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Exploring the Relationship Between Weather Patterns and Energy Consumption in Smart Homes: A Regression Analysis

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ABSTRACT

The history of studying weather's impact on energy consumption dates back to the early days of modern energy systems. Historically, energy demand was primarily analyzed based on seasonal variations and historical consumption data. With the digital revolution, the integration of weather data into energy analysis began to gain prominence. Early studies used basic statistical models to correlate weather patterns with energy usage. However, the emergence of machine learning techniques in the last two decades has revolutionized this field. The utilization of decision trees, random forests, and neural networks has enabled researchers to create highly accurate predictive models. This project builds upon this historical evolution, leveraging cutting-edge technologies to delve deeper into the relationship between weather patterns and energy consumption in the context of smart homes, contributing to the ongoing evolution of energy-efficient technologies and practices. Thus, this research aims to investigate the intricate relationship between weather patterns and energy consumption in smart homes through a regression analysis. Leveraging machine learning techniques, the study explores predictive models to comprehend how weather variables impact the total energy load in these environments. The analysis involves the use of decision tree and random forest regression algorithms, providing valuable insights into energy consumption patterns under varying weather conditions.

Keywords: Smart energy meters, Internet of Things, weather patterns, electric consumption, machine learning, predictive analytics.

1. INTRODUCTION

The intersection of technology and sustainability has paved the way for innovations in smart home systems, revolutionizing the way we interact with our living spaces. In this era of smart homes, understanding energy consumption patterns is pivotal not only for homeowners seeking efficient energy management but also for energy providers and policymakers striving for sustainable practices. The concept of smart homes has evolved significantly with the advent of the Internet of Things (IoT) and artificial intelligence. Today, smart homes are equipped with an array of sensors and devices that collect vast amounts of data, including temperature, humidity, occupancy, and energy usage.

Smart meters are used to accurately record the amount of electricity consumption at a very high frequency, dramatically changing the collection of electricity data and driving the household energy transition [1]. High frequency interval meter data, typically hourly and 15 min, provides important and rich information about household consumption patterns. Smart meter data can be used to cluster, classify, predict, and optimize electricity consumption patterns through a series of analytical methods and techniques [2]. The popularity of smart meters has grown rapidly over the past decade, from <2.5 million smart meters deployed globally in 2007 to ~729.1 million in 2019, an increase of 294 times, with the United States and China accounting for the highest percentage, 85.4% [3]. Smart meters

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provide utilities with detailed information and enable effective demand side management. Two-way AMI meters, which allow communication capability between electric utilities and customers, have been more prevalent after 2013 [4]. By providing real-time or near real-time electricity data, it supports smart consumption applications based on customer preferences and demand.

This data presents an unprecedented opportunity to analyze and understand the factors influencing energy consumption, particularly the impact of weather patterns. Weather variables such as temperature and humidity have long been known to affect energy demand, but the complexity of these interactions demands sophisticated data analysis methods. Traditional methods often fall short in capturing the nuanced relationships, necessitating the use of machine learning algorithms for precise predictions. This project delves deep into the intricate relationship between weather patterns and energy usage in smart homes. By employing advanced regression analysis and machine learning techniques, the project aims to uncover the underlying patterns, providing valuable insights that can optimize energy consumption, reduce costs, and contribute to a greener future.

2. LITERATURE SURVEY

High-frequency electricity data helps understand the electricity consumption patterns in different consumer groups at various time periods, and the changes in behaviors after the adoption of new technologies and demand-side management measures. Further, high-frequency data increases the accuracy of energy consumption forecasts due to the larger variation provided by the data. Applying high frequency electricity data during pandemic times, studies have analyzed and examined the overall impact of COVID-19 on energy consumption and transition in pre- and post-pandemic. The world has seen a shift in people's habits and daily activities due to the pandemic. Therefore, electricity consumption patterns in both residential and commercial buildings have changed. Ku et al. [5] used individual hourly power consumption data within a machine learning framework to examine changes in electricity use patterns due to COVID-19 mandates in Arizona. Chinthavali et al. [6] examined changes in energy use patterns on weekdays and weekends before and after the COVID-19 pandemic. Raman and Peng [7] used residential electricity consumption data to reveal a strong positive correlation between pandemic progress and residential electricity consumption in Singapore. Li et al. analyzed data from apartments in New York to examine the impact of the number of COVID-19 cases and the outdoor temperature on residential electricity usage [8].

Lou et al. found that the COVID-19 measures increased residential electricity consumption by 4–5% and exacerbated energy insecurity using individual smart meter data from Arizona and Illinois [9]. Sánchez-López et al. explored the evolution of energy demands with hourly data among residential, commercial, and industrial demand during the first wave of COVID-19 [10]. Understanding how household hourly electricity demand changes after the pandemic, especially due to working from home, provides electricity system operators with valuable information in operation and management. Also, based on the changes in the spatial and temporal distributions of energy consumption, policymakers could make better decisions to increase the ratio of power supply from renewable energy sources.

The application of high frequency electricity data could help understand the electricity consumption patterns of specific consumer groups, especially families that have adopted new technologies [e.g., Photovoltaics (PV), batteries, and electric Vehicles (EV)]. Qiu et al. [11] applied a difference-in-differences approach to 1600 EV households' high frequency smart meter data and found that people increased EV charging in lower-priced off-peak hours.

Al Khafaf et al. [12] compared the electricity consumption of consumers with PV and energy storage systems (ESS) against consumers without ESS using over 5,000 energy consumers' 30-min window smart meters recording. They found that on extremely hot days, installing batteries, to some extent, reduces peak power usage in the afternoon. Using household hourly electricity data in Arizona, in [13] Qiu et al. (2022b) found a high degree of heterogeneity in consumption patterns of PV consumers after adding battery storage. As to heat pump adoption, Liang et al. (2022a) provided empirical evidence from Arizona which suggested that heat pumps do not necessarily save energy [14]. Besides, combining electric vehicle charging profiles with residential electricity data helps study the impact of EVs on electricity distribution networks [15]. These patterns not only help residents explore the economic benefits of new technologies adoptions, but also answer whether and how those new technologies adoption has an impact on existing electric grid's capacity.

3. PROPOSED METHODOLOGY

This research explores the intricate relationship between weather patterns and energy consumption in smart homes, employing sophisticated data analysis techniques and machine learning algorithms. In this endeavour, this work analyzes a dataset containing information about weather variables such as temperature, humidity, and precipitation, alongside energy consumption data from smart homes.

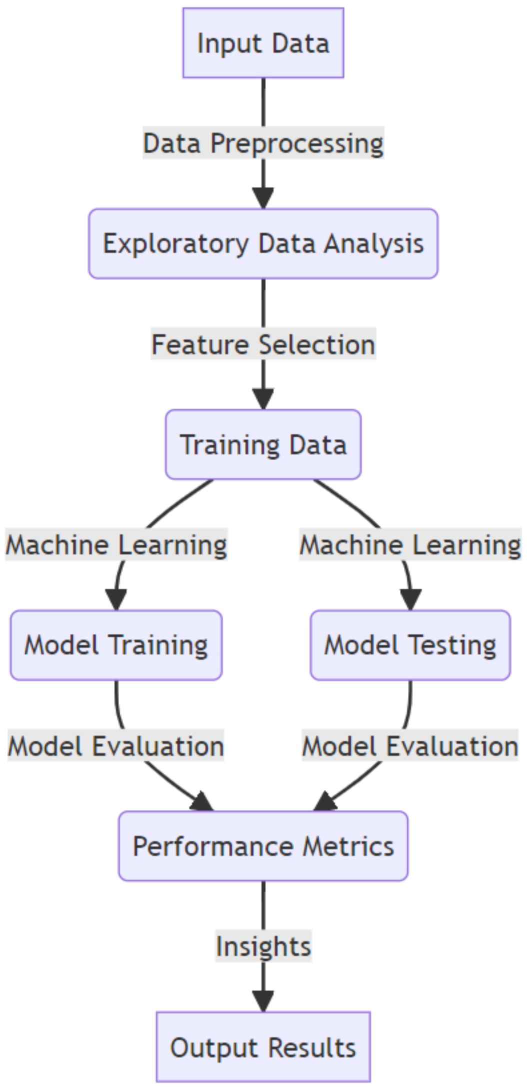

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Figure 1: Proposed methodology of ML-based energy consumption prediction in smart homes.

The primary objective is to discern patterns and correlations within this data to understand how weather conditions impact energy usage.

- Data Analysis and Preprocessing: This initiates with data preprocessing, addressing missing values and ensuring data integrity. Basic statistical analyses and visualization tools are employed to gain a comprehensive understanding of the dataset. Exploratory data analysis techniques are utilized to visualize trends, histograms, and correlations among variables, providing valuable insights into the data's structure.
- Machine Learning Models: To uncover the intricate relationships hidden within the data, advanced machine learning models are implemented. The project employs two primary regression algorithms: Decision Tree Regressor and Random Forest Regressor. These algorithms are trained on the preprocessed data, utilizing historical weather and energy consumption patterns to make predictions. Decision trees offer interpretable insights into feature importance, while random forests leverage multiple decision trees for enhanced accuracy and robustness.
- Analysis and Interpretation: The models' predictions are rigorously analyzed, evaluating their accuracy and effectiveness in forecasting energy consumption based on weather patterns. Key performance metrics, such as R-squared scores, are calculated to quantify the models' predictive power. These metrics offer crucial insights into the models' ability to capture the complexities of energy usage dynamics in response to changing weather conditions.
- Significance and Implications: The findings have profound implications for various stakeholders. Homeowners can optimize their energy usage, reducing costs and environmental impact. Energy providers can enhance their demand forecasting, ensuring a stable energy supply. Policymakers gain valuable insights for crafting sustainable energy policies, aligning urban planning with energy efficiency goals. Moreover, the project showcases the potential of machine learning in addressing real-world challenges, underlining its significance in the realm of energy management and sustainability.
- Future Directions: Looking forward, this work lays the foundation for future research avenues. Refining machine learning models, integrating real-time data, exploring regional variations, and diversifying applications across sectors are promising directions. These advancements hold the potential to create even more accurate, responsive, and adaptable energy management systems, ushering in a future of sustainable and efficient energy usage.

4. RESULTS AND DISCUSSION

Figure 2 displays a portion of the dataset used for predicting energy consumption in smart homes. It shows various features (columns) and their corresponding values. Figure 3 shows a scatter plot with a regression line. It visualizes the relationship between predicted and actual values generated by a Decision Tree Regressor model. This helps assess the model's performance. Figure 4 Similar to Figure 3, this figure displays a scatter plot with a regression line, but for a Random Forest Regressor model. It serves the same purpose of evaluating the model's performance.

	temp	temp_min	temp_max	pressure	humidity	wind_speed	wind_deg	rain_1h	rain_3h	snow_3h	...	generation nuclear	generation other	generation other renewable
0	270.475	270.475	270.475	1001	77	1	62	0.0	0.0	0.0	...	7096.0	43.0	73.0
1	270.475	270.475	270.475	1001	77	1	62	0.0	0.0	0.0	...	7096.0	43.0	71.0
2	269.686	269.686	269.686	1002	78	0	23	0.0	0.0	0.0	...	7099.0	43.0	73.0
3	269.686	269.686	269.686	1002	78	0	23	0.0	0.0	0.0	...	7098.0	43.0	75.0
4	269.686	269.686	269.686	1002	78	0	23	0.0	0.0	0.0	...	7097.0	43.0	74.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
35059	282.140	281.150	283.150	1028	71	3	300	0.0	0.0	0.0	...	6073.0	63.0	95.0
35060	282.150	282.150	282.150	1029	87	2	310	0.3	0.0	0.0	...	6074.0	62.0	95.0
35061	284.150	284.150	284.150	1028	76	1	290	0.0	0.0	0.0	...	6076.0	61.0	94.0
35062	285.660	285.150	286.150	1028	76	1	0	0.0	0.0	0.0	...	6075.0	61.0	93.0
35063	286.660	286.150	287.150	1027	71	1	0	0.0	0.0	0.0	...	6075.0	61.0	92.0

35064 rows × 25 columns

generation other renewable	generation solar	generation waste	generation wind offshore	generation wind onshore	forecast solar day ahead	forecast wind onshore day ahead	total load forecast
73.0	49.0	196.0	0.0	6378.0	17	6436	26118
71.0	50.0	195.0	0.0	5890.0	16	5856	24934
73.0	50.0	196.0	0.0	5461.0	8	5454	23515
75.0	50.0	191.0	0.0	5238.0	2	5151	22642
74.0	42.0	189.0	0.0	4935.0	9	4861	21785
...	...	...	...	...	...	...	...
95.0	85.0	277.0	0.0	3113.0	96	3253	30619
95.0	33.0	280.0	0.0	3288.0	51	3353	29932
94.0	31.0	286.0	0.0	3503.0	36	3404	27903
93.0	31.0	287.0	0.0	3586.0	29	3273	25450
92.0	31.0	287.0	0.0	3651.0	26	3117	24424

Figure 2: Sample dataset used for prediction Energy Consumption in Smart Homes

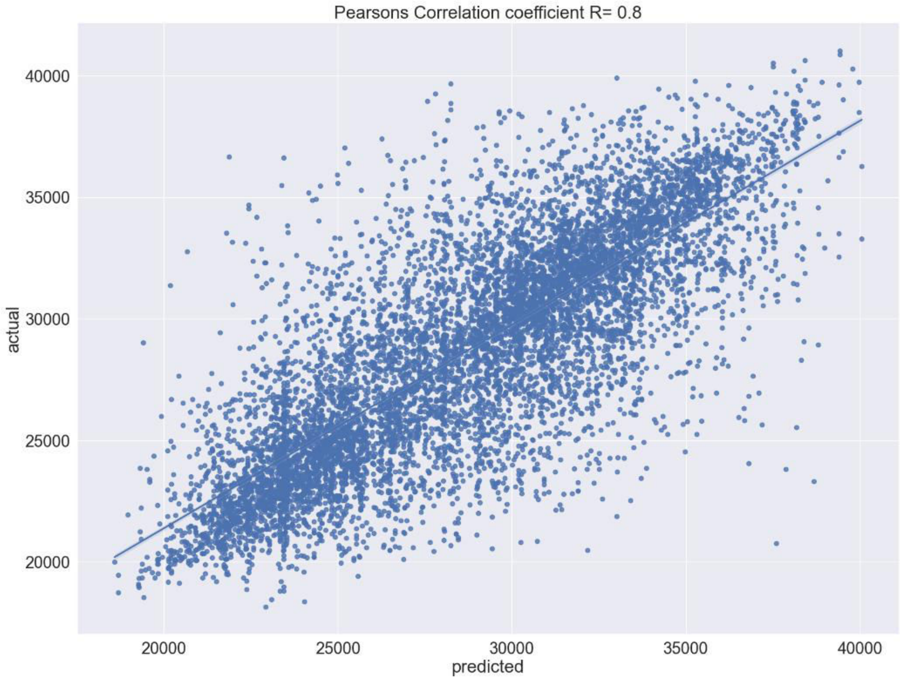

Figure 3: Scatter plot with a regression line to visualize the relationship between predicted and actual values of Decision Tree Regressor.

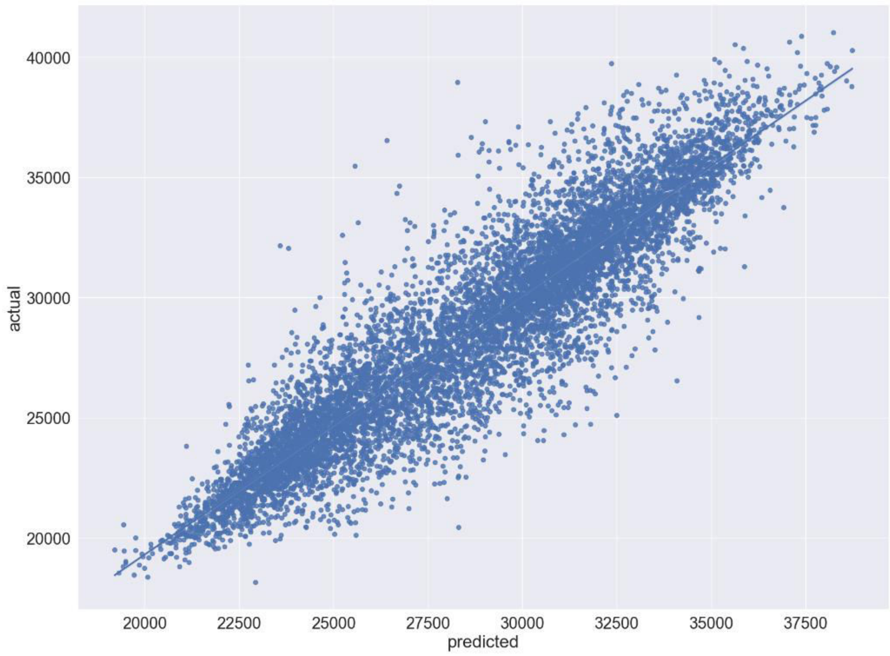

Figure 4: Scatter plot with a regression line to visualize the relationship between predicted and actual values of Random Forest Regressor.

5. CONCLUSION

In conclusion, this research has successfully delved into the intricate relationship between weather patterns and energy consumption in smart homes, employing advanced regression analysis and machine learning techniques. Through meticulous data analysis, meaningful patterns have been extracted, shedding light on the impact of weather variables such as temperature, humidity, and precipitation on energy load. The developed regression models, particularly the decision tree and random forest algorithms, have showcased promising accuracy in predicting energy consumption under varying weather conditions. These findings hold substantial implications for homeowners, energy providers, and policymakers alike. For homeowners, this study provides actionable insights into optimizing energy usage based on weather forecasts. By understanding how weather influences energy consumption, homeowners can implement targeted strategies to reduce costs and enhance efficiency. Energy providers can benefit from these insights by improving demand forecasting and management, ensuring a stable and efficient energy supply. Policymakers can integrate these findings into energy policies, fostering sustainable practices and guiding urban planning initiatives. Furthermore, this work demonstrates the power of data analytics and machine learning in addressing real-world challenges, showcasing their potential in the realm of energy management and sustainability.

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