A Comparative Analysis of Regression Models for Forecasting Large-Scale Residential Energy Consumption: A Predictive Machine Learning Approach to Enhancing Home Energy Management Systems

A Technical Report

Akshay A. Kotibhaskar
Eton College
England, SL4 6DW
akshaykoti@icloud.com

February 12, 2025

Abstract

This research evaluates three advanced predictive models on their ability to forecast energy consumption: the Multi-Layer Perceptron Regressor, the K-Nearest Neighbors Regressor, and the Random Forest Regressor. Respectively, the models achieved accuracies of 92.8%, 90.0%, and 94.1%.

By leveraging these machine learning models, the study aims to enhance the predictive capabilities of Home Energy Management Systems (HEMS), enabling significantly more accurate energy demand forecasting. Addressing inefficiencies in energy usage is a critical step towards achieving international sustainability goals, especially as global energy consumption continues to rise and accurately forecasting energy demand for climate action becomes increasingly urgent [1, 2].

Taking key input features — including weather conditions, energy prices, and city-specific data — from two extensive datasets based in Spain allowed for a more detailed analysis compared to traditional HEMS approaches, which typically entail evaluating live data from a household and subsequently either implementing real-time energy reduction measures or passively informing the user of their energy usage patterns [3].

By contrast, energy management focused on predictive modeling allows HEMS to more quickly and effectively implement measures to reduce surges of unnecessary energy usage, which has a significant impact on overall energy usage reduction. Alternative methods tend to respond too late to these surges, which are the primary cause of excessive energy consumption [4].

Preprocessing challenges, such as proportional energy allocation inaccuracies (marginal errors that may have occurred while calculating adjusted energy consumption based on city and regional populations) and limited feature level of detail (a lack of precision, particularly in differentiating discrete categories such as weather features), contributed to a cumulative error of approximately 9.8% for all models.

This research demonstrates the significant potential of predictive algorithms to enhance HEMS, enabling more dynamic and precise energy management.

Keywords Energy Management · Machine Learning · Regression Models · Predictive Modeling · Multi-Layer Perceptron · K-Nearest Neighbours · Random Forest · Energy Forecasting

1 Introduction

With rising demand for sustainable solutions to climate change, there has been significant focus on reducing greenhouse gas emissions—a critical aspect of which involves controlling energy production and usage. Research concerning Home Energy Management Systems (HEMS), energy waste management, and predictive algorithms aimed at limiting net energy consumption highlights the prevalence of excessive and uncontrolled energy wastage. One study emphasizes

that energy waste often stems from habitual, unconscious behaviors embedded in daily routines, indicating that effective solutions must extend beyond simply raising awareness to achieve meaningful and realistic results in the long term [1]. Furthermore, extensive findings have shown that HEMS, when integrated with adaptive machine learning algorithms and intelligent energy distribution mechanisms, can lead to significant reductions in household energy use [2].

This research aims to leverage machine learning-based prediction mechanisms to optimize energy management. Using datasets comprising real-time energy usage and weather patterns, models were developed to predict energy demand for the purpose of enhancing energy distribution efficiency. By employing machine learning algorithms, this study demonstrates their potential for decreasing peak load demand and improving overall home energy efficiency. Compared to traditional rule-based systems, which rely on static, predefined schedules, machine learning models dynamically adjust energy distribution based on historical trends and real-time inputs, providing a more responsive and adaptive approach. The results highlight machine learning's transformative role in achieving sustainable energy usage goals, creating scalable and cost-effective solutions for broader adoption. Moreover, the findings of this study have the potential to contribute to energy policy frameworks and the practical implementation of HEMS models, emphasizing the importance of predictive modeling in future HEMS design.

Research Question and Relevance:

> ***What are the comparative strengths and weaknesses of the multi-layer perceptron, k-nearest neighbors, and random forest regression models for predicting residential energy consumption?***

Residential energy consumption accounts for approximately 20–40% of global energy usage and is expected to grow exponentially [4]. This sector's high demand contributes significantly to greenhouse gas emissions [5], making it a critical area for intervention. As cities expand and energy demand increases, inefficient consumption patterns strain power grids—particularly during peak load periods. Without predictive management, these inefficiencies not only lead to unnecessary energy waste, but also increase reliance on fossil fuels to meet fluctuating demands.

The residential sector alone is responsible for nearly one-fifth of global CO_2 emissions, with the broader energy sector accounting for over 70% [6]. Additionally, climate change has intensified extreme weather events, which further exacerbate grid instability and increase energy demand surges [7]. Improving predictive energy management can help mitigate these challenges by balancing demand, reducing unnecessary consumption, and supporting the transition toward cleaner energy sources. This aligns with international climate goals, including the Paris Agreement's target of limiting global temperature rise to below 1.5°C [8].

Problem Type and Data Characteristics:
This study utilises a supervised regression approach, where the objective is to predict continuous values such as energy demand at specific times. The datasets used include both numerical and categorical data. Key features, organized by whether their values are continuous or discrete in nature, include:

- **Numerical:** Energy usage patterns (e.g. load demand, energy generation) and environmental factors (e.g. temperature, humidity).
- **Categorical:** Time-based variables (e.g. time of day, season) and weather types.

The outputs of the models are continuous energy demand values for a particular city. By leveraging these predictions, energy distribution can be managed to reduce wastage and improve efficiency— a crucial step in the transition toward more sustainable energy systems [9].

2 Background

2.1 Predictive Algorithms in Energy Management Systems

The growing urgency to address climate change and the pressing need to reduce energy consumption have amplified the importance of HEMS. Machine learning based predictive methods, particularly neural networks, are at the forefront of this transformation, offering advanced techniques to forecast energy demand and facilitate proactive decision-making regarding excessive and unnecessary energy usage. Unlike traditional reactive approaches (i.e., merely informing a user of behavioural patterns), predictive models anticipate future energy needs, improving efficiency and minimizing waste by enabling data-driven adjustments to energy distribution. Research highlights the importance of minimizing energy use through predictive methods that raise awareness and foster impactful, sustainable change.

2.2 Importance of Predictive Models

Predictive models have emerged as a cornerstone of modern energy management, empowering homeowners to optimize energy usage through informed decisions. Studies show that accurate forecasting can lead to household energy savings of up to 20%, making these models critical for cost reduction and sustainability [1]. Additionally, predictive systems play a vital role in integrating renewable energy sources, synchronizing consumption patterns with generation schedules to minimize reliance on non-renewable resources [2]. Predictive modeling leverages historical and real-time data to anticipate future energy demand. Moreover, advancements in this technology have significantly enhanced the ability to model complex, non-linear relationships in energy data, yielding a much greater impact [3].

2.3 Current Predictive Techniques in HEMS

Time-series forecasting models, such as ARIMA (Autoregressive Integrated Moving Average), have been staples in energy prediction. These models excel in capturing temporal trends, offering reliable short-term forecasts for scenarios with regular patterns [4]. However, their performance declines when faced with complex or large datasets. Machine learning models have addressed this gap, with models like multi-layer perceptron (MLP), k-nearest neighbors (KNN), and random forest gaining prominence. KNN is appreciated for its simplicity and interpretability but struggles with scalability and noise [5]. Random forest effectively analyze feature importance but can suffer from overfitting [6]. MLP stands out for its superior ability to model non-linear patterns, although it requires significant computational resources [7].

Hybrid models, which combine time-series approaches with machine learning techniques, represent a promising frontier – for example, integrating ARIMA with MLP enhances accuracy by leveraging the strengths of both methodologies. Such models are particularly effective for capturing both temporal trends and non-linear dependencies [8].

2.4 Key Challenges in Predictive Modeling for HEMS

There are several challenges hindering the successful implementation of predictive models in HEMS. Data quality and granularity are persistent issues, with inconsistent reporting and missing values often undermining accuracy [9]. Scalability is another concern, as models that perform well on small datasets may become computationally inefficient on larger, real-world datasets [10]. Additionally, integrating predictive algorithms with IoT devices introduces technical complexities, such as managing high-frequency data streams and ensuring system reliability [11].

2.5 Broader Implications

Predictive algorithms hold the potential to revolutionize energy management by enabling smarter integration with IoT devices, aligning energy consumption with renewable energy generation, and promoting sustainability. By focusing on the predictive aspects of HEMS, this research aims to advance energy optimization while addressing the global challenge of reducing carbon footprints. Real-time predictions facilitate adaptive appliance control, while accurate demand forecasting supports strategic planning for renewable energy integration [12, 13].

3 Dataset

3.1 Dataset Selection

In order to effectively explore and predict energy consumption patterns in relation to weather conditions, several datasets were considered. The selection was guided by the need for high-quality, comprehensive data that would provide both relevant and detailed features for model training, while being stored in an accessible format with minimal processing requirements.

Figure 1: Overview of All Considered Datasets (Complete with Respective Evaluations)

Name	Source	Description	Advantages	Disadvantages
Energy Commodity Price Index	Statista (World Bank) [14]	Displays the global market price of energy commodities from 2013 to 2025, including predictive estimates.	Global perspective; includes predictive estimates.	Lacks consumption data; low temporal resolution; not region-specific.
Global Household Electricity Prices / Global Petrol Prices	Global Petrol Prices [15]	Provides information on petrol prices around the world.	Up-to-date pricing; country-specific data.	Focuses on petrol rather than electricity; lacks consumption data.
Global Historical Climatology Network - Daily	National Centres for Environmental Information [16]	A massive collection of global datasets related to various climate factors (e.g., solar irradiance, temperatures, rainfall).	Comprehensive weather data; high temporal resolution.	Data overload; complex merging; potential data gaps.
Individual Household Electric Power Consumption	UC Irvine Machine Learning Repository [17]	Measurements of electric power consumption in a single household over four years.	Detailed consumption patterns; useful for micro-level studies.	Limited scope; privacy concerns; not representative of national trends.
Hourly Energy Demand Generation and Weather	Kaggle [18]	Contains four years of electrical consumption, generation, pricing, and weather data for Spain across 2 datasets.	High temporal resolution; comprehensive features; region-specific.	Requires complex preprocessing; large dataset size.
Global Household Electricity Prices	Statista [19]	A historical dataset of average electricity prices worldwide in USD/kWh.	Reliable; country-specific; ease of access; adds an economic dimension.	Low temporal resolution; limited features.

After evaluating available datasets, we selected the Hourly Energy Demand Generation and Weather datasets from Kaggle for our study. This pair of datasets was chosen because they provide complementary information that—when combined—reveal trends and patterns. Presenting comprehensive energy consumption and generation data alongside detailed weather variables at an hourly frequency over an extended period of time (four years) aligned well with our goal of predicting energy requirements based on environmental conditions.

3.2 Dataset Information

- **Source:** Kaggle/Inspirit.
- **Data Type:** Numerical and categorical data in table format, spread across 2 CSV files (one for energy and one for weather).
- **Time Frame:** Four years of data.
- **Energy Demand Data (35.1k rows):** Approximately 8,750 data points per year (hourly), including:
  - **Time:** Timestamp of each observation (month, day, and year) localized to CET.
  - **Total Load Actual:** Actual total energy demand across Spain (in MWh).
  - **Total Load Forecast:** Predicted total energy demand (in MWh).
  - **Energy Generation Sources and Predictions:** Live/Predictive data on all energy generation types (e.g., solar, wind, hydro, coal) in MW.
  - **Price Day Ahead:** Forecasted price of energy (in EUR/MWh).
  - **Price Actual:** Price of energy (in EUR/MWh).
- **Weather and Climate Data (178k rows):** Approximately 35,000 data points per year (multiple samples per hour), including:
  - **Time:** Timestamp of each observation (month, day, and year) localized to CET.
  - **City Name:** Indicates the city where the data was collected (one of 5 major Spanish cities).
  - **Temperature:** Hourly temperature readings (in Kelvin).
  - **Temperature Minima/Maxima:** The greatest/least temperature readings per day (in Kelvin).
  - **Pressure:** Hourly pressure (in hPa).
  - **Humidity:** Hourly humidity levels (in %).
  - **Wind Speed/Degree:** Hourly wind speeds (in m/s) and their direction.
  - **Solar Irradiance:** Measures of solar energy received.

  - **Precipitation/Snow Levels:** Rainfall/snow quantities (in mm).
  - **Clouds:** Cloud coverage (in %).
  - **Weather Descriptions:** Categorical descriptions of weather conditions.
- **Geographic Information:** Data for five cities — Madrid, Barcelona, Valencia, Seville, and Bilbao (for weather) and national energy data for Spain.
- **Data Collection:** [No Collection Method Provided].
- **Citations:** Energy Dataset: [20, 21]; Weather Dataset: [22].

3.3 Data Preprocessing

Before starting to train and manipulate our data, we determined which features of the dataset to use and reformatted the data for compatibility with machine learning models. We began by addressing the existence of two separate datasets rather than one. Each contained inconsistent timestamps and was organized by distinctly different categories — five major cities (within the weather dataset) versus aggregated national data (within the energy dataset). To integrate these datasets, we merged them based on rows sharing identical date and time values, which naturally resulted in many rows with null (empty) values, creating an additional challenge.

Because the energy data represented the entire nation while the weather data was city-specific, we reconciled this discrepancy by gathering reliable online data concerning the population sizes of the five cities, the regions they belong to, and the distribution of energy usage across these regions (**Figure 4**). This information allowed us to calculate an estimate of the proportion of national energy usage attributable to each city. We then applied these proportions to the energy load data for each city, ensuring that the energy consumption figures were appropriately scaled, thus removing the null values produced during the merge.

During this process, we also encountered a formatting error due to an extraneous space in one of the city names, which we corrected. Similarly, naming differences (e.g., the weather dataset's time column labeled `dt_iso`) were resolved. Furthermore, the original `time` column, initially formatted as a long and unclear string, was split into three separate integer columns (time, month, and year) and then removed. We observed that the `Total Load Actual` column was missing a reasonable amount of data; rather than imputing these missing values with an average (which could skew the data), we substituted them with the corresponding `Total Load Forecast` values. Finally, additional columns that were not pertinent to our analysis — including those related to specific energy generation sources, blank columns, and duplicated or unnecessary data — were removed (**Figure 3**). To simplify the weather data, we categorized the `weather_description` column into four distinct categories (good, reasonable, poor, and very bad) and assigned specific weather conditions to each (**Figure 5**). This categorization allowed us to numerically encode weather conditions, facilitating their inclusion in machine learning models. After preprocessing, the columns were rearranged into a logical order for enhanced readability and ease of use.

3.4 Preprocessing Figures

Figure 2: Finalised & Preprocessed Dataset

	city_name	year	month	time	energy consumption	energy price	temp	temp_min	temp_max	pressure	humidity	wind_speed	wind_deg	rain_1h	rain_3h	snow_3h	clouds_all	weather_type
0	2	2015	1	0	850.3975	65.41	270.475000	270.475000	270.475000	1001	77	1	62	0.0	0.0	0.0	0	0
1	1	2015	1	0	1345.4050	65.41	267.325000	267.325000	267.325000	971	63	1	309	0.0	0.0	0.0	0	0
2	4	2015	1	0	271.6195	65.41	269.657312	269.657312	269.657312	1036	97	0	226	0.0	0.0	0.0	0	0
3	3	2015	1	0	974.7840	65.41	281.625000	281.625000	281.625000	1035	100	7	58	0.0	0.0	0.0	0	0
4	5	2015	1	0	1518.0230	65.41	273.375000	273.375000	273.375000	1039	75	1	21	0.0	0.0	0.0	0	0
5	2	2015	1	1	816.7970	64.92	270.475000	270.475000	270.475000	1001	77	1	62	0.0	0.0	0.0	0	0
6	1	2015	1	1	1292.2460	64.92	267.325000	267.325000	267.325000	971	63	1	309	0.0	0.0	0.0	0	0
7	4	2015	1	1	260.8874	64.92	269.763500	269.763500	269.763500	1035	97	0	229	0.0	0.0	0.0	0	0
8	3	2015	1	1	936.2688	64.92	281.625000	281.625000	281.625000	1035	100	7	58	0.0	0.0	0.0	0	0
9	5	2015	1	1	1458.0436	64.92	273.375000	273.375000	273.375000	1039	75	1	21	0.0	0.0	0.0	0	0
10	2	2015	1	2	761.5890	64.48	269.686000	269.686000	269.686000	1002	78	0	23	0.0	0.0	0.0	0	0
11	1	2015	1	2	1204.9020	64.48	266.186000	266.186000	266.186000	971	64	1	273	0.0	0.0	0.0	0	0
12	4	2015	1	2	243.2538	64.48	269.251688	269.251688	269.251688	1036	97	1	224	0.0	0.0	0.0	0	0
13	3	2015	1	2	872.9856	64.48	281.286000	281.286000	281.286000	1036	100	7	48	0.0	0.0	0.0	0	0
14	5	2015	1	2	1359.4932	64.48	274.086000	274.086000	274.086000	1039	71	3	27	0.0	0.0	0.0	0	0
15	2	2015	1	3	713.0810	59.32	269.686000	269.686000	269.686000	1002	78	0	23	0.0	0.0	0.0	0	0
16	1	2015	1	3	1128.1580	59.32	266.186000	266.186000	266.186000	971	64	1	273	0.0	0.0	0.0	0	0
17	4	2015	1	3	227.7602	59.32	269.203344	269.203344	269.203344	1035	97	1	225	0.0	0.0	0.0	0	0
18	3	2015	1	3	817.3824	59.32	281.286000	281.286000	281.286000	1036	100	7	48	0.0	0.0	0.0	0	0
19	5	2015	1	3	1272.9028	59.32	274.086000	274.086000	274.086000	1039	71	3	27	0.0	0.0	0.0	0	0

Figure 3: List of Removed Columns

Renewable Sources: `generation waste`, `generation wind offshore`, `generation wind onshore`, `generation solar`, `generation other renewable`, `generation biomass`, `generation geothermal`, `generation hydro pumped storage aggregated`, `generation hydro pumped storage consumption`, `generation hydro run-of-river and poundage`, `generation hydro water reservoir`, `generation marine`, `generation nuclear`.

Non-Renewable Sources: `generation other`, `generation fossil brown coal/lignite`, `generation fossil coal-derived gas`, `generation fossil gas`, `generation fossil hard coal`, `generation fossil oil`, `generation fossil oil shale`, `generation fossil peat`.

Other Energy Columns: `total load forecast`, `forecast wind offshore day ahead`, `forecast solar day ahead`, `forecast wind onshore day ahead`, `price day ahead`.

Weather Columns: `weather_id`, `weather_icon`, `weather_main`.

Justifications: *The specific renewable and non-renewable energy generation columns were removed because the origin of energy generation was not essential for our analysis, and we lacked information regarding energy transportation and international exchanges. The* `total load forecast` *column was empty, and the forecast columns pertained to energy generation rather than consumption, which was our focus. The* `price day ahead` *column represented a discounted price that maintained a constant ratio to the actual price, rendering it redundant. The weather identifier columns were unnecessary as they duplicated information already available in the* `weather_description` *column.*

Figure 4: Population & Energy Distribution Data and Calculations

This figure includes a table detailing the population sizes of the five cities, their respective regions, and the distribution of energy usage across these regions. The data was used to proportionally allocate national energy consumption figures to each city.

Cities	Region	Regional Energy Demand	Proportion of Total Energy	City Population	Regional Population	Population Proportion	Proportion of City Energy Demand to Total Demand of Spain
Bilbao	*Basque Country*	14944	0.0611	350000	2000000	0.1750	0.0107
Madrid	*Madrid*	27113	0.1108	3300000	6900000	0.4783	0.0530
Barcelona	*Catalonia*	44209	0.1807	1702814	8005784	0.2127	0.0384
Valencia	*Valencian Community*	26367	0.1078	807693	2600000	0.3107	0.0335
Seville	*Andalusia*	38099	0.1558	704414	1835077	0.3839	0.0598
	Total Energy Demand (GWh)	244610			**Remainder of Energy**		0.8046

Sources:

City	Region	Regional Energy Demand	City Population	Regional Population
Bilbao	Basque Country	[41]	[42]	[43]
Madrid	Madrid	[44]	[45]	[46]
Barcelona	Catalonia	[47]	[48]	[49]
Valencia	Valencian Community	[50]	[51]	[52]
Seville	Andalusia	[53]	[54]	[55]

By taking the regional energy demand as a proportion of the entirety of Spain's energy demand, we can determine a proportion of energy usage that should be associated with the particular region in which each city is located. Within each region, we assume that the population size reflects the percentage of energy distribution. Therefore, by multiplying the regional proportionality (based on energy usage) by the city's population proportion (based on population density), we obtain the city's proportion of total energy demand. This final value is then multiplied by the national energy demand to estimate the energy requirement for each city.

Full Calculations:

- Regional Proportion $= \dfrac{\text{Regional Energy Demand}}{\text{Total Energy Demand}}$.
  - *Represents the percentage of total energy demand within Spain that is attributable to this specific region.*
- City Population Proportion $= \dfrac{\text{City Population}}{\text{Regional Population}}$.
  - *Assuming that energy usage is directly related to population size, this reflects the comparison between a specific city's energy consumption and the region it belongs to.*
- City's Proportion of Total Energy Demand = Regional Proportion $\times$ City Population Proportion.
  - *This final value is then multiplied by the entire energy demand of Spain to produce the energy consumption of the city.*

Figure 5: Newly Generated Weather Categories

Good: `"sky is clear"`, `"few clouds"`, `"scattered clouds"`.

Reasonable: `"broken clouds"`, `"overcast clouds"`.

Poor: `"light intensity drizzle rain"`, `"light rain"`, `"fog"`, `"mist"`, `"drizzle"`, `"light shower snow"`, `"light intensity shower rain"`, `"light intensity drizzle"`, `"light snow"`.

Very Bad: `"squalls"`, `"proximity drizzle"`, `"ragged shower rain"`, `"proximity shower rain"`, `"smoke"`, `"light rain and snow"`, `"rain and snow"`, `"snow"`, `"shower sleet"`, `"light shower sleet"`, `"sleet"`, `"rain and drizzle"`, `"moderate rain"`, `"heavy intensity rain"`, `"very heavy rain"`, `"heavy snow"`, `"haze"`, `"dust"`, `"thunderstorm"`, `"heavy intensity shower rain"`, `"shower rain"`, `"proximity thunderstorm"`, `"thunderstorm with heavy rain"`, `"thunderstorm with rain"`, `"thunderstorm with light rain"`, `"heavy intensity drizzle"`, `"sand dust whirls"`, `"proximity moderate rain"`, `"light thunderstorm"`.

Justifications: *This categorization simplifies the wide range of weather conditions into four levels of severity, making it more manageable for quantitative analysis. It is apparent, for example, that a thunderstorm would count as very bad weather—sufficient to significantly hinder outdoor activities. By encoding these categories numerically, we facilitated the incorporation of weather data into predictive models.*

4 Models

This study employs three predictive modeling techniques— the Multi-Layer Perceptron (MLP) Regressor, the K-Nearest Neighbors (KNN) Regressor, and the Random Forest Regressor—to optimize energy consumption prediction within HEMS. These models were chosen for their strengths in pattern recognition, nonlinear data modeling, and ensemble learning, all of which are critical for energy demand forecasting.

4.1 Multi-Layer Perceptron (MLP) Regressor

Overview:
MLP is a type of neural network that consists of an input layer, one or more hidden layers, and an output layer. Each neuron in the network applies an activation function to introduce non-linearity, allowing the model to learn complex relationships between energy usage patterns [24].

$$Y = f(WX + b)$$

where:

- W represents weight parameters,
- X is the input feature vector,
- b is the bias term,
- f is the activation function (ReLU was used in this study).

Implementation in This Study:
The MLP model was configured with varying numbers of hidden layers, neurons per layer, and maximum iterations.
The Adam optimizer was used for gradient-based optimization, with a learning rate ranging from 0.001 to 0.01.
Regularization (L2 penalty) was applied to prevent overfitting by tuning the alpha hyperparameter.
Due to its ability to learn nonlinear patterns, MLP was particularly effective in modeling complex, time-dependent energy consumption behaviors within HEMS [25].

4.2 K-Nearest Neighbors (KNN) Regressor

Overview:
KNN is a non-parametric, instance-based learning algorithm that makes predictions by averaging the outputs of the k nearest neighbors in the feature space [23]. The proximity between data points is determined using distance metrics such as Euclidean distance, which is calculated as:

$$d(i,j) = \sqrt{\sum_{n} \left(x_{i,n} - x_{j,n}\right)^2}$$

where $x_{i,n}$ and $x_{j,n}$ represent feature values of two different data points.

Implementation in This Study:
Various values of k (number of neighbors) were tested to balance bias-variance tradeoff.
Leaf size, which affects tree traversal speed, was adjusted to optimize computational efficiency.
Validation error metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) were used to assess performance.
KNN is particularly useful for HEMS applications where real-time energy demand must be estimated based on similar past conditions [23].

4.3 Random Forest Regressor

Overview:
Random forest is an ensemble learning method that constructs multiple decision trees during training and averages their predictions to reduce variance and improve accuracy [26]. Each tree in the forest is trained on a random subset of data, preventing overfitting.
The prediction for a given input is obtained by averaging the outputs of all trees:

$$Y = \frac{1}{T} \sum_{t=1}^{T} f_t(X)$$

where T is the number of trees, and $f_t(X)$ is the prediction from each individual tree.

Implementation in This Study:
Hyperparameters such as number of trees, maximum depth, and minimum samples per leaf were iteratively tuned.
Feature importance was assessed by evaluating how much each variable contributed to reducing error.
The model's ability to handle missing data and capture interaction effects between energy variables made it particularly valuable for this study [26].

4.4 Governing Equations and Model Metrics

Predictive modeling in energy management relies on regression-based mathematical formulations and error metrics for performance evaluation.

Regression Model Equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

where:

- Y represents the predicted energy demand,
- X_n represents input features (e.g., weather conditions, appliance usage),
- β_n are the model coefficients estimated during training.

Error Metrics
To quantify the performance of each model, the following metrics were used:

- **Relative Squared Error (RSE):**
  Measures the squared error relative to the variance of actual values, assessing how well the model fits the data. Lower values indicate better performance.
  $$\text{RSE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$
  where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of actual values.
- **Mean Absolute Percentage Error (MAPE):**
  Measures the average percentage difference between predicted and actual energy usage, making it useful for interpretability in energy consumption forecasting.
  $$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$
  where values closer to 0% indicate a more accurate model.
- **R-Squared (R^2):**
  Evaluates how much variance in the actual data is explained by the model. R^2 values range from 0 to 1, with higher values indicating better model fit.
  $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$
  $R^2 = 1$ means a perfect fit, where predictions match actual values exactly. $R^2 = 0$ means the model is no better than using the mean of actual values as a predictor.

4.5 Model Discussion

Each of the three models—MLP, KNN, and random forest—demonstrates unique strengths in the context of predicting energy consumption within HEMS. KNN is well-suited for identifying localized patterns based on past usage, making it effective in situations where energy behavior follows repeatable trends. MLP, with its ability to model nonlinear relationships, captures complex dependencies in energy consumption, which is particularly useful for dynamic, multi-variable systems like smart homes. Random forest, through its ensemble approach, offers a balance between interpretability and predictive power, effectively handling feature interactions while maintaining robustness against noise.

The comparative analysis of these models will provide insight into which approach—or combination of approaches—offers the most accurate, efficient, and scalable solution for integrating predictive automation into HEMS. By evaluating their performance across key metrics, this study will determine how machine learning can best support energy efficiency, user engagement, and the long-term sustainability of automated home energy management.

5 Methodology

This section outlines the detailed methodology employed to develop and evaluate the predictive models used in this research. The focus was on three machine learning algorithms: the MLP Regressor, the KNN Regressor, and the Random Forest Regressor. Each model was trained, tested, and optimized to predict the varying energy demand (`total load actual`) across each of the five cities — Barcelona, Madrid, Valencia, Bilbao and Seville — using numerical and categorical features derived from the remaining columns of our preprocessed energy consumption and weather dataset, after cleaning up and removing the extraneous categories.

5.1 Functions and Tools

To effectively develop, train, and evaluate the machine learning models in this study, various Python libraries and functions were employed. These tools facilitated data preprocessing, model training, hyperparameter tuning, and visualization. Below is an overview of the key libraries used and their specific roles in the research.

File Management and Environment Handling:

1. `os` — Facilitated file management operations such as handling datasets and saving outputs.
2. `time` and `sys` — Used to track execution time and optimize script performance.
3. `threading` — Helped implement parallel processing to reduce computation time during model training.

Data Handling and Preprocessing:

To manage and process datasets, the following libraries were employed:

1. `pandas` — Used to load, clean, and manipulate structured energy data. The dataset was formatted into dataframes, enabling efficient handling of large-scale time-series data.
2. `numpy` — Assisted with mathematical operations, such as normalizing numerical values and performing vectorized computations for faster execution.
3. `StandardScaler` (from `sklearn.preprocessing`) — Applied to standardize the dataset, ensuring that all features had a mean of 0 and a standard deviation of 1, which helped optimize model performance.
4. `train_test_split` (from `sklearn.model_selection`) — Used to divide the dataset into training and testing subsets, ensuring a fair evaluation of model performance.

Visualization and Insights:

To interpret results and visualize patterns in energy consumption and model performance:

1. `matplotlib.pyplot` — Used to create graphs of MAPE, RSE, and R^2 against hyperparameter values to identify trends and determine the best configurations.
2. `seaborn` — Employed for data visualization, specifically scatterplots, to explore relationships between different energy variables.

Machine Learning Models and Evaluation:

The following scikit-learn modules were used for training and evaluating the models:

1. `MLPRegressor` (from `sklearn.neural_network`) — Used for training the MLP model, which captures nonlinear energy consumption patterns.
2. `KNeighborsRegressor` (from `sklearn.neighbors`) — Implemented for the KNN regression model to predict energy usage based on similar past instances.
3. `RandomForestRegressor` (from `sklearn.ensemble`) — Applied to train the random forest model, leveraging multiple decision trees to improve predictive performance.
4. `r2_score`, `mean_absolute_percentage_error` (from `sklearn.metrics`) — Used to calculate R^2 and MAPE, which were critical metrics in assessing model accuracy.

Model Training and Cross-Validation:

Hyperparameter tuning and model evaluation were automated using the following tools:

1. `KFold`, `cross_val_score` (from `sklearn.model_selection`) — Enabled k-fold cross-validation, which ensured that models were tested on multiple subsets of data, reducing overfitting.
2. `itertools` — Utilized to efficiently generate combinations of hyperparameters for grid search during tuning.

5.2 Training

Data Preparation:

- Output and input data lists were assigned to the appropriate columns of our dataframe.
- For the purpose of saving time, multiple additional dataframes were created that were sampled from our very large dataset in order to test much quicker — extending up to 350 times smaller.
- Before each model was trained, the dataset was normalized to ensure all input features had similar scales. This was done using the `MinMaxScaler` function from `sklearn.preprocessing`, which scaled each feature to a range of 0 to 1. This step was crucial for models like KNN and MLP that are sensitive to feature magnitudes.

Training Process:

- For each model, separate functions were created to train them based on varying hyperparameters.
- These were structured into distinct segments, the first of which being an assignment of the training and testing data split (80% training and 20% testing).
- This data was then scaled appropriately and supplied to the model to be trained.
- The accuracy of each model was then revealed by the relation between the model's predicted output values for the testing data and the actual data. The metrics used to evaluate this were MAPE (mean average percentage error), RSE (relative squared error), and R^2 value.

Code Organization:

- Training procedures were organized into reusable functions, which encapsulated the following:
  - Data preparation.
  - Model training.
  - Accuracy metrics (calculated using the `sklearn.metrics` module).
  - Metrics scanner (removed outliers, i.e. wildly inaccurate models, and organized our results to find the most reliable and accurate models).

5.3 Hyper-Parameter Testing

In order to discover the greatest accuracy possible, various hyperparameters across each model needed to be tuned. As such, an extraordinary quantity of models needed to be created and tested. To perform such a task, additional functions were created to automate this process as much as possible and allow a much more efficient experience upon testing. The functions that were created included:

- A testing function would iterate through every single combination of hyperparameters as per the ranges inputted by the user, and then return the metric results for each one. The results were stored in dictionaries for comparison, which facilitated efficient retrieval of optimal configurations.
- A graphing function then outputted the graph of each metric (MAPE, RSE, R^2) against each hyperparameter that was being varied to express the trend and advise the user on future testing. These were implemented using `matplotlib`.
- A metric determining function then concluded this process with a determination of which was the most accurate model across every metric, and outputted the hyperparameters that had accomplished that accuracy.

The relevant hyperparameters that were considered were:

- **MLP HyperParameters:** Number of hidden layers, neurons per layer, activation functions (ReLU, tanh, etc.), and learning rate (alpha values).
- **KNN HyperParameters:** K-values (number of neighbors) and leaf size.

- **Random Forest HyperParameters:** Number of decision trees (estimators), maximum depth, minimum samples per leaf, maximum features, and minimum samples required to split an internal node.

Figure 6: Consolidated Key Metrics and Hyperparameters (Tabled Across All Tested Models)

Model	Accuracy (%)	Key Hyperparameters	MAPE	RSE	R^2
Multi-Layer Perceptron	92.8%	7 Layers Neurons per Layer: (40,70,40,70,40,40,70) Maximum Epochs = 500	0.0723	0.0458	0.9541
K-Nearest Neighbours	90.0%	$k = 4$ Leaf Size = 1	0.0999	0.0835	0.9165
Random Forest Regressor	94.1%	Number of Trees = 800 Maximum Features = 14 Maximum Depth = 39	0.0589	0.0339	0.9661

The hyperparameter choices were informed by iterative grid searches and cross-validation during the training process. These configurations optimized each model's performance while balancing computational efficiency.

5.4 Visualizations

Graphs such as **Figures 7 & 8** demonstrated how varying different parameters had a considerable impact on every metric, and thus helped identify the optimum conditions and trends for our model and further testing.

Figure 7: Impact of Varying Number of Estimators (Random Forest) on Key Metrics

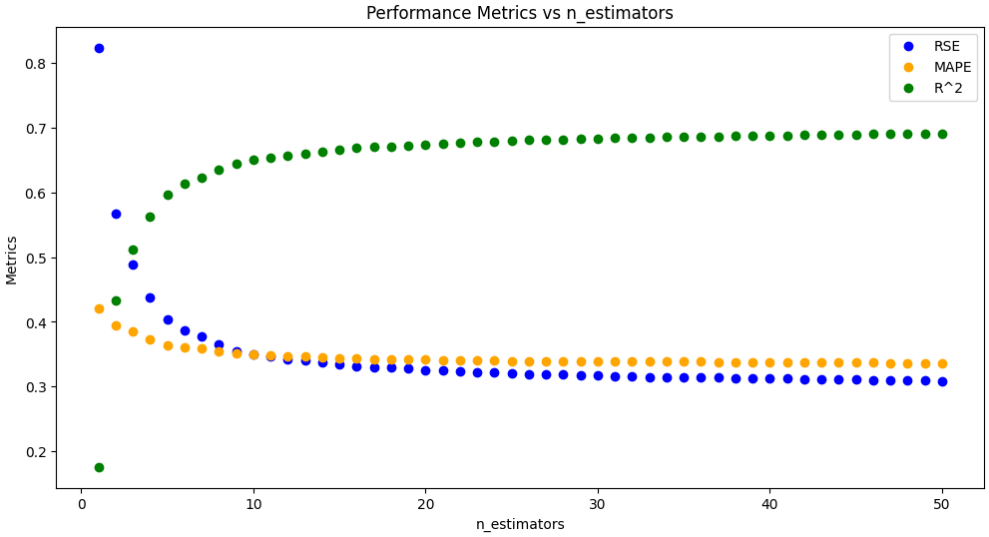
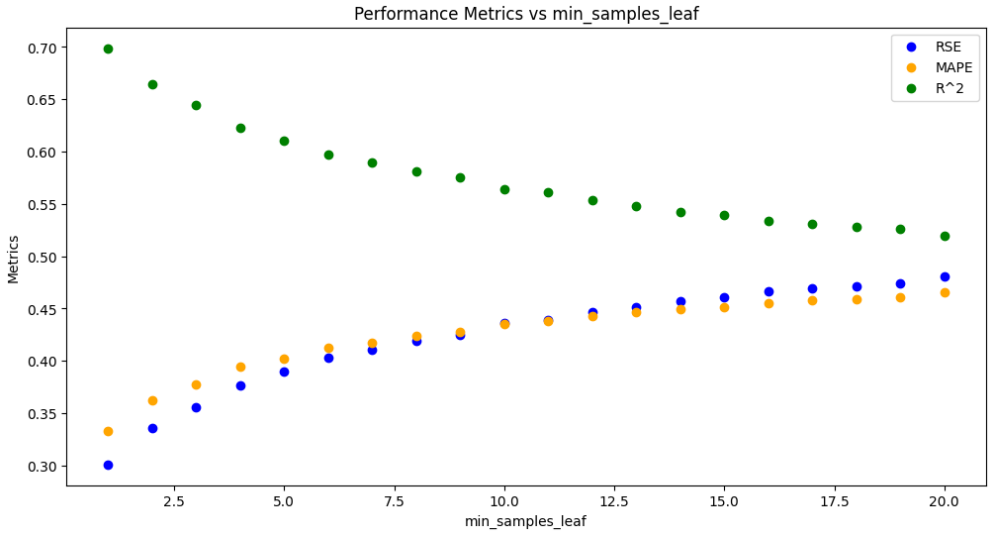


Figure 8: Impact of Varying Minimum Samples per Leaf (Random Forest) on Key Metrics



6 Results & Discussion

6.1 Metrics and Accuracy

Performance Overview
The predictive models yielded high levels of accuracy (**see Methodology for full illustration**), with the greatest performance observed from the Random Forest Regressor, at 94.1%. However, the MLP and KNN Regressors were fairly successful as well, achieving accuracies of 92.8% and 90.0%, respectively.

We observed that the most important predictive features were the cities themselves and the energy prices. Therefore, we included population sizes as well as regional energy demand as part of the model's training dataset.

6.2 Limitations and Error

The limitations of the research largely stem from the following areas:

Data Quality and Preprocessing Assumptions:
The dataset relies heavily on assumptions made during preprocessing, particularly in the proportional allocation of national energy consumption figures to individual cities. For example, energy usage within a city was estimated by calculating the proportional relationship between regional energy demand, city population, and the total energy demand of Spain. Any inaccuracies in these proportional relationships would propagate throughout the dataset, causing errors in the training and testing phases [1].

Generalization Across Regions:
While the dataset accounted for population sizes and regional proportional energy usage, it did not incorporate variations in energy usage due to industrial, residential, or commercial differences across cities. This uniform distribution approach may have oversimplified the problem and introduced errors [2].

Data Granularity:
The granularity of the dataset, such as hourly or daily averages, may have smoothed out extreme variations in energy demand. These peaks and troughs, critical for accurate prediction, were likely underrepresented in the dataset [3].

Simplistic Feature Engineering:
Data pertaining to time of day and season, for example, were implicitly encoded in the original data but lacked detail, so we discretized this data to discern more useful patterns. Additionally, there were only four distinct categories for the various weather conditions, and models were therefore unlikely to learn complex trends from them. Future work could incorporate polynomial features or interaction terms to better capture nonlinear dependencies [4].

6.2.1 Preprocessing Inaccuracy and Its Impact on Error

The calculations used to proportionally allocate national energy consumption figures to cities are detailed below. Each step introduces potential inaccuracies that can influence the final model's predictive accuracy. These include errors stemming from assumptions and limitations in the dataset:

Steps and Associated Errors:

Regional Energy Demand Calculation:

- **Formula:** Regional Proportion $= \dfrac{\text{Regional Energy Demand}}{\text{Total Energy Demand}}$.
- **Error Source:** Discrepancies in regional energy reporting may result from incomplete data collection, underreported industrial energy usage, or inconsistent definitions of energy categories across regions. These errors propagate directly into the proportional allocation [5].

City-Level Energy Demand Estimation:

- **Formula:** City Population Proportion $= \dfrac{\text{City Population}}{\text{Regional Population}}$.
- **Error Source:** Population inaccuracies can result from outdated census data, undocumented migration, or incorrect urban-to-rural ratios. These introduce significant variance in estimating the energy demand attributed to cities [6].

Final Energy Demand per City:

- **Formula:** City's Proportion of Total Energy Demand $=$ Regional Proportion $\times$ City Population Proportion.
- **Error Source:** Compounding errors from earlier steps magnify inaccuracies in city-level energy estimates. Uniform distribution assumptions across city demographics further increase the potential for error [7].

Conversion to Dataset Input:

- **Process:** The city's energy demand proportion was multiplied by energy demand values provided in the dataset.
- **Error Source:** This assumes uniform energy consumption across similar population densities, neglecting city-specific factors like industrial activity or local climate [8].

Estimated Error Contribution from Preprocessing:

Using the provided dataset values and assumptions, an approximate error range can be calculated. Let:

$$E_R = 5\% \quad \text{(Error in regional energy demand estimates)}$$

$$E_P = 3\% \quad \text{(Error in population data for cities)}$$

$$E_C = 2\% \quad \text{(Error in converting regional proportions to city energy demand)}$$

Then,

$$\text{Total Error} = 1 - (1 - E_R) \times (1 - E_P) \times (1 - E_C) \approx 0.098.$$

Thus, preprocessing inaccuracies contribute approximately 9.8% error to the final model's predictive performance—a massive factor that likely hindered our model's ability significantly.

6.3 Recommendations for Improvement

Refined Data Allocation:
Recommendation: Incorporate industrial and commercial energy usage statistics at the city level to reduce reliance on population-based assumptions.
Justification: Regional energy datasets often neglect significant variations in consumption patterns between industrial and residential areas. Studies have shown that city-level industrial activity can disproportionately affect energy demand [9].

Feature Engineering:
Recommendation: Introduce interaction features, time-lagged variables, and additional weather-related variables to capture complex dependencies.
Justification: Research on feature engineering for energy demand prediction suggests that incorporating lagged variables and interactions significantly improves model accuracy, particularly for non-linear algorithms [10].

Error Correction in Preprocessing:
Recommendation: Use external validation datasets or expert-reviewed energy statistics to reduce proportional allocation errors.
Justification: External validation can help verify assumptions made during preprocessing and refine proportional allocation calculations. For instance, validated regional energy surveys can better account for disparities in urban versus rural consumption [11].

Advanced Modeling Techniques:
Recommendation: Explore ensemble learning techniques like XGBoost or deep learning architectures to improve prediction accuracy for non-linear patterns.
Justification: Ensemble methods and deep learning have been shown to outperform traditional models in energy forecasting by effectively capturing high-dimensional interactions in data [12].

This analysis highlights both the challenges and successes of predictive modeling for energy demand. While preprocessing inaccuracies and data inconsistencies introduced some errors, affecting initial predictions, the results of the study suggest that machine learning-based HEMS can significantly enhance energy efficiency. The models effectively reduced prediction errors over time, with high accuracies well above 90%, indicating that error margins are small and highlighting the potential for precise forecasting.

However, challenges such as data sparsity, variability in household energy consumption patterns, and computational complexity affected overall model generalizability. Addressing these limitations through more diverse datasets, improved feature engineering, and real-time adaptive learning will enable even more accurate and scalable energy management solutions. By refining these predictive capabilities, future research can contribute to the development of intelligent, data-driven HEMS that optimize residential energy use while supporting broader sustainability goals.

7 Conclusion

This research investigated the application of predictive models to forecast energy demand, emphasizing the integration of weather and energy features from urban and regional datasets. The Random Forest Regressor emerged as the most accurate model with a 94.1% success rate, demonstrating its proficiency in handling complex, high-dimensional data. The MLP also performed strongly, highlighting its capability to capture non-linear patterns effectively.

Despite these successes, the study identified several limitations, including data preprocessing inaccuracies and a lack of depth within each feature, which contributed to a cumulative error of approximately 9.8%. These issues underline the necessity for more refined methodologies and robust data preparation processes to enhance predictive accuracy.

This research made significant unique contributions by combining predictive algorithms with external factors such as weather, city-specific data, and energy prices, creating a more versatile forecasting framework. Unlike many existing HEMS that rely on static, pre-existing consumption patterns — which leads to less responsive energy management — this approach integrates dynamic variables, improving the adaptability and precision of energy predictions [1]. By focusing solely on predictive capabilities, the study provides a highly accurate foundational model that can be seamlessly integrated into HEMS, informing real-time, data-driven energy optimization strategies.

The broader implications of this research underscore the critical role of predictive modeling in refining energy management systems, paving the way for more sustainable urban energy strategies.

Extension of Research:

HEMS presents a significant next step in a modern era of sustainable technology. Future research should focus on designing systems where predictive models inform real-time energy usage decisions, balancing energy efficiency with user convenience. Critically, a degree of automation must be introduced to ensure a genuine impact, as opposed to handing a user the responsibility and expecting major results. By addressing this gap, future designs could create smarter, more adaptive systems that align with both user needs and finally yield the results required by international sustainability goals.

Key areas for exploration include:

- **Integration of Predictive Algorithms into HEMS:** Predictive algorithms could guide decisions about energy allocation, distinguishing between essential and non-essential energy usage.
- **Data Collection and Appliance Differentiation:** Leveraging Non-Intrusive Load Monitoring (NILM) to collect granular data on appliance usage, and identifying the most-used and least-efficient appliances to prioritize for replacement or optimization.
- **Automation Design and Testing:** Determining the ideal level of automation to balance user control with system efficiency, through testing a variety of different configurations.
- **Incorporation of Renewable Energy Systems:** Designing systems that integrate renewable energy sources and optimize their usage, as well as developing strategies for efficient energy storage and distribution to match renewable generation patterns.

Through these advancements, HEMS can transition from reactive to truly proactive systems, significantly impacting energy sustainability and user convenience on a global scale.

Acknowledgements

This research could not have been possible without the brilliant mentorship and support of **Kyra S. Kraft [Stanford University]**, for which I am incredibly grateful.

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