

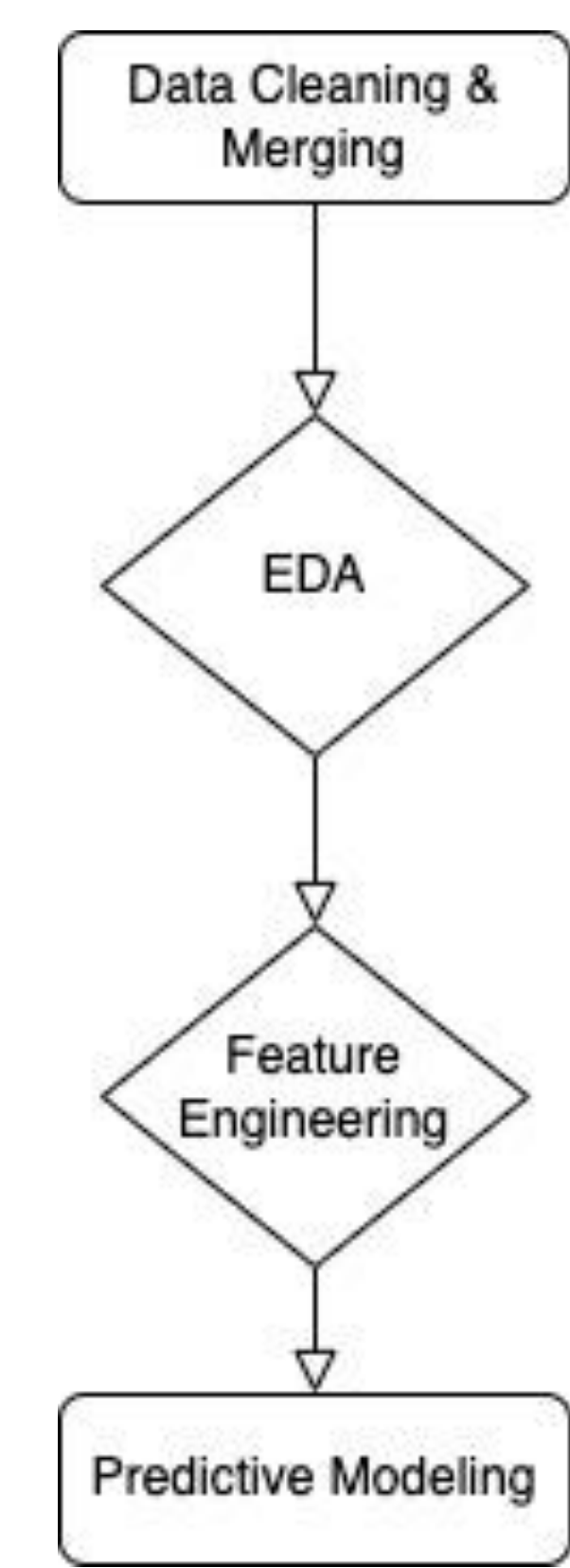
## INTRODUCTION

Energy consumption has become a critical concern for both homeowners and business owners, prices have constantly been increasing, and the weather has been drastically changing over the past decades. There have been significant increases in electricity rates across the United States; Georgia Power raised rates by 3.5%, PSE&G in New Jersey by 17.24%, and Con Edison in New York proposed an 11.4% increase. This project explores how machine learning can be used to optimize energy usage in the U.S. using historical data. It combines sector-specific electricity prices, electricity generation data, weather conditions to understand the main drivers of energy consumption and prices to build predictive models to identify key trends. Through exploratory data analysis and predictive modeling, the research identifies natural gas, coal, nuclear, wind, and cooling degree days as the most significant factors.

## DATASETS

- This study used three datasets from 2001-2023:
- Weather data: Average temperature indicators, including cooling degree days (CDD), heating degree days(HDD), precipitation, humidity, direct normal irradiance(DNI), global horizontal irradiance (GHI), from the International Energy Agency(IEA)
  - Energy Cost: Includes electricity prices for residential, commercial and industrial sectors from the U.S Energy Information Administration
  - Energy Generation: Includes electricity production by source from the U.S Energy Information Administration (EIA).

## METHODS



The analysis followed a step-by-step guideline, beginning with data cleaning followed by exploratory analysis, feature selection, and model training using various regressors.

To evaluate the model’s performance, four metrics were used: Mean Absolute Error ( $MAE=1/n(\sum|y_i-\hat{y}_i|)$ ), Mean Squared Error ( $MSE=1/n(1/n(\sum|y_i-\hat{y}_i|^2))$ ), Root Mean Squared Error ( $RMSE=\sqrt{MSE}$ ) and lastly, R-Squared ( $R^2= 1-[\sum(y_i-\hat{y}_i)^2/\sum(y_i-\hat{y}_i)^2]$ ).

Figure 1: Energy Generation Trends

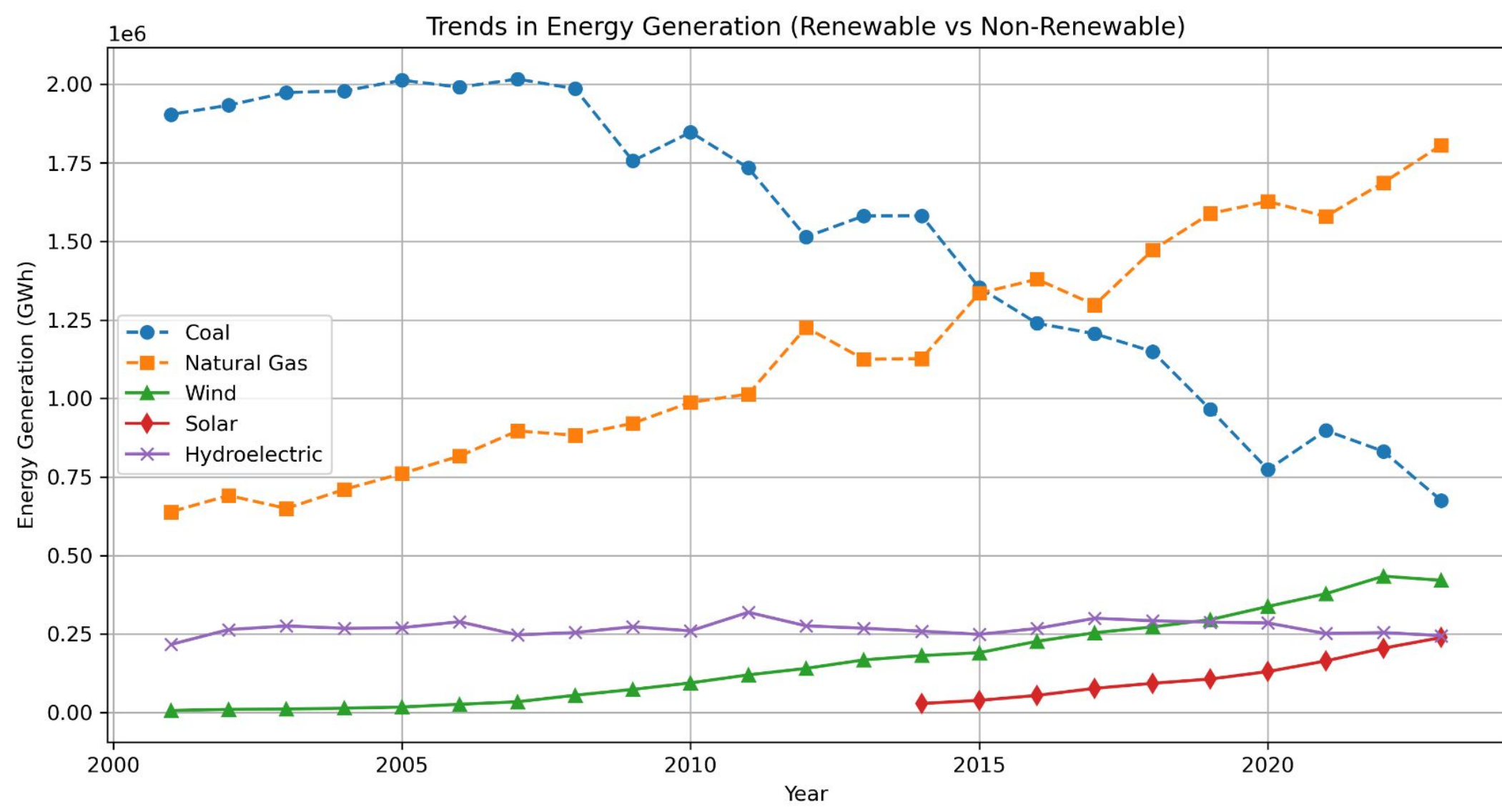


Figure 3: Random Forest Prediction Visualization

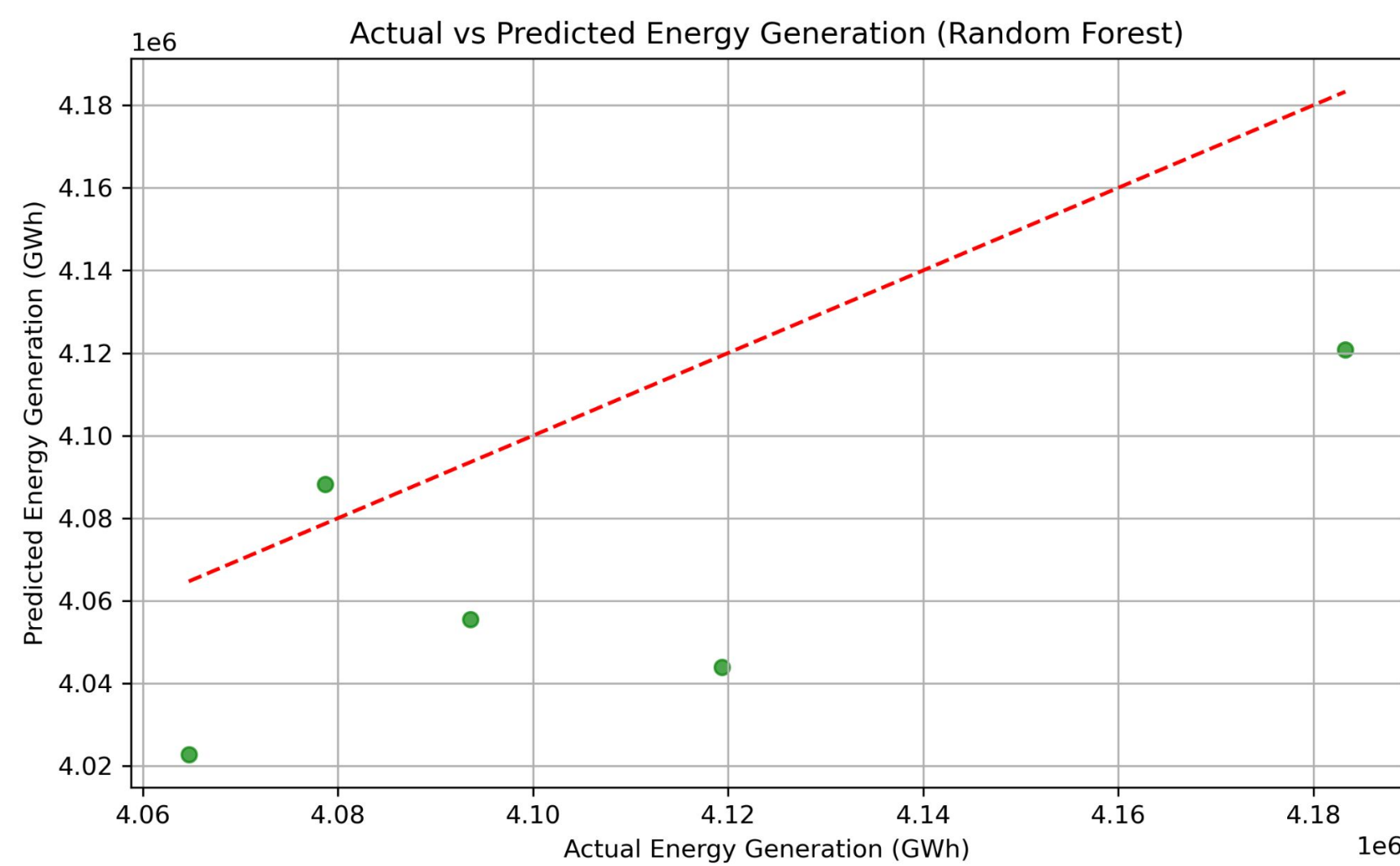


Figure 5 :Price Correlation Across Sectors

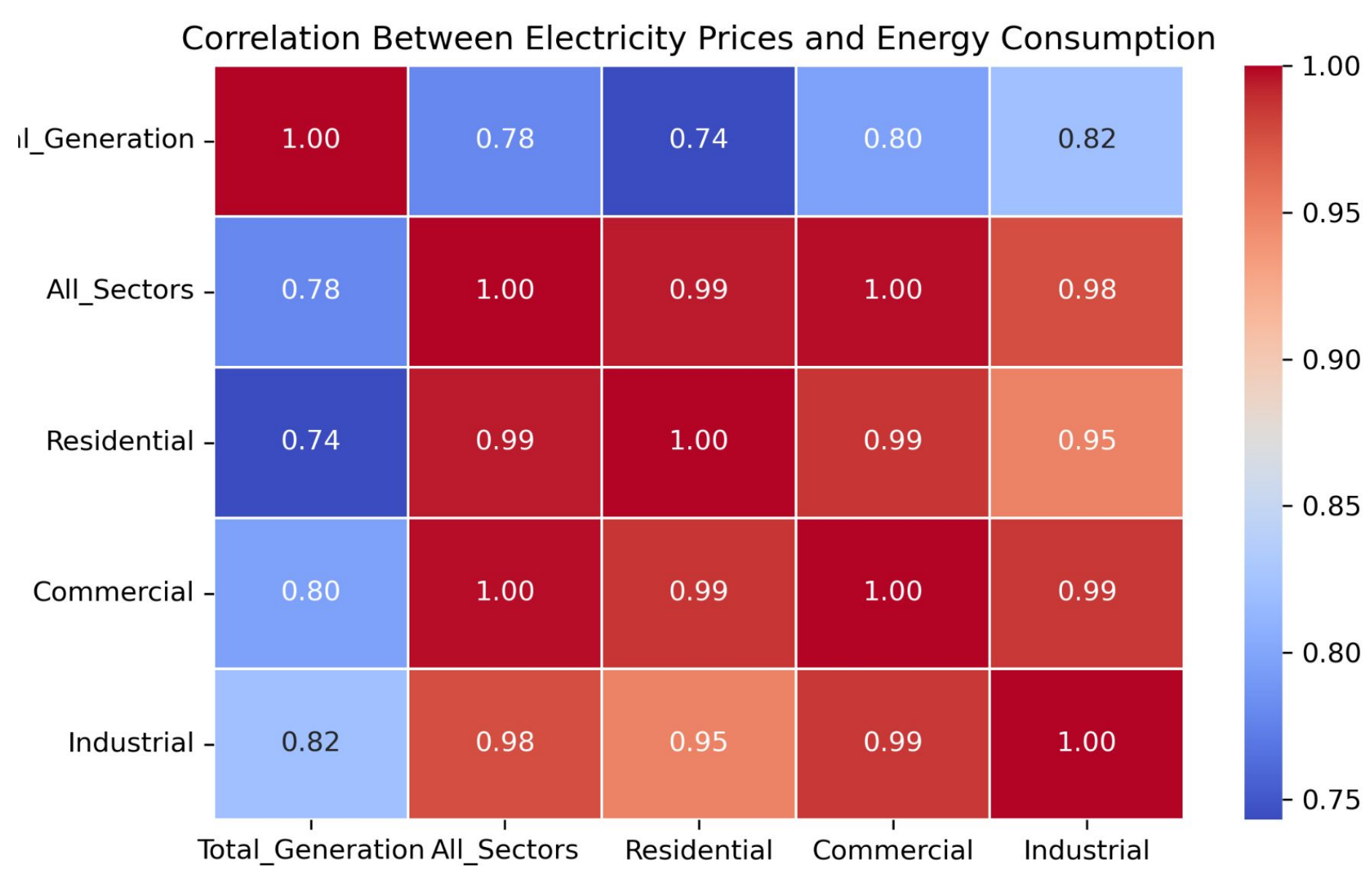


Figure 7a: Weather vs. energy

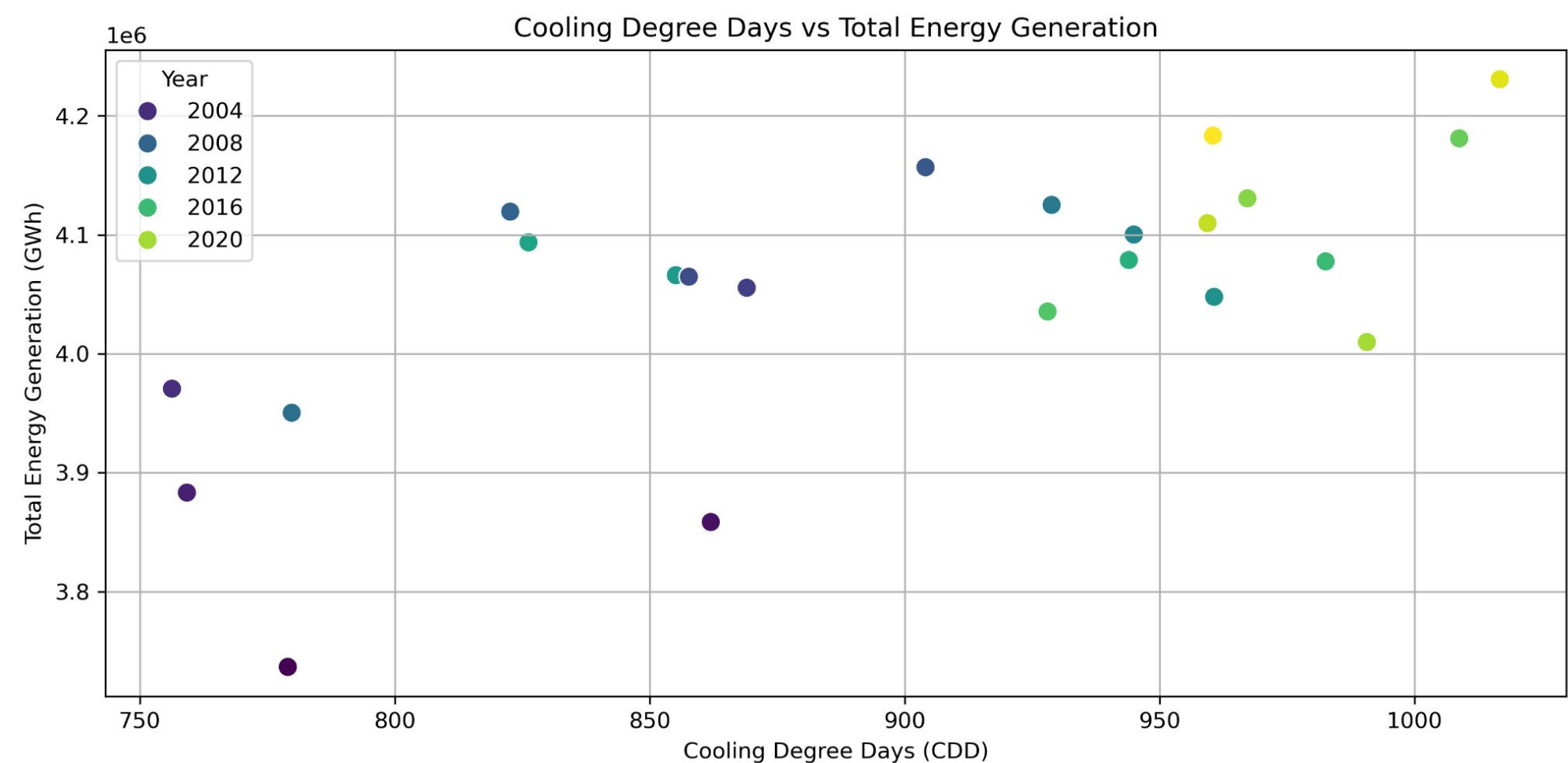


Figure 2: Electricity Prices Have Increased Steadily Over Time

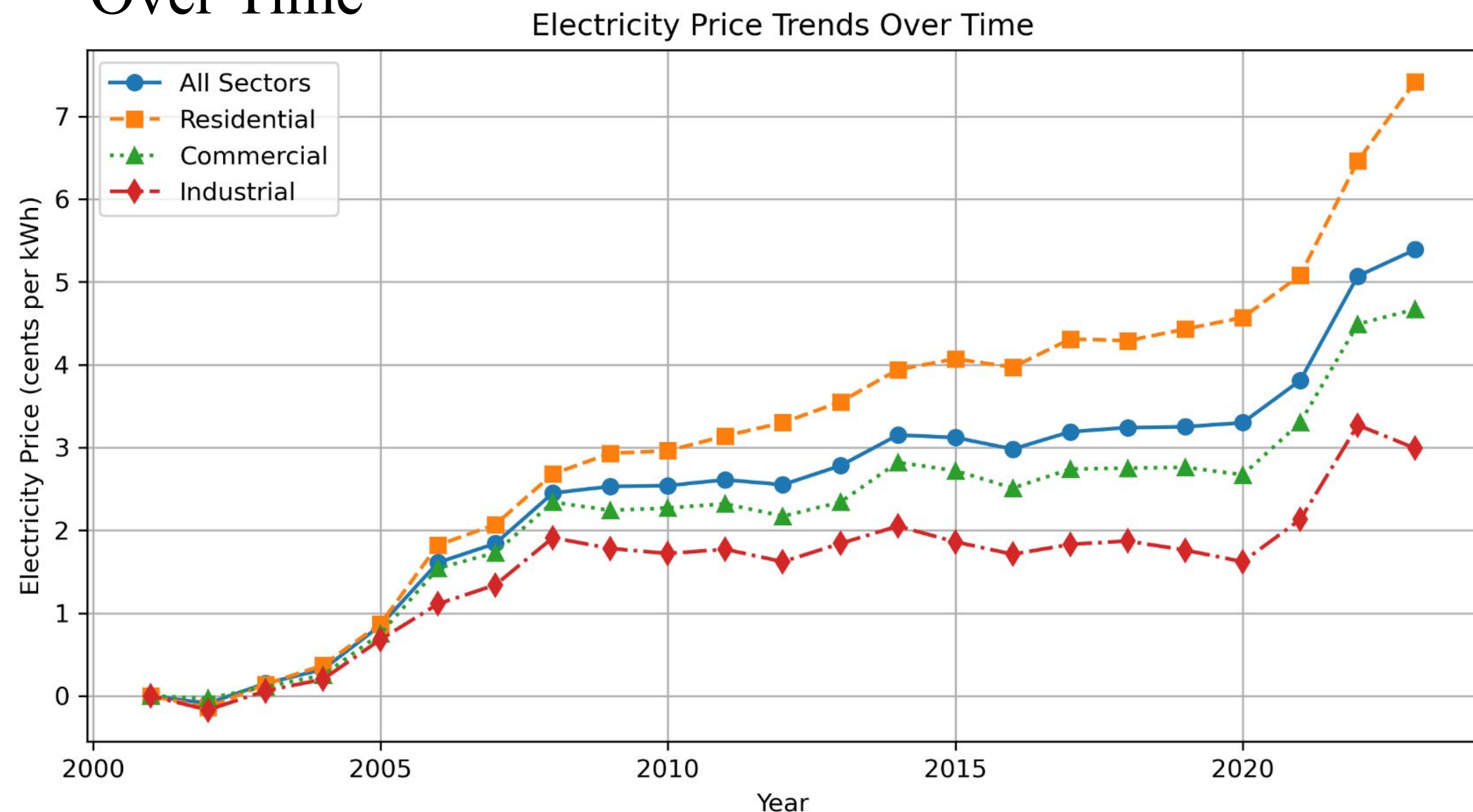


Table 1: Evaluation Metric Table

Evaluation Metrics Across Regression Models			
Model	MAE (MWh)	RMSE(MWh)	R²
Linear Regression	27074.55	27992.15	0.55
Random Forest	53622.96	61324.38	-1.152
XGBoost	71765.35	89499.83	-3.58
Neural Network	55955.63	66485.15	-1.53
Gradient Boosting	63962.25	78883.32	-2.56
SVM	47233.39	63072.47	-1.28

Figure 6: Random Forest Feature Importance Plot

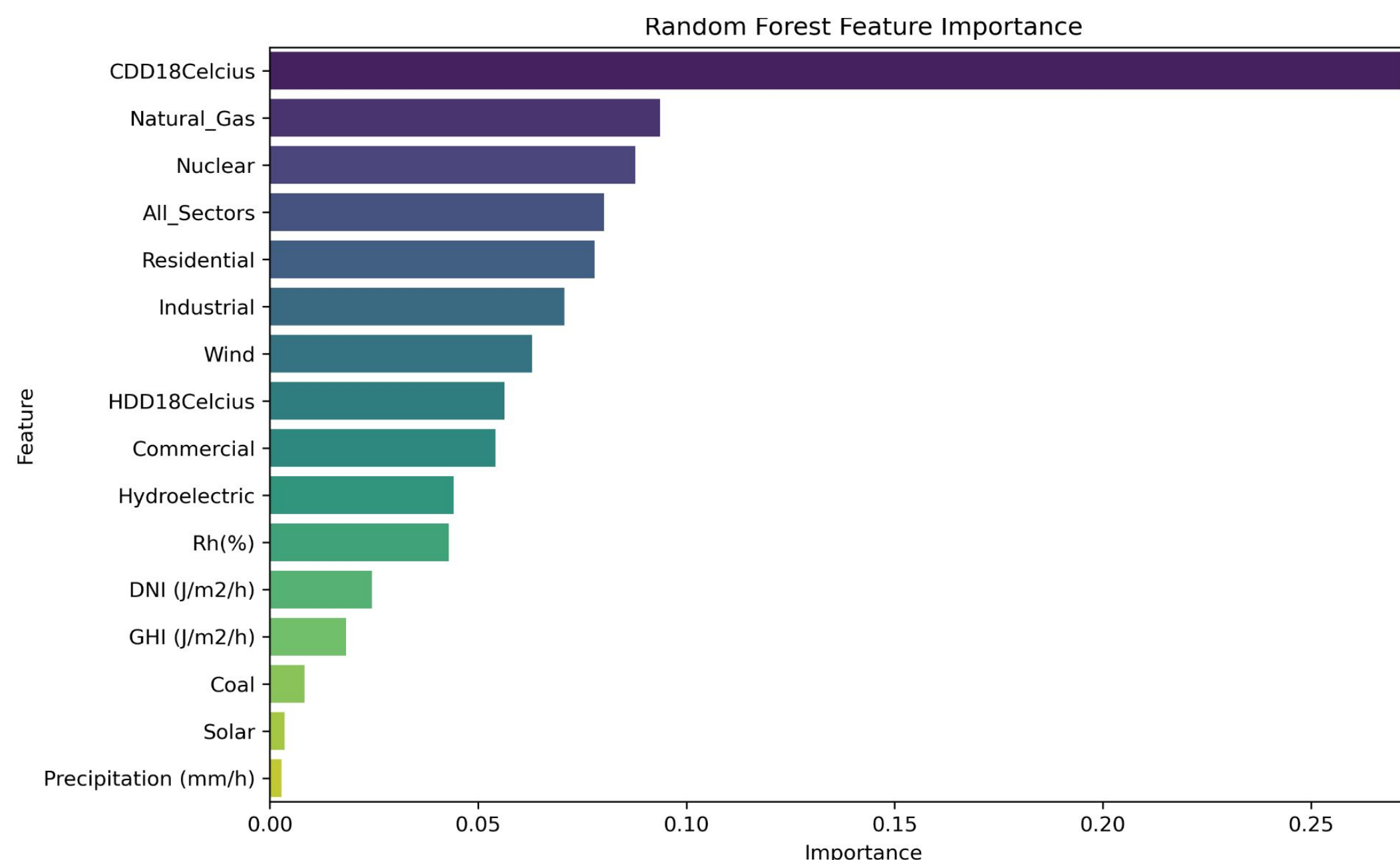
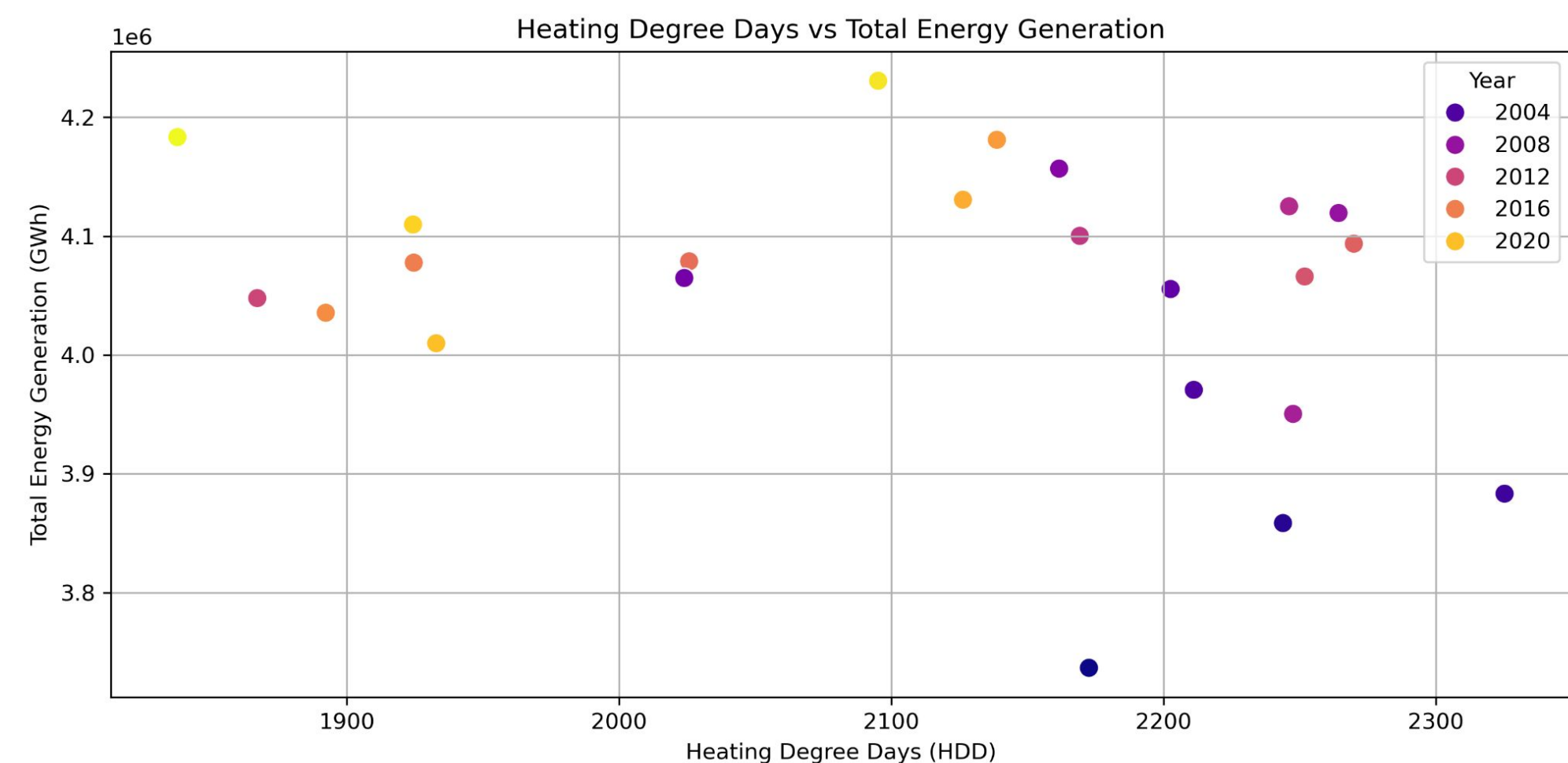


Figure 7b: Weather vs. energy



## RESULTS

**Price Trends:** Electricity prices have increased across all sectors, though the residential sector experienced the sharpest increased in the most recent years ( **Figure 2**).

**Energy generation** has shifted,(**Figure 1**) coal had a significant decline, while natural gas became the dominant energy source. Wind and hydroelectric power have remained consistent over time, and solar energy has gained momentum in the past decade.

The heatmap in (**Figure 5**) implies there’s a moderate correlation between prices and energy generation, **r = 0.74** to **0.82** across all sectors. Showing that consumption is weather driven as opposed to price driven.

**Weather Sensitivity:** CDD and HDD as seen in **Figure 7a and 7b**, years with extreme temperatures, correspond with higher electricity demand. This was supported by the feature importance analysis (**Figure 6**). CDD was ranked as the most influential predictor.

**Model Performance:** Six Models were trained using selected features to predict total energy generation (**Table 1**). Linear Regression performed the best with **MAE = 27074**, **RMSE 27992** and **R = 0.55** the model explains 55% of the variation in energy usage, more complex models, like Random Forest, XGBoost, SVM and Neural Networks, underperformed, likely due to the small datasets (**n=23**). Though Random Forest didn’t perform as well as the Linear Regression model the plot in **Figure 3**, showed that it still followed the trend in predicting the the overall energy usage.

## DISCUSSION

Energy usage is influenced more by weather than pricing. While energy prices have steadily increased over time, the analysis shows that consumption levels remained relatively unchanged, showcasing that users, do not significantly reduce usage in response to higher cost. Instead demand appears to be more influenced by climate conditions and operational needs. Smart technology and climate aware policies are necessary to optimize energy usage and price based strategies alone are not enough to lower energy demand or reduce consumption.

- Based on these finding, energy optimization should focus on:
- Investment in energy efficient technologies, such as smart thermostat and upgraded insulation systems.
  - Expanded support for renewable energy, especially in regions with strong wind and the highest number of sunshine days per year.