–2050). SSP-based population projections used in this study are compared against TURKSTAT's official projections, illustrated as shaded area.

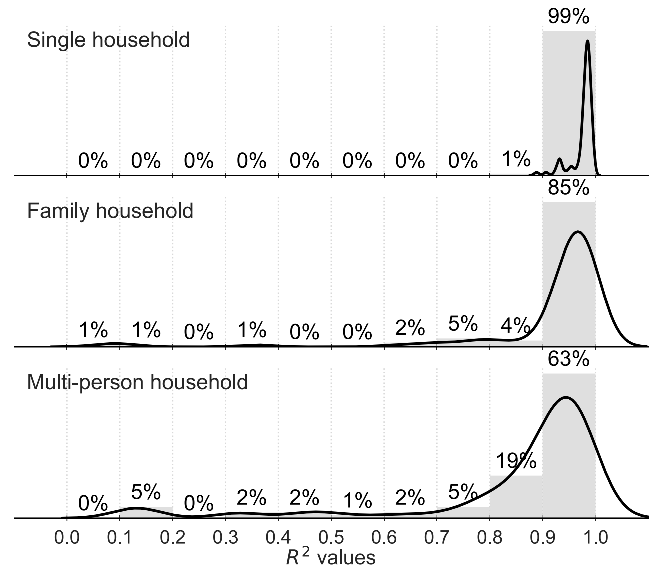


Fig. 5. R^2 distribution of provincial household trends. Histograms illustrate the distribution of R^2 values (along with kernel density estimate line) for household trends from 2014 to 2024, conducted for each of Turkey's 81 provinces.

projections up to 2100, the lack of official provincial-level projections beyond 2030 makes it challenging to incorporate or benchmark TURKSTAT's data at the subnational level. However, at the national level, Fig. 4 illustrates that four of our five SSP scenarios (SSP1, SSP2, SSP4, and SSP5) closely align within TURKSTAT's nationally projected ranges [81], thus supporting the validity and plausibility of our SSP-based approach. The SSP3 scenario, however, indicates significantly higher population growth, serving as an upper-bound projection reflecting more extreme demographic outcomes. Moreover, TURKSTAT's projection methodology lacks transparency, limiting detailed methodological comparisons, whereas our SSP-based approach explicitly incorporates internationally recognised scenario assumptions, demographic drivers, and transparent analytical steps.

Households: Household composition data for each province in three categories: single, multi-person, family, were obtained from TURKSTAT for the period 2014–2024, and calculated based on published household sizes for the period 2008–2013 [82]. In order to obtain future data for households beyond 2024, we employed province-specific linear trend models, which showed strong statistical fit, as illustrated in the histograms and kernel density estimates of R^2 distribution of 81 province for 3 household types in Fig. 5.

Linear fit of single households has $R^2 > 0.9$ for 99% of the provinces, with only one province having R^2 between 0.8 and 0.9. The trend is similar for other household types. Household data from 2014 to 2024 was the foundation for estimating household counts for 2025–2050. While linear regression assumes a constant rate of change and may not fully capture fluctuations due to various external factors, the strong R^2 values suggest that this method offers a reliable framework for our projections. It is worth noting that this approach was conducted separately for each province and did not account for inter-provincial relationships or trends, which is beyond the scope of the study.

Gross domestic product: Historical provincial-level GDP data covering 2008–2023 were obtained from TURKSTAT [83–86] in Turkish lira (TRY) and converted to US dollars using annual exchange rates from the World Bank [87]. We utilised a global gridded GDP dataset of Murakami et al. [88], which comes with projections under all five SSP scenarios at 1/12° (≈ 5 arc-minutes) spatial resolution in decadal steps up to 2050. Python is used together with the rasterio [78], geopandas [79], and rasterstats [80] libraries to compute zonal statistics, aggregating the gridded projections into provincial-level GDP totals under five SSP scenarios. To interpolate annual values from decadal figures, we calculated compound annual growth rate for each province and SSP, then applied them to the official 2023 GDP baseline. This procedure yielded annual, province-specific GDP trajectories to 2050 that reflect the spatially explicit growth patterns of each SSP while remaining anchored to the most recent official economic data.

COVID-19 impact: During the COVID-19 pandemic, residential energy consumption increased significantly as people spent more time at home due to lockdowns and remote activities [89]. Therefore, this study incorporated COVID-19 as a variable to include its impact on electricity demand forecasts in Turkey. The first case of COVID-19 was announced in Turkey on 11 March 2020, followed by the government declaring a school holiday starting on 14 March 2020, which lasted until 6 September 2021 [90,91]. We quantified the COVID-19 variable as a fraction between 0 and 1, representing the proportion of the year when schools were on holiday or conducting remote education. This approach allowed us to account for years with normal schooling (0), full-year school closures/remote education (1), or partial periods of altered school schedules (fractional values).

4. Model development

4.1. Comparison of ML algorithms

We evaluated six machine learning algorithms of three different types: tree-based (RF and XGBoost), neural networks (FFNN and LSTM), and kernel-based (SVR and GPR), known for their effectiveness in handling time series data and complex nonlinear relationships. The selection of these methods was based on their demonstrated capabilities in handling temporal dependencies, computational efficiency, and widespread adoption in relevant literature [92], as well as their distinct algorithmic approaches which allow for a comprehensive comparison of different modelling paradigms. FFNN was included because neural network approaches are widely used in electricity demand forecasting literature, and its architecture is a suitable candidate for annual time series data [93]. XGBoost, an advanced implementation of gradient boosting, was included for its high performance in various prediction tasks and its ability to handle complex relationships in data [94]. SVR was included as a robust, non-parametric alternative that often performs well in forecasting scenarios [95]. LSTM was included given its widely reported strength in managing temporal dependencies within sequential data [96]. RF was included for its ability to handle nonlinear relationships and its generally strong performance in diverse applications [97]. GPR was included as a second kernel-based method due to

Table 2
Comparison of forecasting algorithm performance. Metrics shown are the mean across the two test folds.

Category	Algorithm	MAE (GWh)	RMSE (GWh)	MAPE (%)	R^2	EV
Tree-based	RF	42.5	55.5	17.4	0.9359	0.9403
Tree-based	XGBoost	47.8	64.7	16.7	0.9191	0.9254
Kernel-based	SVR	50.1	71.7	15.5	0.9004	0.9218
NN-based	FFNN	64.9	86.1	23.5	0.8585	0.8813
Linear	Linear(Global)	68.2	91.4	30.9	0.8423	0.8481
Kernel-based	GPR	72.4	116.3	23.7	0.7340	0.7399
NN-based	LSTM	117.7	169.2	51.2	0.4617	0.6389

its suitability for small-to-medium-sized datasets and its flexibility in modelling complex functional dependencies [98].

Additionally, two linear regression approaches were included as benchmark models to serve as baselines for evaluating the added value of more complex machine learning methods. The first was a global linear model trained using pooled Ordinary Least Squares on panel data combining all provinces, where a single model was fitted across all province-year observations without accounting for province-specific effects. The second approach involved training separate linear regression models for each of Turkey's 81 provinces individually, allowing for localised fitting specific to the historical patterns of each province. Including both global and individual linear models provided a comparative foundation to assess whether the use of more sophisticated algorithms yields substantial predictive improvements over simpler, traditional modelling techniques.

The evaluation and selection of forecasting models requires careful consideration of appropriate performance metrics. In established forecasting practice, several studies [99–101] have demonstrated the importance of employing multiple decision criteria for comprehensive assessment such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), the coefficient of determination (R^2)— moving beyond single-metric evaluations to capture different aspects of model performance. Some research prioritise RMSE minimisation using other metrics as secondary criteria [35], while R^2 is consistently used as a supplementary metric rather than a standalone decision criterion [102,103]. The importance of MAPE in model selection is emphasised in studies due to its interpretability and utility in aiding comparison between different models [104,105]. Our approach combines established practices by prioritising MAE as the primary indicator due to its interpretability and practical relevance to electricity generators, who require explicit error margins for operational readiness and strategic planning [106–108]. Although R^2 is frequently reported as a measure of fit quality, it may sometimes present overly optimistic interpretations when values approach unity [109], thereby obscuring meaningful differences in forecasting performance. Hence, we rely primarily on MAE, complemented by RMSE, MAPE, explained variance (EV), and cautiously interpreted R^2, to ensure a comprehensive and practically meaningful evaluation.

All ML methods were trained using pooled panel data combining all provinces, allowing each model to capture inter-regional variation and shared temporal dynamics. Provincial forecasts were generated from globally trained ML models. Both global and individual linear models were also assessed as benchmarks. We also briefly tested province-specific ML models trained separately for each region, but these models consistently underperformed, often producing flat or unrealistic trends, likely due to insufficient data available at the provincial level. This suggests that localised ML models suffer from limited data diversity and volume, limiting their ability to generalise beyond observed patterns. As a result, we used a single global modelling strategy.

Each ML algorithm was subjected to comprehensive hyperparameter tuning via grid search with cross-validation (CV). We used `TimeSeriesSplit` rather than traditional k-fold CV, as standard k-fold fails to preserve temporal dependencies in time-series data and can introduce data leakage by allowing future observations to inform the training process [110]. `TimeSeriesSplit` maintains temporal integrity by ensuring each training set contains only historical data relative to its corresponding validation set, thereby preventing information leakage [111,112]. Following the tuning phase, the optimal hyperparameter configurations—identified based on the lowest mean MAE across validation folds—were used to retrain each model on the full training set. All analyses were conducted using Python's scikit-learn library [113]. Final model performance was also evaluated using a time-aware cross-validation approach to preserve temporal dependencies in the data. Accordingly, we conducted a two-split evaluation with a test size of 162 instances (corresponding to 2 years × 81 provinces), generating the following sequential train-test partitions over the full time span (2008–2023):

- **Split 1:**
  - Training: 2008–2019
  - Testing: 2020–2021
- **Split 2:**
  - Training: 2008–2021
  - Testing: 2022–2023

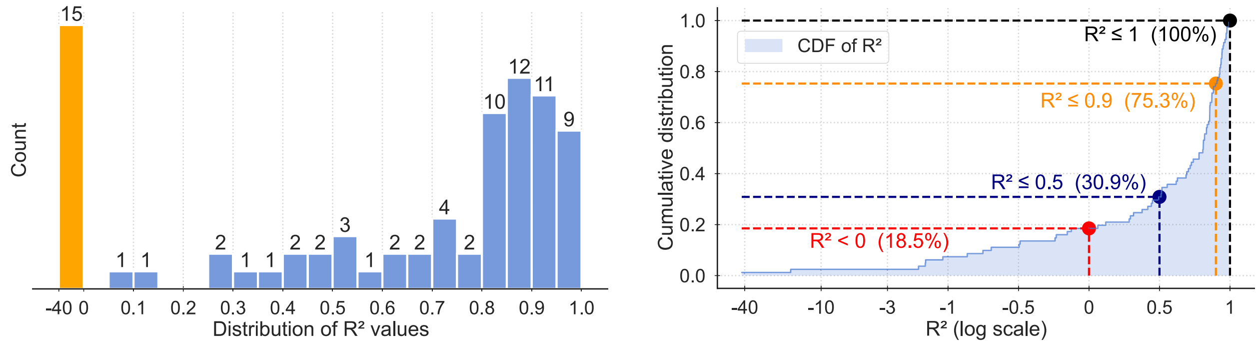
Comparative results indicated the RF model—an ensemble learning method that utilises multiple decision trees to generate a more accurate and stable prediction [97]—consistently delivered superior forecasting accuracy, achieving the lowest MAE and RMSE (42.5, and 55.5 GWh respectively) and the highest R^2 value (0.9359), as summarised in Table 2. SVR, XGBoost, FFNN, LSTM, and the global LR model—all exhibited higher prediction errors and lower stability in forecasts. Furthermore, the outputs generated by these models were visually aberrant, suggesting a poorer fit to the complex dynamics of the dataset.

Analysis of the individually trained LR models (one per province) revealed significant variability in performance, with only nine provinces achieving R^2 scores above 0.9, while fifteen provinces exhibited negative R^2 values (Fig. 6). These findings emphasise the limitations of individually trained models and the benefit of developing a global modelling approach to capture shared patterns and enhance forecast reliability across provinces. While RF demonstrated better performance in our specific context, it is important to note that model performance can vary significantly depending on the specific characteristics of the region and data being analysed, with recent studies showing how different algorithms can outperform each other under varying circumstances [114].

Consequently, the RF model, trained globally on panel data from all provinces for the period 2008–2023, was selected as the primary forecasting method for residential electricity demand across Turkey's 81 provinces up to 2050, based on its strong performance across all evaluation metrics and demonstrated stability in long-term forecasting. The following sections present the setup, tuning process, evaluation, and forecasting outcomes of the RF model.

4.2. Technical setup of the RF model

The hyperparameters for the RF model was tuned for optimal performance. Effective tuning has been shown to improve forecasting accuracy by up to 10% [115]. The hyperparameter ranges were selected based on empirical evidence from literature and theoretical foundations



(a) Histogram of R^2 scores

(b) Empirical CDF of R^2 scores

Fig. 6. Distribution of R^2 scores across 81 independently trained linear regression models, each fitted to data from a single province. **(a)** The histogram highlights the wide variability in local model performance. Fifteen provinces have negative R^2 values, indicating models that perform worse than a horizontal mean. Only nine province exceed $R^2 > 0.9$. **(b)** The empirical cumulative distribution function (CDF) of R^2 values quantifies this disparity, showing that 18.5% of models have $R^2 < 0$, 30.9% have $R^2 \leq 0.5$, and 75.3% fall below $R^2 = 0.9$. Together, these results illustrate the limitations of localised linear models in capturing the complex, nonlinear dynamics of residential electricity demand when trained on limited data from individual provinces.

(Table 3). Similar studies typically employ 100–500 trees [116–118]; we tested up to 1000 trees based on Breiman's demonstration that random forests converge to a limiting generalisation error and "do not overfit as more trees are added", ensuring stable model performance without overfitting risk [97].

The maximum depth parameter was explored across a broad range of values (2, 5, 8, 10, 12, 14, 15, 20) to ensure adequate representation of both shallow and deeper tree structures. This range was selected to balance model complexity and computational efficiency, while capturing potential nonlinear interactions at varying depths. The inclusion of depths from very shallow (2) to deep (20) allowed us to assess underfitting and overfitting behaviours in a controlled manner during grid search. To better understand the effect of key hyperparameters on model performance, we conducted sensitivity analyses on the number of trees and maximum depth, as illustrated in Fig. 7.

Fig. 7(a) shows the effect of the number of estimators on RF performance, with all other hyperparameters held constant (max. depth: 15, min. samples split: 2, min. samples per leaf: 1). For ensemble sizes below 250 trees, both MAE and R^2 exhibit substantial fluctuations, indicating an unstable region. Beyond this point, the curves stabilise, with MAE showing a steady decline and R^2 gradually increasing after approximately 400 trees. Grid search up to 1,000 estimators revealed that the lowest mean MAE is achieved at 810 trees. This value was therefore selected as the optimal number of estimators.

Fig. 7(b) presents the results of the max depth sensitivity analysis, where the number of estimators was fixed at 810 and other parameters kept constant (min. samples split: 2, min. samples leaf: 1). The maximum depth parameter was systematically increased from 1 to 20, and the corresponding training and test MAE values were recorded. Both training and test errors decreased sharply for depths up to around 5, after which the test error curve plateaued. The first local minimum in test MAE was observed at a depth of 15, which was therefore selected as the optimal value. Notably, no signs of overfitting were detected within this range, as the gap between training and test errors remained consistent up to 20, indicating strong generalisation.

The ranges for minimum samples to split (2, 5, 10) and minimum samples at a leaf (1, 2, 4) were set to explore various levels of tree pruning, aiming to control overfitting while maintaining sufficient detail in the model structure. These ranges were selected to facilitate a thorough grid search, enabling the identification of an optimal configuration for the specific characteristics of the provincial-level residential electricity demand forecasting task [119].

We identified the optimal configuration for the model with an ensemble of 810 trees, max. depth: 15, min. split: 2, and min. leaf: 1. This setup is used to train the final model and cross-validation resulted mean MAE of 42.5 GW, RMSE of 55.5 GWh, MAPE of 17.4%, R^2 score of 0.9359 (Table 2).

Table 3
Tuning ranges and step sizes.

Parameter	Range/Steps
Number of trees (estimators)	10 to 1000 (steps of 10)
Maximum depth of the trees	2, 5, 8, 10, 12, 14, 15, 20
Minimum samples to split	2, 5, 10
Minimum samples at a leaf	1, 2, 4

4.3. Feature importance analysis

We conducted a feature importance analysis (Fig. 8) using two complementary methods: standard feature importance and permutation-based importance.

As illustrated in Fig. 8(a), the RF model assigns the highest importance to family households, followed closely by population and GDP, indicating these socio-demographic and economic factors are the most influential drivers of electricity consumption in the dataset. Multi-person households and single-person households contribute moderately, suggesting the relevance of household structure beyond just family units. In contrast, HDD, CDD, and COVID-19 have comparatively low importance scores, indicating a limited role in the model's predictive performance.

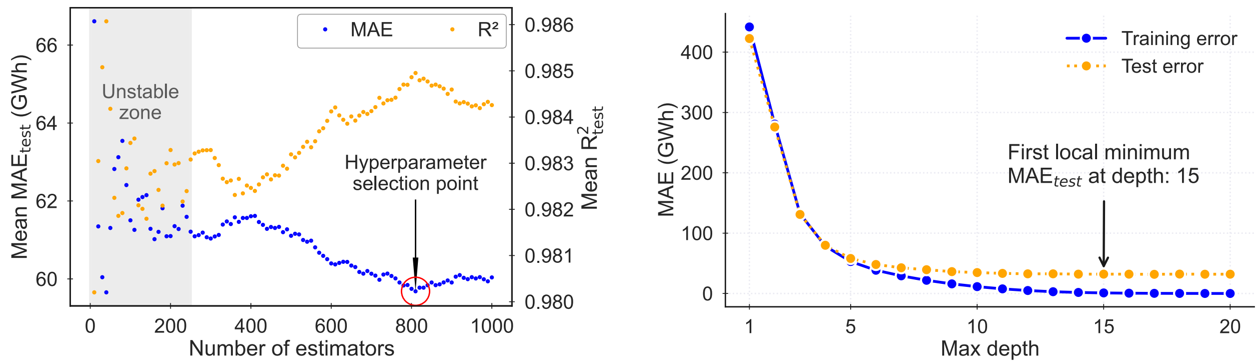
Fig. 8(b) presents permutation-based feature importance, which quantifies the influence of each variable by measuring how much the model's performance deteriorates when that variable's values are randomly shuffled. This method reveals the features most essential to accurate prediction by their impact on the model's R^2 score. The largest decreases in R^2 are observed when population and family households are permuted, confirming their importance in the model's predictive structure. GDP, multi-person, and single-person households also result in moderate performance drops, indicating they play a secondary but meaningful role. In contrast, climate-related variables (HDD and CDD) and the COVID-19 indicator produce minimal change when shuffled, suggesting they contribute relatively less to the model's forecasting capability.

These results support the assertion that residential electricity demand is driven primarily by demographic and economic trends, while the influence of climate and short-term disruptions remains marginal in long-term forecasting

5. Results and discussions

5.1. Partial dependence

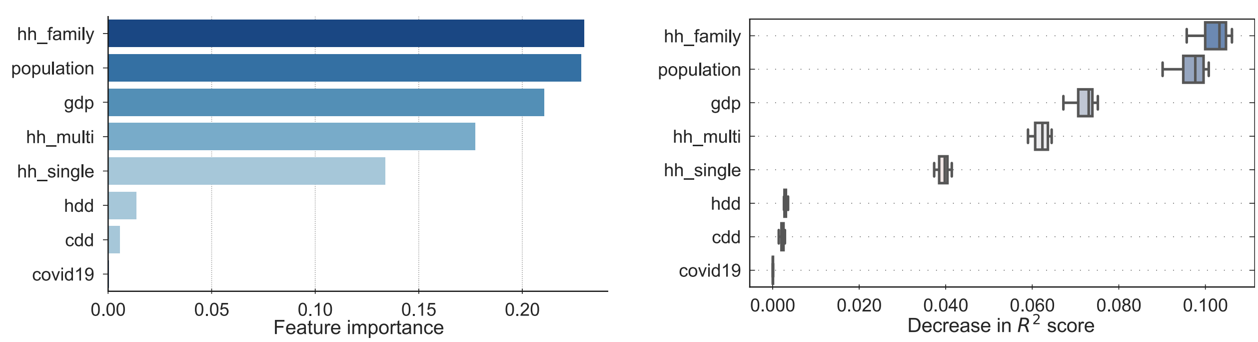
Partial dependence plots simplify a model's complexity by holding other features constant at their average values and isolate the effects



(a) Effect of number of estimators on MAE and R^2

(b) Model complexity and overfitting analysis

Fig. 7. Random Forest hyperparameter optimisation and complexity analysis. **(a)**: Effect of number of estimators on MAE and R^2 performance, showing optimal selection at 810 trees where the model achieves stability. **(b)**: Training and test error curves as a function of maximum tree depth, with the first local minimum at depth 15 indicating optimal complexity without overfitting.



(a) Feature importance of the RF model using internal scoring.

(b) Permutation-based feature importance.

Fig. 8. Feature importance analysis for residential electricity demand prediction. **(a)** Standard feature importance scores from the Random Forest model, showing households, population, and GDP as the primary drivers of electricity consumption, while climate variables (HDD, CDD) and COVID-19 show minimal influence. **(b)** Permutation-based feature importance measured by decrease in R^2 score when features are randomly shuffled, confirming population and family households as the most critical predictors for model performance.

of specific features, as shown in Fig. 9, allowing us to observe how changes in the variables shift the predictions within the given data range.

As HDD increases, there could be a shift from electric to more cost-effective heating options such as gas or central heating due to rising heating demands. Conversely, at lower HDD levels with minimal heating needs, electricity consumption rises, reflecting a preference for electric heating for light demands [120]. At very low CDD values, electricity usage remains unchanged, suggesting that mild temperatures do not trigger significant cooling-related electricity demand, possibly due to moderate cooling needs being met through passive or less electricity-intensive means. However, as CDD values continue to increase, there is a notable rise in electricity consumption driven by an increased reliance on electricity-intensive cooling solutions such as air conditioning. This pattern of higher electricity consumption during warmer periods aligns with expectations, reflecting electricity's significant role in cooling in Turkey [121]. These pronounced and nonlinear changes in electricity consumption, especially the sharper increases associated with higher CDD compared to HDD, could be driven by the greater sensitivity of cooling demand to increases in temperatures and by behavioural or technological thresholds that trigger increased electricity use for cooling [122,123]. As Turkey experiences varying climate conditions across regions, energy efficiency measures and building standards should ideally be tailored to local climate patterns.

Population has a positive relationship with energy consumption, which increases gradually until reaching a threshold, after which predictions sharply increase, indicating a nonlinear response. Beyond a critical point, energy consumption increases significantly, possibly due to changes in behaviour at higher population densities [124]. Sudden shift around 2.2 million may reflect a structural transition in electricity usage patterns as provinces reach larger urban scales. Previous research has shown that urbanisation and electricity demand relationships exhibit nonlinear scaling behaviour, with super-linear consumption increases emerging beyond certain population thresholds, likely driven by increased social interactions, economic activities, and infrastructure demands that scale faster than population growth [125].

Family households result in a linear rise in energy usage as their numbers increase, indicating a direct correlation with higher energy consumption. Multi-person households exhibit a gradual steady increase with sharp rises at certain thresholds, suggesting varied electricity consumption profiles or a complex relationship with household size that requires further investigation. This step-wise increase aligns with empirical evidence showing that economic scale effects in electricity consumption only emerge for households with three or more members, while smaller households exhibit different consumption dynamics [126]. Single-person households exhibit a smoother, more gradual increase in electricity consumption, with smaller increments spread over a wider range, suggesting a more consistent scaling effect that possibly reflects stable consumption behaviour across different

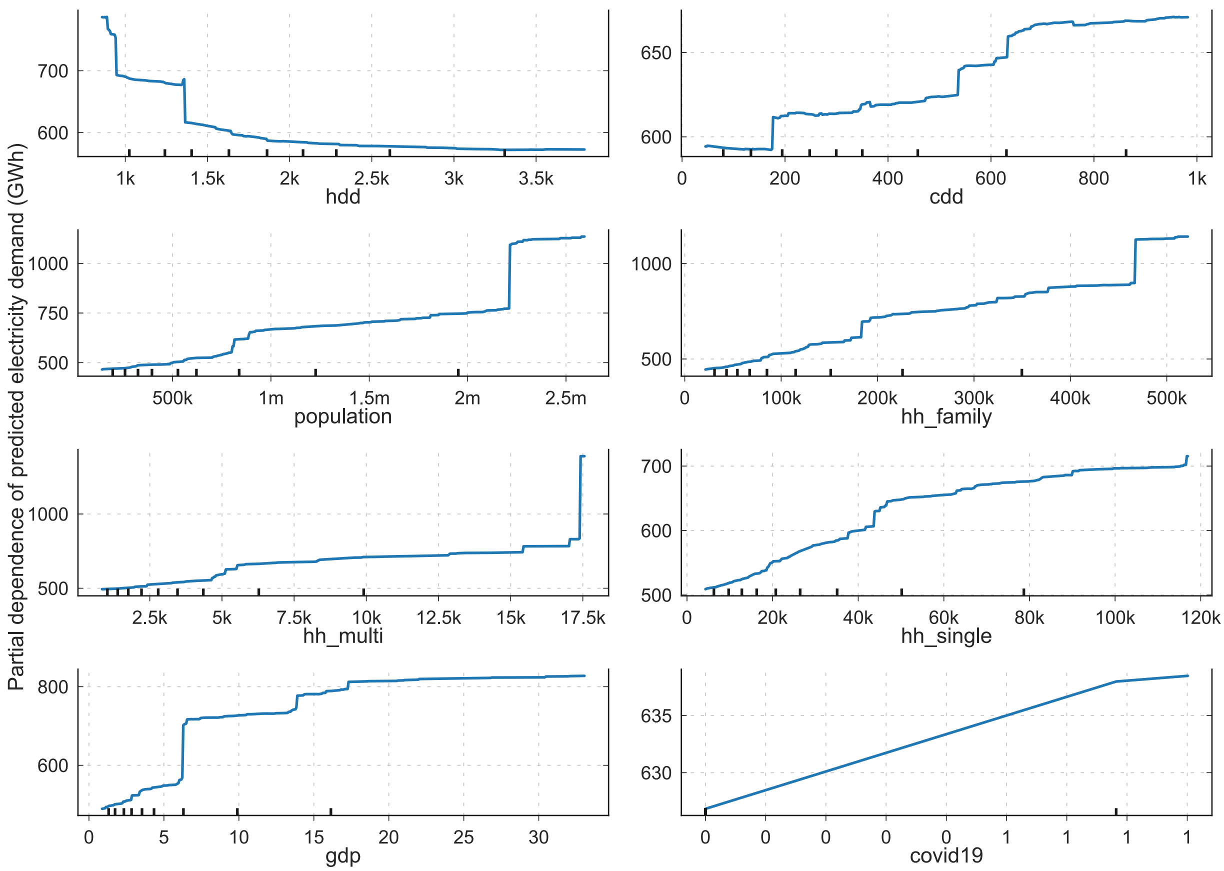


Fig. 9. Partial dependence plots showing the effect of features on the model's predictions. The plot visualises how changes in feature values influence the predicted outcome, with rug marks along the *x*-axis indicating the distribution of data points in the training set.

household counts. The strong influence of population and household composition on electricity consumption emphasises the importance of integrating demographic projections into long-term energy planning [127]. These findings indicate that different household structures could uniquely impact electricity usage patterns, making a nuanced approach to demographic data valuable in forecasting and planning efforts [128].

As GDP rises, energy consumption increases, possibly because increased wealth leads to larger homes and more energy-demanding appliances [129,130]. The positive relationship between GDP and electricity consumption suggests that economic development policies should be coupled with energy efficiency initiatives to manage increasing demand sustainably [131]. The sharp threshold increases observed in GDP predictions might reflect super-linear scaling behaviour typical of emerging economies, where cities become powerful drivers of economic activity that disproportionately attract population and investment [132].

The linear trend of COVID-19 indicates that the model predicts an increase in residential electricity consumption due to lockdown measures, as people typically consume more electricity while staying at home [133]. This consistent upward slope suggests a proportional relationship between lockdown presence and increased residential electricity usage. Although the pandemic's effect appears limited within our model, the observed rise in residential consumption during lockdowns points to the importance of developing flexible energy systems that can quickly adapt to such sudden shifts in consumption patterns [134].

5.2. 2050 electricity demand projections

5.2.1. National outlook

Fig. 10 presents the national outlook for residential electricity demand projections in Turkey across five SSPs from 2025 to 2050. All SSP trajectories closely align with historical consumption trends up to the early 2030s, after which their paths diverge modestly, reflecting differences inherent in each SSP's socioeconomic assumptions. By 2050, SSP5 projects the highest residential electricity demand, consistent with its narrative of fossil-fuel-intensive economic growth and high GDP increases, followed by SSP1, which, despite emphasising sustainable development, still anticipates substantial electricity demand growth. SSP2 and SSP3 projections closely track each other, illustrating moderate electricity demand growth. Their similar outcomes reflect the offsetting influences of slower economic growth coupled with higher population increases in SSP3, versus the more balanced middle-of-the-road assumptions in SSP2. SSP4, characterised by pronounced inequality and regional disparities, yields the lowest electricity demand projection, likely due to restrained GDP growth and limited economic activity in many regions.

It is important to note that scenario differentiation in this model arises solely from variations in GDP and population projections. The remaining independent variables in the model (e.g. household composition, cooling and heating degree days, COVID-19 impacts) remain constant across scenarios. Thus, the observed divergence between SSP trajectories primarily reflects changes driven by economic and demographic assumptions alone, contributing to the relatively limited range of outcomes between scenarios by 2050.

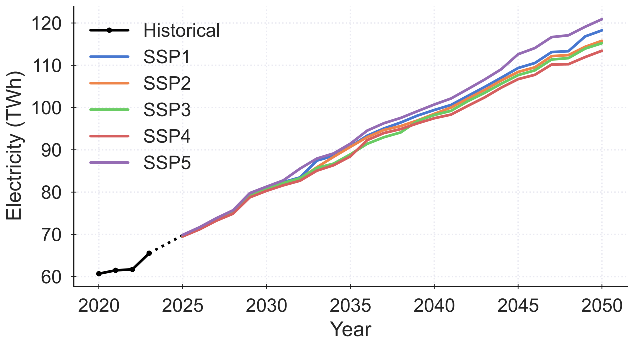


Fig. 10. Total national electricity demand projections with five SSP scenarios up to 2050.

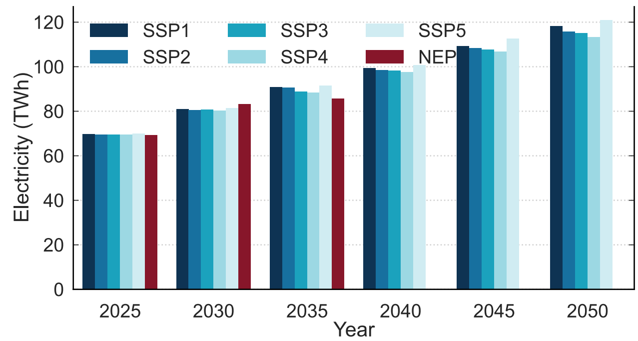


Fig. 11. Validation of model projections against Turkey's National Energy Plan (NEP). Projected residential electricity demand (TWh) from 2025 to 2050 under five SSP scenarios compared with official NEP projections (shown in red) [137].

Table 4
Projected residential electricity demand (TWh) in Turkey (2025–2050) under five SSP scenarios.

Year	SSP1	SSP2	SSP3	SSP4	SSP5	Mean ± SD
2025	69.8	69.5	69.6	69.5	69.9	69.7 ± 0.2
2030	80.9	80.6	80.8	80.3	81.3	80.8 ± 0.4
2035	90.8	90.7	88.9	88.4	91.5	90.1 ± 1.3
2040	99.4	98.5	98.2	97.5	100.7	98.9 ± 1.2
2045	109.3	108.4	107.7	106.7	112.6	108.9 ± 2.3
2050	118.3	115.8	115.2	113.4	120.9	116.7 ± 2.9

Table 4 summarises the projections at five-year intervals from 2025 to 2050. Initially, the projected demand in 2025 is nearly identical across all scenarios (approximately 69.7 TWh), indicating minimal divergence at this early stage due to the short-term predictability and narrow differences in near-future GDP and population estimates. By 2035, however, noticeable divergence begins to emerge albeit modestly, with SSP5 projecting the highest demand (91.5 TWh) and SSP4 the lowest (88.4 TWh). This variation expands further by 2050, highlighting differentiated long-term outcomes linked to scenario assumptions: SSP5, characterised by high economic growth and resource-intensive development, projects the highest demand (120.9 TWh), while SSP4, reflecting greater socioeconomic inequalities and slower economic growth, anticipates the lowest demand level (113.4 TWh). SSP1, despite its sustainability-driven focus, predicts substantial demand (118.3 TWh) by 2050, demonstrating a moderate yet consistent upward trajectory with an average quinquennial increase of approximately 9.7 TWh, underlining the significant role electrification may play in sustainable economic growth scenarios. It may be that despite its green growth orientation, electricity demand in SSP1 remains substantial, largely due to deep decarbonisation strategies prioritising clean electricity as a substitute for fossil fuels across sectors [135]. This could highlight that even under environmentally progressive scenarios, significant investment in low-carbon electricity infrastructure might still be required to meet future demand while supporting sustainable development objectives. SSP2 and SSP3 yield very similar intermediate projections (115.8 and 115.2 TWh, respectively), illustrating that demographic factors in SSP3 partially compensate for its lower economic assumptions compared to SSP2. The total range of scenario projections by 2050 is relatively narrow—approximately a 6.6% difference between the highest (SSP5) and lowest (SSP4) outcomes. Additionally, the standard deviation (±0.2 TWh in 2025 to ±2.9 TWh by 2050) across scenarios highlights uncertainty stays narrow over time, albeit still modest.

The consistent upward trend across all scenarios, with demand roughly doubling from 2025 to 2050, points to the crucial need for infrastructure expansion regardless of the development pathway. This growth trajectory raises important questions about grid capacity, energy security, and the necessity of diversifying energy sources to meet increasing demand while maintaining system reliability [3,10,136].

5.2.2. *Comparison with the national energy plan*

To validate our model's projections, we compared our results with Turkey's official national energy plan. This comparison provides important insights into our model's performance and its alignment with existing projections. The Turkish national energy plan is a comprehensive strategic document published by the Ministry of Energy and Natural Resources in Turkey [137]. This plan was developed in 2022 to outline the country's energy strategy up to 2035, aiming to support Turkey's net zero emission target. The plan covers various aspects of the energy sector, including primary energy consumption, electricity demand and generation, installed capacity projections, and the integration of renewable energy sources. It takes into account factors such as population growth, economic development, and fuel prices to project sectoral energy demands across industry, residential, services, agriculture, and transportation sectors.

In evaluating the efficacy of our model for projecting residential electricity demand in Turkey, we compared our results with the official residential electricity demand projections up to 2035 from Turkey's national energy plan. For 2025, our model's projections range from 69.5 to 69.9 TWh, which closely align with the official estimate of 69.2 TWh. In 2030, our model projects demand between 80.3 and 81.3 TWh, again very similar to the official 83.1 TWh estimate. For 2035, our model's range of 88.4 to 91.5 TWh slightly exceeding the official projection of 85.6 TWh. Overall, our model matches the official figures with 99.3% agreement in 2025, 97.2% in 2030, and 94.7% in 2035, indicating high consistency across all compared years.

The close alignment between our model's outputs and the official projection figures, particularly for the near-term years of 2025 and 2030, suggests a strong predictive capability of our approach. Official estimates only extend up to 2035, which limits direct comparison for projections for 2040 and beyond. This similarity lends credibility to our approach and indicates that our model effectively captures the underlying trends and factors influencing residential electricity consumption in Turkey. These comparisons are illustrated in Fig. 11, which shows the alignment between our model's five scenarios and the official national energy plan projections.

The methodology presented in this study highlights the importance of granular, sub-national forecasts in energy planning. We recommend that official energy planning bodies in Turkey consider applying similar approaches to provincial-level forecasting. By leveraging their access to more extensive datasets and resources, they could further refine and enhance the accuracy of these projections, providing an even more reliable groundwork for regional energy policy and infrastructure planning.

These findings show the potential of machine learning techniques, specifically random forest models, in energy demand forecasting [138]. The integration of shared socioeconomic pathways into our model framework provides a nuanced and potentially more comprehensive projection of future electricity demand scenarios compared to single-point estimates in the National Energy Plan. This alignment with official projections, particularly in the near term, validates the robustness of our methodology and its potential applicability in energy policy planning and decision-making processes.

5.2.3. Provincial forecasts

The projected province-level residential electricity demand from 2025 to 2050 is presented in Fig. 12, showing significant variations across provinces and scenarios. Since displaying plots for all 81 provinces is impractical, the trends for 27 major cities (by population) are displayed, arranged in rows of similar 2050 projections, to facilitate a visually meaningful comparison.

Across most provinces, the SSP trajectories evolve in close alignment, with no substantial divergence between scenarios, indicating broadly consistent expectations for residential demand growth across socioeconomic pathways. In Ankara, projections begin to diverge markedly after 2030, suggesting that different SSP narratives could exert more pronounced effects in highly urbanised and populated provinces. In contrast, Izmir exhibits a stable projection over the next decade, with nearly flat growth across all scenarios. This apparent stagnation is consistent with observed trends. Izmir's residential electricity demand has shown relatively minimal variation since 2017, supporting the plausibility of the model's subdued forecasts. Similarly, projections for Antalya suggest that demand will stabilise beyond 2030, potentially indicating a saturation point in residential demand or plateauing population growth. For the remaining provinces, demand is projected to increase gradually and steadily over time, with consistent upward trends across all scenarios. Projections support a broader narrative of uniform national growth in residential electricity demand, punctuated by a few provincial deviations likely linked to region-specific demographic, economic, or climatic factors.

The provincial estimates for SSP2 are presented in Table 5, as this scenario provides a balanced middle-of-the-road projection incorporating moderate challenges to both climate change mitigation and adaptation, thus serving as a pragmatic 'business as usual' baseline [18]. The projections for the remaining four scenarios: SSP1, SSP3, SSP4, and SSP5, are documented in Appendix A.1. Under the SSP2 scenario, substantial increases in residential electricity demand are projected across most provinces by 2050. Istanbul, functioning as Turkey's primary economic and demographic centre [139], demonstrates the highest demand, with projections indicating an increase from 12.8 TWh in 2023 to 22.4 TWh in 2050. Similarly, significant growth is anticipated in other major urban centers, with Ankara and Izmir projected to reach 7.2 TWh and 5.9 TWh, respectively, by 2050.

Tables 6 and 7 shows the provinces which had more than 150% and less than 40% increases between 2023 and 2050. The most dramatic increase is observed in Yalova under all scenarios, with a more than 270% rise in projected electricity demand. This substantial increase aligns with earlier scenario-based planning studies of Yalova, which identified the province as highly sensitive to alternative development trajectories involving rapid urbanisation, demographic shifts, and economic transformation [140], representing the highest increase across all provinces and scenarios. Other notable high increases are observed in Tunceli and Eskisehir, both showing consistent growth of around 170% across all SSP scenarios, and Erzincan exhibiting a significant rise of approximately 155% under SSP5.

Agri and Artvin consistently show increases between 30% and 40% across all five scenarios, indicating a persistently slow growth trajectory in residential energy demand. This trend may reflect limited population growth, economic stagnation, or already-saturated demand levels in these regions. Rize and Sivas also exhibit similarly low increases across most scenarios, showing a pattern of subdued residential electricity expansion in certain eastern and northeastern provinces. İzmir, despite being a major urban centre, appears in the low-growth category under SSP2, SSP3, and SSP4, with increases not exceeding 28%, suggesting a potential plateau in residential demand that may be linked to mature infrastructure and stabilised demand levels. Additionally, Bayburt and Çanakkale join this group under SSP3 and SSP4 respectively, highlighting the scenario-specific variation in regional energy trajectories. Findings suggest that in contrast to high-growth provinces requiring infrastructure expansion, the provinces listed here may benefit more from strategies focused on maintaining system resilience, improving energy efficiency, and addressing regional disparities in development.

Differentiated growth in residential electricity demand indicates the necessity for region-specific policies [141]. For provinces such as Bursa, residential demand is expected to rise from 2,405 GWh in 2023 to 4,319 GWh by 2050, marking a 79.5% increase. Bursa's projected increase in electricity demand reflects its role as one of Turkey's leading industrialised cities, where economic growth, urbanisation, and domestic migration—driven by employment opportunities, a high quality of life, and strong infrastructure—collectively fuel residential electricity consumption alongside industrial demand [142]. Additionally, Bursa's per capita electricity demand has consistently exceeded national averages, driven by both population density and strong industrial presence, making it critical to address the city's residential infrastructure needs to meet rising demand sustainably [41]. Similarly, Kocaeli is projected to experience a surge from 1,449 GWh to 3,151 GWh, reflecting a 117.5% increase. Kocaeli's rapid urbanisation, marked by substantial conversion of agricultural lands to urban areas to accommodate expanding residential and industrial zones, reinforces our findings and aligns with other studies documenting these shifts as critical factors driving increased energy demands in the province [143]. These regions would benefit from proactive investments in renewable energy and energy efficiency enhancements to mitigate potential environmental and economic impacts of increased fossil fuel consumption.

Several provinces are projected to have low levels of residential electricity demand in 2050, with Bayburt at 67 GWh, Ardahan at 78 GWh, Tunceli at 129 GWh, G´um´uşhane at 127 GWh, Iğdır at 162 GWh, and Artvin at 178 GWh. For these provinces the focus might be on understanding the various factors influencing their electricity demand. In Gumushane, climate-related events—such as storms, floods, and other extreme weather conditions—are noted as recurring issues that may disrupt local infrastructure and economic activities, potentially impacting demand growth [144]. Given these climate-related challenges, policies in Gumushane could prioritise resilience-building measures that address both disaster preparedness and sustainable energy practices. Moreover, a separate study highlights that Artvin and Gumushane have among the lowest solar radiation and sunshine duration values across Turkey, limiting the feasibility of photovoltaic (PV) electricity generation in these areas [145]. This limitation could further discourage investments in renewable infrastructure, thereby influencing local demand. Recognising these unique regional constraints, targeted policies might focus on stimulating economic growth through resilient infrastructure improvements, while also exploring alternative energy sources suited to the local context.

To support accessibility and exploration of the model outputs, an interactive dashboard was developed, allowing users to visualise the projected residential electricity demand across Turkey from 2025 to 2050 under five SSP scenarios at both national and provincial levels. It also features a spatial mapping interface for exploring provincial demand distributions in 2050 under a selected scenario. The tool is publicly available at: https://2050-demand-turkey.streamlit.app/

5.2.4. Implications of SSP scenarios

Studies using SSPs mostly focus on national or global scales [146–148]. Our application of SSPs at the provincial level aimed to capture subnational dynamics. Study findings show that most provinces exhibit broadly consistent electricity demand trajectories across scenarios, with relatively modest divergences. As illustrated in Fig. 12, the SSP

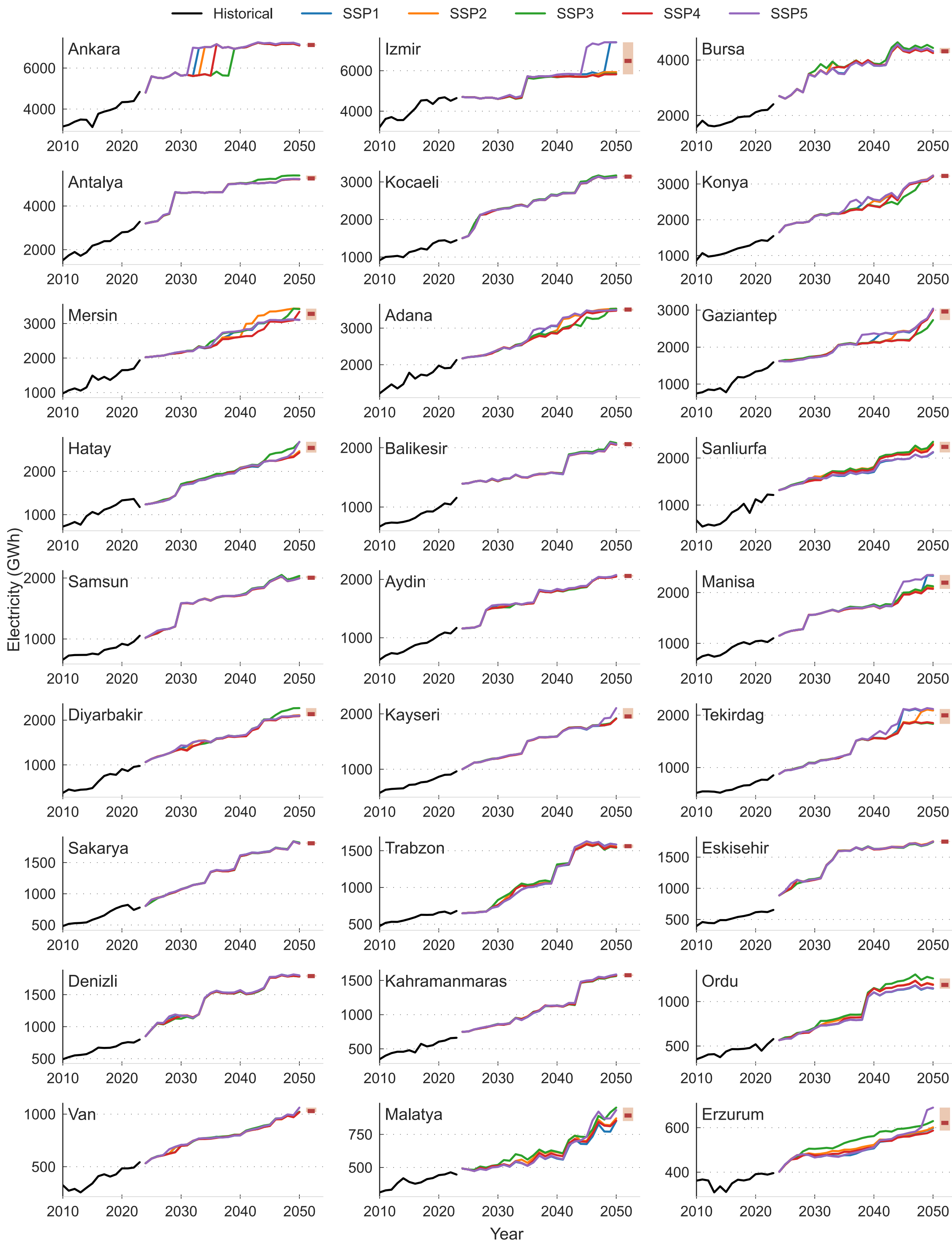


Fig. 12. Residential electricity demand projections up to 2050 for 27 major provinces. The figure illustrates historical data alongside forecasts under five SSP scenarios, with end-year bars indicating scenario ranges and means.

Table 5
Projected annual residential electricity demand (GWh) in Turkish provinces between 2025 and 2050 under SSP2 scenario.

Province	2025	2030	2035	2040	2045	2050	Province	2025	2030	2035	2040	2045	2050
Adana	2209	2413	2642	2942	3467	3532	K.maras	754	859	975	1135	1489	1575
Adiyaman	350	396	426	511	554	667	Karabuk	182	240	258	284	311	309
Afyonk.	462	467	523	535	600	713	Karaman	166	186	214	225	239	336
Agri	218	229	249	280	319	332	Kars	132	143	158	167	187	193
Aksaray	281	322	397	395	405	481	Kastamonu	268	307	339	352	428	412
Amasya	230	256	278	304	326	340	Kayseri	1061	1199	1510	1594	1728	1913
Ankara	5595	5626	7023	6997	7178	7126	Kilis	122	131	137	160	184	196
Antalya	3257	4597	4635	5040	5084	5237	Kirikkale	201	242	257	284	292	396
Ardahan	52	54	60	67	72	78	Kirklareli	284	398	397	411	445	455
Artvin	130	141	149	167	173	178	Kirsehir	160	186	212	240	248	272
Aydin	1167	1517	1582	1828	1874	2054	Kocaeli	1560	2264	2340	2641	2984	3151
Balikesir	1401	1441	1494	1574	1915	2062	Konya	1838	2101	2200	2529	2845	3240
Bartin	145	170	195	206	221	235	Kutahya	378	447	464	465	482	514
Batman	346	379	414	485	571	659	Malatya	486	514	536	615	701	871
Bayburt	45	49	51	55	59	68	Manisa	1208	1563	1664	1755	1976	2102
Bilecik	152	183	199	221	319	346	Mardin	572	643	739	820	900	1035
Bingol	159	195	214	256	275	300	Mersin	2039	2175	2324	2611	3349	3432
Bitlis	177	198	214	253	275	308	Mugla	1508	1760	1844	1902	2088	2156
Bolu	237	272	372	384	394	392	Mus	176	202	216	245	262	284
Burdur	201	234	248	264	280	296	Nevsehir	211	246	274	286	312	354
Bursa	2609	3411	3729	3830	4319	4252	Nigde	233	263	284	311	329	390
Canakkale	495	557	549	600	637	712	Ordu	595	699	831	1150	1185	1193
Cankiri	141	161	187	203	236	259	Osmaniye	365	433	491	514	611	698
Corum	327	368	406	454	471	479	Rize	260	270	291	335	364	373
Denizli	958	1171	1517	1563	1767	1788	Sakarya	905	1073	1349	1612	1678	1807
Diyarbakir	1134	1352	1511	1650	2005	2111	Samsun	1068	1581	1635	1713	1939	2002
Duzce	263	309	401	398	413	434	Sanliurfa	1354	1610	1700	1812	2090	2311
Edirne	323	380	440	452	510	519	Siirt	162	192	209	241	255	272
Elazig	388	496	492	510	532	627	Sinop	169	189	205	220	241	263
Erzincan	155	174	199	220	233	251	Sirnak	246	294	415	460	483	554
Erzurum	433	480	501	523	568	602	Sivas	396	452	452	463	486	493
Eskisehir	950	1139	1609	1624	1663	1755	Tekirdag	946	1086	1229	1561	1868	2090
Gaziantep	1617	1742	2077	2149	2442	3027	Tokat	360	434	459	482	516	525
Giresun	343	434	418	451	495	514	Trabzon	655	761	1017	1299	1600	1557
Gumushane	81	98	110	119	124	127	Tunceli	55	76	83	94	99	129
Hakkari	128	145	166	186	211	222	Usak	270	302	316	343	420	440
Hatay	1258	1674	1872	2089	2249	2469	Van	578	700	768	799	888	1019
Igdir	96	110	119	134	142	162	Yalova	280	313	449	832	882	928
Isparta	316	346	404	414	428	444	Yozgat	278	301	320	337	350	425
Istanbul	13106	15006	16803	18632	20591	22441	Zonguldak	445	516	542	551	589	596
Izmir	4684	4605	5721	5682	5701	5932							

Table 6
Projected increases in electricity demand (2023–2050) for provinces with the highest changes (≥ 150%) under multiple SSP scenarios.

SSP1		SSP2		SSP3		SSP4		SSP5	
Province	Increase	Province	Increase	Province	Increase	Province	Increase	Province	Increase
Eskisehir	168%	Eskisehir	169%	Eskisehir	167%	Eskisehir	168%	Erzincan	155%
Tunceli	178%	Tunceli	174%	Tunceli	168%	Tunceli	172%	Eskisehir	168%
Yalova	272%	Yalova	273%	Yalova	273%	Yalova	272%	Tunceli	201%
								Yalova	273%

Table 7
Projected increases in electricity demand (2023–2050) for provinces with the lowest changes (≤ 40%) under multiple SSP scenarios.

SSP1		SSP2		SSP3		SSP4		SSP5	
Province	Increase	Province	Increase	Province	Increase	Province	Increase	Province	Increase
Agri	38%	Agri	40%	Agri	40%	Agri	37%	Agri	39%
Artvin	34%	Artvin	30%	Artvin	27%	Artvin	30%	Artvin	38%
Rize	36%	Izmir	28%	Bayburt	28%	Bayburt	31%		
Sivas	34%	Rize	36%	Canakkale	37%	Canakkale	37%		
		Sivas	33%	Izmir	26%	Izmir	25%		
				Rize	33%	Rize	36%		
				Sivas	33%	Sivas	32%		

trajectories exhibit close alignment, indicating that the impact of SSP-specific socioeconomic assumptions—implemented through GDP and population variations—was relatively limited especially in small cities.

Although the majority of provinces exhibited limited divergence in residential electricity demand across SSP scenarios, major urban centers, such as Istanbul, Ankara, and Izmir, did show notable differences in their projected trajectories. This suggests that SSP-based scenario analysis were most pronounced in large urban provinces where higher population densities and economic activity appear to amplify the influence of SSP-specific socioeconomic trajectories.

Previous studies have investigated the quantification of SSP narratives [69] and their regional extensions [149]; Building on this, our findings suggest that the effectiveness of SSPs in subnational electricity demand forecasting can be strengthened by broadening the range of scenario variables considered. Our approach implemented SSPs by varying only two variables—population and GDP—while other inputs remained constant across scenarios. Since only GDP and population projections were varied, the SSP framework could be more effective if expanded to include additional factors. The SSP framework provides a robust foundation for scenario-based forecasting and highlights the value of long-term planning under uncertainty [150]. Even with converging projections across SSPs, long-term infrastructure planning benefits from identifying areas—such as Bursa and Kocaeli—where growth is consistently high and relatively insensitive to specific scenario assumptions. In such cases, targeted investments can be considered ‘no-regret’ strategies, offering value across a range of plausible futures [151]. This illustrates how even modest scenario differentiation can still inform spatially nuanced energy planning decisions.

Our study contributes to the broader SSP literature by highlighting both the potential and limitations of downscaling global narratives to the provincial level. While regional heterogeneity can influence the expression of global pathways [152,153], its impact depends strongly on how comprehensively the scenarios are implemented. Strengthening this alignment can enable scenario-based modelling to more effectively support resilient, adaptive, and regionally tailored energy strategies for Turkey and other countries with high spatial variability.

5.2.5. Regional outliers

The projections for Istanbul, Turkey’s economic and demographic hub, presented unique challenges in this study due to its significantly higher population and household numbers compared to other provinces. While the RF model demonstrated excellent performance across the remaining eighty provinces, its outputs for Istanbul’s electricity demand exhibited notable deviations from observed trends. This anomaly was predominantly due to Istanbul being an outlying case due to its considerable population and household numbers and higher relative electricity usage, which made it challenging to effectively capture its features within a single modelling framework.

A hybrid modelling approach was implemented to address the anomaly. FFNN was employed specifically for Istanbul, as it produced more coherent and rational projections for this province. The remaining eighty provinces were modelled using RF, ensuring consistency and reliability across the broader dataset. The hybrid approach enabled the integration of FFNN’s strengths in handling large and complex datasets with RF’s performance, thus accommodating Istanbul’s unique profile without compromising the study’s overall methodological framework. This case highlights the importance of considering the distinct characteristics of outlier regions, particularly in studies that aim to capture regional heterogeneity. Using two models not only demonstrates the complexity of forecasting electricity demand in highly urbanised and economically active areas, but also validates the adaptability and reliability of the methodological approach proposed in this research.

5.3. Limitations and future research

This study has some limitations that present opportunities for future research. Our projections may not fully capture the impact of potential technological disruptions. One example is the increasing adoption of electric vehicles, a large number of which are expected to be predominantly charged from residential connections, potentially leading to significant changes in household electricity demand. According to TURKSTAT, electric vehicles represented only 1.2% of Turkey’s total vehicle fleet in 2023 [154], indicating minimal current impact on residential electricity demand. While EV adoption is expected to accelerate and significantly influence future residential consumption patterns, the current penetration rates were insufficient to meaningfully affect our historical training data or near-term projections. The growing use of rooftop photovoltaic (PV) systems represents another factor that may reduce grid-observed residential demand; however, province-level PV adoption data—such as household penetration or installed residential capacity—remains unavailable despite the introduction of enhanced feed-in tariffs for systems installed between 2021-2030 [155].

Future studies could develop scenarios that explicitly model these technological shifts and their implications for residential electricity demand such as incorporating PV trends when such data becomes accessible. The methodology could also be extended to other sectors such as commercial and industrial, providing a more comprehensive view of future electricity demand. In addition, future work should explore more holistic integration of SSP elements—beyond population and GDP—into machine learning frameworks to better capture local dynamics and regional disparities. Addressing these areas in future research will enhance our understanding of long-term electricity demand trends, contributing to more comprehensive energy planning and policy-making.

6. Conclusion

This study developed a machine learning model to forecast long-horizon residential electricity demand at the provincial level in Turkey through 2050. The model integrates socioeconomic and climatic variables and analyses the impact of SSPs on future demand patterns.

The selection of the ML algorithm was based on the evaluation of prediction performance of six algorithms: FFNN, XGBoost, SVR, LSTM, GPR and RF, against a global linear regression model. RF emerged as the most effective model, achieving an R^2 score of 0.9359, MAE of 42.5 GWh, and RMSE of 55.5 GWh. By incorporating key factors such as population, GDP, household types, and climate data—aligned with SSPs to reflect projected socioeconomic and environmental trajectories—the model provides a perspective not only on the present drivers of residential electricity demand but also on how these drivers may evolve in the future.

The findings indicate that Turkey’s residential electricity demand is likely to increase from 65.5 TWh in 2023 to between 113.4 TWh and 120.9 TWh by 2050, depending on socioeconomic pathways. This highlights the substantial impact of demographic and economic changes on future energy needs. Analysis at the provincial level revealed marked disparities: while provinces such as Yalova, Tunceli, and Eskisehir may see demand increases exceeding 150%, others, including Agri, Artvin, and Izmir, may experience more modest growth, often below 40%. Such insights highlight the importance of regional forecasting in informing targeted policy interventions and infrastructure planning.

This study makes several novel contributions to energy forecasting. First, it demonstrates the suitability of the Random Forest algorithm for long-horizon, provincial-level electricity demand forecasting, showing improved accuracy and adaptability over traditional statistical methods. Second, by incorporating SSPs, the model provides a holistic, scenario-based approach that accounts for diverse socioeconomic futures, offering a more comprehensive picture than a single-scenario analysis. Third, the comprehensive sub-national focus in a

Table A.1
Projected annual residential electricity demand (GWh) in Turkish provinces between 2025 and 2050 under SSP1 scenario.

Province	2025	2030	2035	2040	2045	2050
Adana	2208	2399	2674	3049	3479	3498
Adiyaman	353	397	433	506	552	666
Afyonk.	461	463	479	532	599	839
Agri	218	225	249	278	312	327
Aksaray	281	325	396	393	408	480
Amasya	230	257	278	305	321	382
Ankara	5595	5626	7023	6997	7202	7151
Antalya	3257	4602	4635	5036	5074	5215
Ardahan	52	54	62	70	73	81
Artvin	130	141	153	169	178	183
Aydin	1168	1557	1586	1828	1883	2057
Balikesir	1401	1443	1501	1565	1912	2052
Bartin	145	170	196	210	221	244
Batman	346	381	414	514	563	654
Bayburt	45	49	51	56	64	74
Bilecik	152	182	197	220	327	343
Bingol	159	189	210	253	273	300
Bitlis	177	198	217	257	273	306
Bolu	237	272	382	385	396	393
Burdur	202	225	245	262	277	357
Bursa	2609	3400	3518	3796	4320	4314
Canakkale	495	557	551	601	708	718
Cankiri	141	160	188	210	236	259
Corum	327	367	406	448	470	483
Denizli	957	1176	1525	1566	1775	1795
Diyarbakir	1134	1369	1501	1647	2013	2099
Duzce	263	315	397	397	414	433
Edirne	323	380	450	452	507	523
Elazig	388	498	492	508	531	630
Erzincan	155	174	201	222	236	251
Erzurum	435	468	476	507	564	598
Eskisehir	953	1144	1603	1627	1659	1749
Gaziantep	1615	1724	2070	2201	2420	3017
Giresun	343	435	418	441	482	564
Gumushane	81	98	111	120	126	128
Hakkari	127	148	167	192	210	220
Hatay	1258	1674	1856	2058	2247	2449
Igdir	96	110	119	136	142	164
Isparta	315	346	410	413	423	443
Istanbul	13332	15350	17324	19368	21452	23441
Izmir	4682	4609	5724	5699	5827	7403
K.maras	755	859	965	1130	1492	1583
Karabuk	181	239	258	284	309	313
Karaman	166	186	213	225	249	341
Kars	132	144	157	169	189	194
Kastamonu	268	308	338	410	426	408
Kayseri	1060	1194	1509	1590	1714	1922
Kilis	122	131	138	161	183	197
Kirikkale	199	242	257	284	352	397
Kirklareli	284	398	398	414	444	457
Kirsehir	160	190	214	238	244	274
Kocaeli	1560	2260	2340	2630	2967	3128
Konya	1838	2093	2200	2543	2861	3232
Kutahya	378	447	463	468	488	520
Malatya	485	507	513	567	677	851
Manisa	1208	1564	1669	1747	1970	2329
Mardin	572	640	725	815	868	1025
Mersin	2038	2174	2310	2770	3100	3109
Mugla	1517	1760	1848	1907	2108	2151
Mus	176	205	219	246	261	283
Nevsehir	211	247	273	288	312	406
Nigde	235	263	283	310	377	394
Ordu	581	697	781	1103	1135	1145
Osmaniye	365	434	499	518	611	699
Rize	260	273	291	342	365	375
Sakarya	905	1073	1344	1613	1683	1807
Samsun	1069	1585	1630	1716	1936	1997
Sanliurfa	1353	1578	1620	1704	1973	2120
Siirt	162	192	215	241	255	269
Sinop	169	194	206	220	242	264
Sirnak	245	292	419	460	484	558
Sivas	397	450	451	469	490	496
Tekirdag	946	1079	1228	1568	2115	2092
Tokat	360	434	455	476	494	501
Trabzon	653	742	1002	1284	1593	1584
Tunceli	56	76	84	96	103	131
Usak	270	302	316	392	413	435
Van	577	707	773	798	891	1022
Yalova	283	313	455	832	881	927
Yozgat	278	301	320	337	351	434
Zonguldak	456	517	541	551	595	604

geographically and socioeconomically diverse country such as Turkey provides valuable insights for regional energy policy, often overlooked in national-level studies. Lastly, this research shows that socioeconomic factors such as population growth and GDP are stronger predictors of residential electricity demand in Turkey than climate variables, as supported by both internal feature importance and permutation-based model analyses.

Beyond its academic contributions, this research has practical implications. The granular, long-term projections are highly beneficial for guiding region-specific energy policies, optimising infrastructure investments, and supporting sustainable energy transitions in Turkey. It also supports strategic decisions around renewable energy deployment, especially in provinces where demand is projected to rise rapidly and where local generation can be aligned with demand growth.

The methodological approach developed in this study has broader implications. It provides a framework that can be adapted to other countries or regions encountering similar challenges in energy demand forecasting and management. As countries around the globe face the challenge of meeting increasing energy demands while transitioning to more sustainable systems, the approach and findings presented in this study serve as a valuable resource for informed decision-making and strategic planning in the energy sector.

CRediT authorship contribution statement

Oguzhan Gulaydin: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monjur Mourshed:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

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Appendix

A.1. Provincial electricity demand projections

The following tables present detailed projections of provincial electricity demand under SSP1 (Table A.1), SSP3 (Table A.2), SSP4 (Table A.3), and SSP5 (Table A.4) scenarios for all 81 provinces of Turkey, at 5-year intervals. These scenarios supplement the SSP2 results discussed in Section 5.2.3.

Data availability

Data will be made available on request.

Table A.2
Projected annual residential electricity demand (GWh) in Turkish provinces between 2025 and 2050 under SSP3 scenario.

Province	2025	2030	2035	2040	2045	2050
Adana	2210	2378	2669	2867	3292	3529
Adiyaman	350	395	423	480	591	721
Afyonk.	464	498	523	565	680	812
Agri	219	231	249	281	319	333
Aksaray	281	322	339	399	413	485
Amasya	230	254	274	307	325	345
Ankara	5595	5626	5628	6997	7178	7106
Antalya	3270	4593	4637	5052	5242	5393
Ardahan	52	54	57	61	63	75
Artvin	130	140	147	166	170	174
Aydin	1164	1511	1584	1806	1866	2055
Balikesir	1402	1434	1502	1574	1935	2080
Bartin	145	170	185	202	217	234
Batman	346	377	416	491	568	715
Bayburt	45	49	51	55	58	60
Bilecik	151	182	202	234	252	262
Bingol	159	201	217	252	279	296
Bitlis	177	199	212	252	275	304
Bolu	237	274	320	384	396	390
Burdur	201	235	250	263	279	296
Bursa	2606	3607	3740	3871	4437	4434
Canakkale	495	555	550	599	633	638
Cankiri	141	159	179	197	224	257
Corum	328	370	408	431	472	484
Denizli	957	1124	1519	1550	1769	1783
Diyarbakir	1134	1357	1513	1652	2019	2269
Duzce	262	308	358	405	415	439
Edirne	323	379	386	447	511	522
Elazig	387	462	493	512	536	632
Erzincan	155	174	196	219	231	248
Erzurum	433	505	531	562	596	630
Eskisehir	944	1151	1605	1634	1649	1742
Gaziantep	1652	1750	2089	2138	2197	2733
Giresun	343	436	425	461	506	518
Gumushane	82	103	110	121	125	127
Hakkari	128	150	170	193	206	229
Hatay	1259	1706	1890	2081	2389	2677
Igdir	96	109	118	135	142	160
Isparta	316	346	363	413	434	449
Istanbul	13138	14945	16625	18294	20066	21691
Izmir	4683	4605	5647	5678	5706	5854
K.maras	753	865	966	1137	1479	1565
Karabuk	182	236	259	278	311	314
Karaman	165	188	216	236	250	268
Kars	133	143	159	169	190	196
Kastamonu	268	308	339	355	376	415
Kayseri	1058	1199	1510	1594	1729	1918
Kilis	122	127	135	154	176	194
Kirikkale	201	244	257	283	296	333
Kirklareli	284	385	396	411	445	453
Kirsehir	160	187	212	232	254	280
Kocaeli	1563	2276	2346	2651	3020	3173
Konya	1838	2107	2205	2388	2634	3208
Kutahya	377	450	465	461	480	509
Malatya	485	520	560	619	731	953
Manisa	1207	1563	1684	1769	2000	2125
Mardin	572	647	740	834	901	1012
Mersin	2039	2152	2470	2766	3099	3420
Mugla	1505	1754	1839	1902	2090	2148
Mus	176	200	215	242	262	285
Nevsehir	211	246	276	287	311	356
Nigde	233	263	284	311	330	343
Ordu	596	706	835	1152	1236	1260
Osmaniye	365	434	448	515	611	699
Rize	260	268	290	336	357	366
Sakarya	867	1076	1351	1602	1674	1822
Samsun	1062	1585	1628	1722	1953	2034
Sanliurfa	1362	1555	1715	1804	2118	2347
Siirt	161	189	209	237	252	269
Sinop	169	188	207	224	254	272
Sirnak	246	290	355	463	505	592
Sivas	396	447	451	464	480	493
Tekirdag	947	1091	1227	1564	1854	1833
Tokat	360	433	474	507	561	587
Trabzon	655	830	1035	1314	1586	1542
Tunceli	55	77	80	93	97	126
Usak	270	302	313	346	371	396
Van	578	700	776	805	901	1023
Yalova	278	315	348	832	882	929
Yozgat	278	300	317	334	354	375
Zonguldak	442	518	543	552	594	610

Table A.3
Projected annual residential electricity demand (GWh) in Turkish provinces between 2025 and 2050 under SSP4 scenario.

Province	2025	2030	2035	2040	2045	2050
Adana	2209	2399	2645	2848	3432	3473
Adiyaman	350	395	423	496	553	663
Afyonk.	462	468	510	528	589	691
Agri	218	228	246	278	317	326
Aksaray	281	322	390	394	409	474
Amasya	230	255	277	303	318	339
Ankara	5595	5626	5628	6997	7178	7106
Antalya	3257	4599	4637	5039	5079	5217
Ardahan	52	54	58	63	71	77
Artvin	130	140	149	166	172	178
Aydin	1169	1514	1582	1811	1876	2046
Balikesir	1403	1436	1495	1571	1912	2050
Bartin	144	169	189	205	216	233
Batman	346	379	405	462	557	657
Bayburt	45	49	51	55	57	61
Bilecik	152	182	198	219	245	332
Bingol	159	193	213	249	274	286
Bitlis	177	198	214	252	272	304
Bolu	237	272	322	386	394	386
Burdur	201	226	246	261	277	295
Bursa	2607	3404	3726	3834	4324	4251
Canakkale	495	556	550	599	634	639
Cankiri	141	160	185	197	231	257
Corum	327	368	403	450	472	482
Denizli	958	1167	1519	1562	1766	1784
Diyarbakir	1134	1351	1510	1636	2000	2089
Duzce	263	308	392	397	412	428
Edirne	323	379	387	455	507	522
Elazig	388	462	493	511	527	626
Erzincan	155	174	195	220	232	248
Erzurum	433	475	492	513	560	587
Eskisehir	949	1136	1601	1623	1660	1749
Gaziantep	1616	1741	2072	2130	2188	3000
Giresun	343	434	415	446	484	503
Gumushane	81	98	109	119	123	126
Hakkari	128	144	161	185	204	219
Hatay	1258	1672	1862	2060	2247	2435
Igdir	96	110	119	134	141	161
Isparta	316	346	364	418	428	446
Istanbul	13120	14901	16527	18170	19891	21460
Izmir	4682	4608	5715	5699	5704	5820
K.maras	754	854	970	1128	1485	1573
Karabuk	182	234	254	279	309	308
Karaman	165	186	213	223	237	256
Kars	133	142	155	165	185	188
Kastamonu	268	307	338	350	418	412
Kayseri	1059	1193	1505	1588	1725	1913
Kilis	122	129	136	154	183	195
Kirikkale	200	242	257	282	291	328
Kirklareli	284	387	394	410	443	456
Kirsehir	160	185	211	233	245	269
Kocaeli	1560	2264	2338	2632	2972	3124
Konya	1838	2103	2189	2379	2832	3214
Kutahya	377	448	465	461	478	507
Malatya	485	511	514	592	694	855
Manisa	1207	1563	1665	1738	1961	2073
Mardin	572	643	734	821	888	1005
Mersin	2039	2153	2319	2612	3058	3343
Mugla	1508	1759	1842	1901	2087	2138
Mus	176	201	217	244	262	284
Nevsehir	211	245	273	283	310	353
Nigde	233	263	284	310	327	340
Ordu	582	697	806	1148	1182	1188
Osmaniye	365	433	451	518	611	696
Rize	260	270	290	334	356	372
Sakarya	904	1070	1350	1606	1675	1804
Samsun	1062	1583	1626	1712	1936	1995
Sanliurfa	1353	1530	1675	1773	2069	2283
Siirt	162	191	211	238	251	267
Sinop	169	189	202	218	240	254
Sirnak	246	294	363	462	483	549
Sivas	396	450	452	461	485	488
Tekirdag	946	1081	1228	1562	1854	1850
Tokat	360	433	458	473	500	512
Trabzon	654	763	1011	1285	1588	1547
Tunceli	55	76	83	94	98	128
Usak	270	301	316	341	366	438
Van	577	698	766	804	888	1019
Yalova	280	313	350	834	881	926
Yozgat	278	300	319	335	350	371
Zonguldak	442	517	542	551	589	589

Table A.4
Projected annual residential electricity demand (GWh) in Turkish provinces between 2025 and 2050 under SSP5 scenario.

Province	2025	2030	2035	2040	2045	2050
Adana	2209	2407	2673	3066	3482	3495
Adiyaman	353	398	490	507	554	674
Afyonk.	460	462	481	543	721	855
Agri	218	223	249	278	315	331
Aksaray	282	330	394	397	409	486
Amasya	230	258	279	306	372	391
Ankara	5595	5626	7023	6997	7231	7154
Antalya	3257	4599	4636	5037	5074	5234
Ardahan	52	54	67	71	76	81
Artvin	130	141	154	172	186	189
Aydin	1168	1564	1598	1836	1889	2075
Balikesir	1402	1444	1500	1567	1918	2060
Bartin	145	170	198	212	231	248
Batman	345	381	428	515	560	657
Bayburt	45	49	51	59	72	77
Bilecik	152	184	198	308	328	345
Bingol	159	192	212	256	281	304
Bitlis	177	198	218	259	275	307
Bolu	237	274	379	386	402	401
Burdur	202	226	246	262	341	369
Bursa	2609	3400	3489	3805	4355	4314
Canakkale	495	559	553	656	716	728
Cankiri	141	161	189	211	238	264
Corum	327	367	433	447	474	485
Denizli	959	1168	1528	1572	1778	1802
Diyarbakir	1134	1436	1514	1653	2018	2098
Duzce	263	321	397	402	418	440
Edirne	324	380	450	450	511	524
Elazig	391	504	489	517	533	643
Erzincan	155	177	201	226	236	334
Erzurum	435	466	478	511	570	690
Eskisehir	961	1144	1602	1631	1656	1751
Gaziantep	1615	1722	2073	2373	2424	3042
Giresun	343	435	425	443	551	562
Gumushane	81	101	112	123	128	135
Hakkari	127	149	167	198	212	225
Hatay	1258	1674	1859	2075	2247	2685
Igdir	96	112	120	136	148	169
Isparta	315	347	408	410	426	450
Istanbul	13411	15540	17671	19932	22257	24536
Izmir	4677	4609	5724	5808	7156	7403
K.maras	755	861	966	1133	1499	1588
Karabuk	182	240	264	283	316	313
Karaman	167	187	214	231	325	343
Kars	132	144	158	169	192	195
Kastamonu	268	309	341	409	424	414
Kayseri	1061	1200	1509	1589	1722	2105
Kilis	122	131	141	162	185	205
Kirikkale	199	242	259	292	360	398
Kirklareli	284	399	399	414	446	485
Kirsehir	160	191	222	239	250	276
Kocaeli	1560	2260	2339	2636	2979	3128
Konya	1838	2093	2271	2568	2859	3237
Kutahya	378	448	468	474	495	619
Malatya	485	504	512	572	732	934
Manisa	1207	1565	1679	1746	2215	2348
Mardin	571	640	728	817	896	1036
Mersin	2037	2184	2342	2790	3104	3104
Mugla	1515	1759	1848	1904	2102	2174
Mus	176	205	224	248	261	285
Nevsehir	211	247	274	288	360	410
Nigde	238	264	284	314	389	396
Ordu	581	697	783	1104	1139	1151
Osmaniye	365	436	498	519	616	715
Rize	259	274	292	342	365	435
Sakarya	906	1076	1355	1618	1678	1810
Samsun	1076	1586	1630	1720	1937	1994
Sanliurfa	1353	1584	1636	1727	1975	2129
Siirt	163	192	220	244	260	336
Sinop	169	196	209	224	248	267
Sirnak	246	293	420	462	492	570
Sivas	397	448	451	474	496	580
Tekirdag	946	1080	1229	1618	2117	2118
Tokat	360	435	456	474	491	505
Trabzon	653	741	1002	1283	1630	1584
Tunceli	56	79	84	101	106	142
Usak	270	302	316	400	413	442
Van	576	708	771	798	897	1063
Yalova	283	317	453	832	881	928
Yozgat	278	302	320	337	399	433
Zonguldak	457	517	543	554	596	694

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