Smart House Power Usage and Temperature Prediction Model

Final Project | Team 7

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Introduction

Our model is specifically designed to transform the way energy consumption is optimized in residential environments. Central to its functionality is the integration of the Smart Home Dataset along with Weather Information, enabling the model to perform robust predictive analytics. The focus of this model is on analyzing the intricate relationship between weather conditions, particularly temperature variations, and household energy usage patterns. This advanced model serves a diverse group of users, primarily encompassing homeowners, property managers, and energy consultants. By offering deep insights into how temperature fluctuations impact energy consumption, the Temperature Prediction Model enables these users to make informed decisions about their energy usage. This leads to more efficient energy consumption practices, which in turn helps in reducing energy costs and improving the overall energy efficiency of their homes.

Positioned within the smart home sector of the IoT landscape, our Power Usage and Temperature Prediction Model addresses the urgent need for energy-efficient solutions in the face of escalating energy expenses and environmental concerns. By combining weather data, especially temperature, with energy consumption analytics, the model presents a refined approach to managing home energy usage. The benefits of this approach are twofold: it aids in cutting down energy costs and promotes sustainable living. As a pioneering solution in the smart home industry, the Power Usage and Temperature Prediction Model stands as an emblem of innovation, offering both economic and environmental benefits.

IoT System Design

Device Description: A network of sensors on home devices/rooms/solar panels and weather sensors on the home gather weather-related and energy usage/generation data. This data is processed by our predictive model to make predictions on energy usage and temperature and sent to an app. The user can turn on "predictive mode" to allow the IoT system to turn on and shut off appliances to optimize energy consumption i.e. it would turn off the furnace if it predicts the temperature rising would make it unnecessary.

Sensors

Weather Sensors – located on top of the smart home

- Solar sensor:
  - Measures solar radiation or solar energy.
  - Can provide measurements such as solar irradiance or solar power.
  - Accurate within a specific range according to the manufacturer's specifications.
- Temperature sensor:
  - Measures ambient temperature.
  - Accurate within temperature range -10 to 45 degrees Celsius.
  - Operates using various technologies like thermocouples, resistance temperature detectors (RTDs), or thermistors.

- Humidity sensor:
    - Measures the relative humidity (RH) in the air.
    - Accurate within range ±2% RH.
- Apparent temperature sensor:
    - Calculates the perceived temperature by taking into account the combined effects of temperature, humidity, wind speed, and solar radiation.
- Pressure sensor:
    - Measures atmospheric pressure.
    - Can be a barometer, manometer, or pressure transducer.
    - Provides pressure readings in various units (e.g., pascal, bar, or millibar).
- Wind speed sensor:
    - Measures the speed or velocity of the wind.
    - Uses technologies like cup anemometers or sonic anemometers.
    - Provides wind speed readings in units such as meters per second or miles per hour.
- Cloud cover sensor:
    - Estimates the percentage of the sky covered by clouds.
    - Can use sky cameras, pyranometers, or satellite imagery.
- Wind direction sensor (wind bearing):
    - Measures the direction from which the wind is blowing.
    - Direction represented as degrees 0° for north, 90° for east.
- Precipitation intensity sensor:
    - Measures the rate at which precipitation (rain, snow, etc.) is falling.

- Uses tipping bucket rain gauges, weather radars, and rain sensors.

- Dew point sensor:
  - Measures the temperature at which the air becomes saturated and condensation occurs.
  - Determined from temperature and humidity readings
- Precipitation probability sensor:
  - Estimates the likelihood of precipitation occurring, represented as a percentage.

Energy Monitoring Sensors – located in the home for devices, plugs and on the solar panel

- Smart Energy Meter:
  - Measures the total energy consumption of the household.
  - Provides real-time monitoring of power in kilowatts (kW). Could be capable of differentiating consumption by circuit or appliance with integrated software.
- Solar Generation Meter:
  - Monitors the total energy generated by the home i.e. solar panels producing kW.
  - Measures power output in kW.

· Smart Plugs and Appliance Monitors:

  - Tracks energy usage for individual appliances or specific circuits within the home when detailed granulation is needed.
  - Each plug or monitor measures energy usage in real-time and reports in kW.

Networking

· Connectivity: Utilizes Wi-Fi for seamless data transmission to the database and facilitating IoT device/mobile app interactions i.e. turn off furnace.

· Messaging Protocol: Employs MQTT for efficient device communication between mobile/IoT devices.

Edge Processing:

- Engages edge computing for immediate processing needs, particularly for sensor data reliant on synthesis from other sources (e.g., Apparent Temperature Sensor, total energy usage).
- Implements a short-term caching mechanism in the smart home to support edge operations, holding data for up to 24 hours.

Data Management

- Data Composition: Encompasses both weather-related information (solar, temperature, etc.) and power usage details (total energy usage, appliance-specific consumption, solar energy production, etc.).
- Data Storage:
  - Short-term: Localized caching for edge computing.
  - Long-term: Cloud-based storage via AWS RDS or other cloud database for durable SQL database management.
- Data Processing:
  - Processed in the cloud with an LSTM model to analyze trends and make predictions.
  - Outputs, including energy consumption forecasts and temperature predictions, are relayed to the mobile app, empowering users to manage home devices manually or through an automated "Predictive Mode."

Figure 1: Full IoT System Diagram

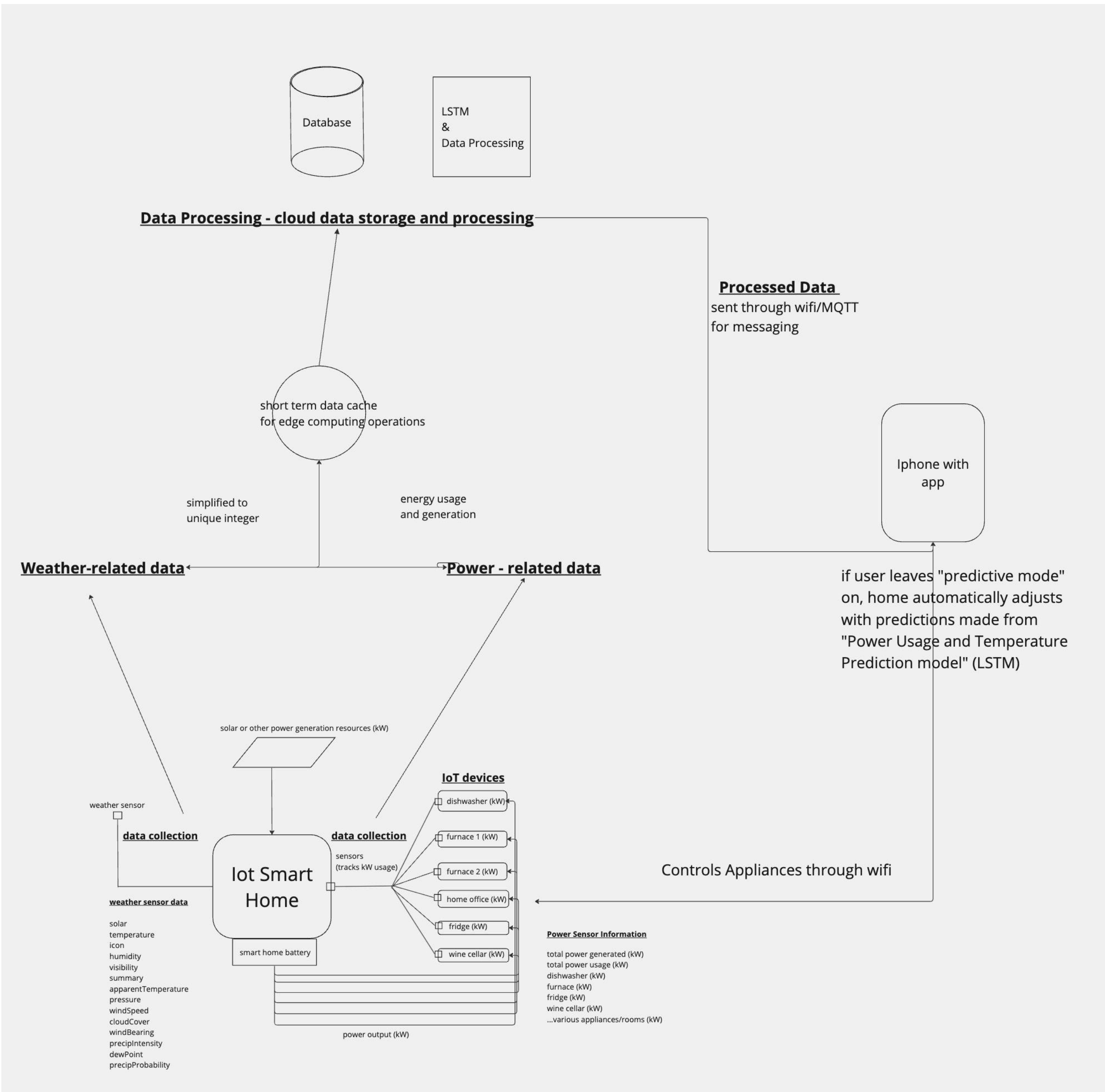
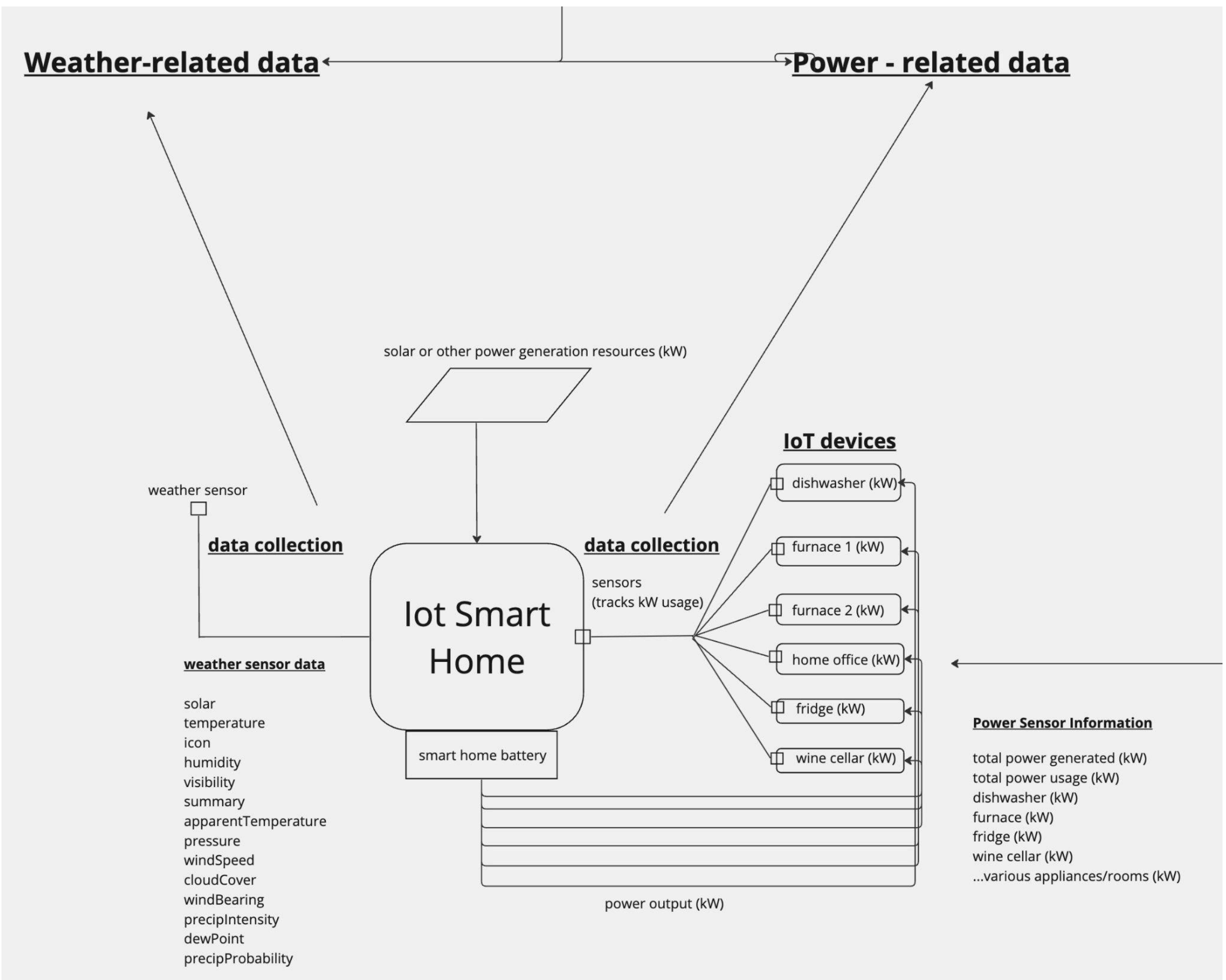


Figure 2: Close-up of IoT Smart Home



Data Processing and Insights

The initial phase of processing the dataset for the "Power Usage and Temperature Prediction Model" entailed a series of critical cleaning and encoding operations. These steps were essential to ensure that the data was suitable for detailed analysis and effective modeling. Comprising a variety of power and weather-related columns, the dataset offered a thorough perspective on how energy usage patterns correlate with varying weather conditions. To address the issue of missing values, the team adopted a strategy where such values in the 'cloudCover' column were replaced with the column's mean. This method was pivotal in maintaining data continuity and preserving the integrity of future analyses. In the case of the 'summary' column, which contained categorical data describing weather conditions, a transformation was undertaken. This involved encoding the column into a numerical format through factorization, effectively converting each distinct string in the 'summary' column into a corresponding unique integer. Such a transformation simplified the complexities inherent in the modeling process.

The Exploratory Data Analysis focused on understanding the relationships between various power-related and weather-related features.

- Categorization of Columns: For a structured analysis, columns were categorized into 'power-related' and 'weather-related' groups. This categorization helped in identifying patterns and correlations specific to each group.

- Visualization of Energy Usage: Visualization of daily average energy usage ('use [kW]') and energy generation ('gen [kW]') provided insights into consumption and production patterns. This analysis highlighted the alignment (or lack thereof) between energy usage and weather conditions.

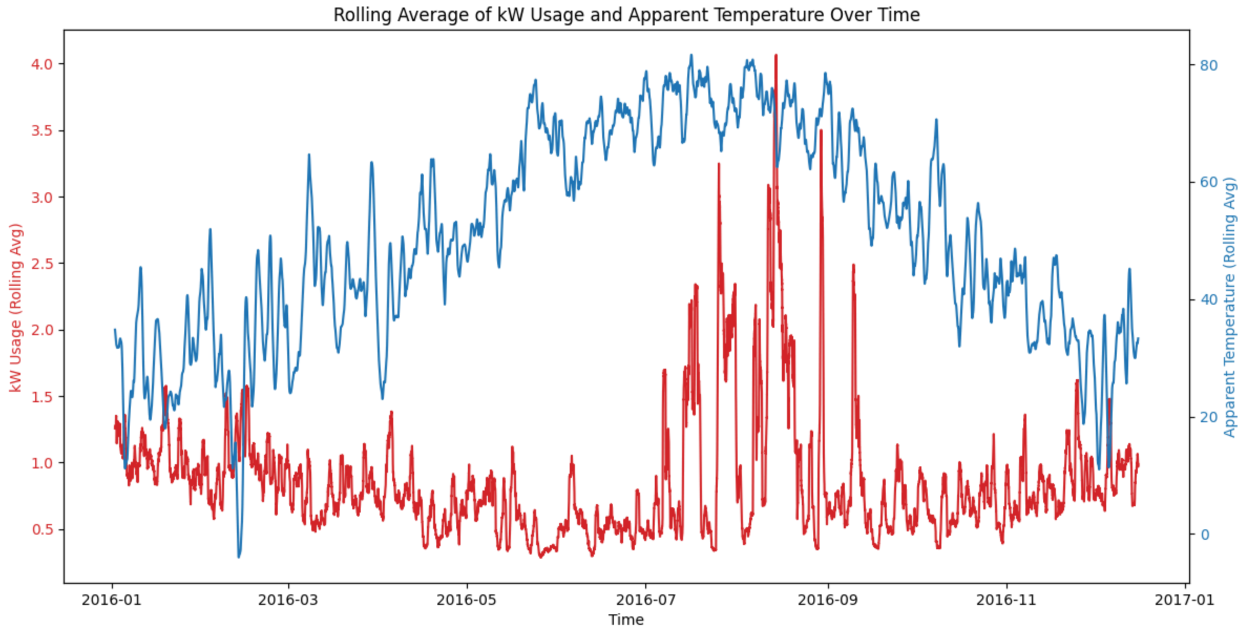
- Redundancy Removal: It was observed that the columns 'House overall [kW]' and 'Solar [kW]' were redundant, as their information overlapped perfectly with 'use [kW]' and 'gen [kW]', respectively. To streamline the dataset, these duplicate columns were removed.

Through this process of data cleaning, encoding, and exploratory analysis, several key insights were gained:

- The transformation and encoding of weather data into a numerical format enabled more sophisticated analytical techniques, paving the way for accurate predictive modeling.
- The visualization of energy usage and generation patterns highlighted the impact of weather conditions on energy dynamics in smart homes.
- The refinement of the dataset by removing redundancies and ensuring data quality set the stage for developing a robust Power Usage and Temperature Prediction Model, capable of effectively correlating weather conditions with energy usage patterns.

The graph titled 'Rolling Average of kW Usage and Apparent Temperature Over Time' serves as a pivotal piece of our analysis. It elucidates the potential correlation between energy consumption and temperature. The simultaneous visualization of these two metrics offers a valuable perspective, supporting the hypothesis that changes in temperature could have a significant influence on energy usage patterns in smart homes. This insight is instrumental for the ongoing development of the Power Usage and Temperature Prediction Model, underscoring the importance of incorporating weather data, especially temperature, into our predictive algorithms.

Figure 3: kW Usage and Temperature Over Time



Machine Learning Methods

Long Short-Term Memory (LSTM) neural network was implemented to enhance the prediction accuracy of energy usage in smart homes. LSTM, known for its effectiveness in handling time series data, was chosen due to its ability to remember long-term dependencies, making it ideal for this application. The data was then scaled using MinMaxScaler, normalizing the feature values to a range between 0 and 1. This normalization is crucial for LSTM models as it aids in speeding up the training process and improves overall model performance.

A Linear Regression Model was used to forecast future temperature values. This approach is part of a broader strategy to enhance the accuracy and reliability of temperature predictions, which are crucial for optimizing energy usage in smart homes. The process began with the calculation of the correlation matrix for the weather-related variables. The focus was on identifying features that showed a strong correlation with temperature, excluding 'temperature' and 'apparentTemperature' from the analysis. The team identified features with a correlation coefficient of 0.3 or higher as highly correlated with temperature.

Deep Learning Prediction

The LSTM model consisted of an LSTM layer with 50 neurons and a dense output layer. The model was compiled with the Adam optimizer and mean squared error loss function. To optimize training, early stopping and learning rate reduction techniques were employed. Early stopping halted training when the validation loss ceased to improve, preventing overfitting. The learning rate reduction adjusted the learning rate when the validation loss plateaued, enhancing the training process. During training, the LSTM model displayed a consistent reduction in loss, indicating effective learning. The training process was automatically stopped after 12 epochs, as per the early stopping criteria, ensuring the model's generalization capability. Post-training, the model's performance was evaluated on the test set.

```
MSE: 0.2506907470532965
RMSE: 0.5006902705798232
MAE: 0.31568480847868097
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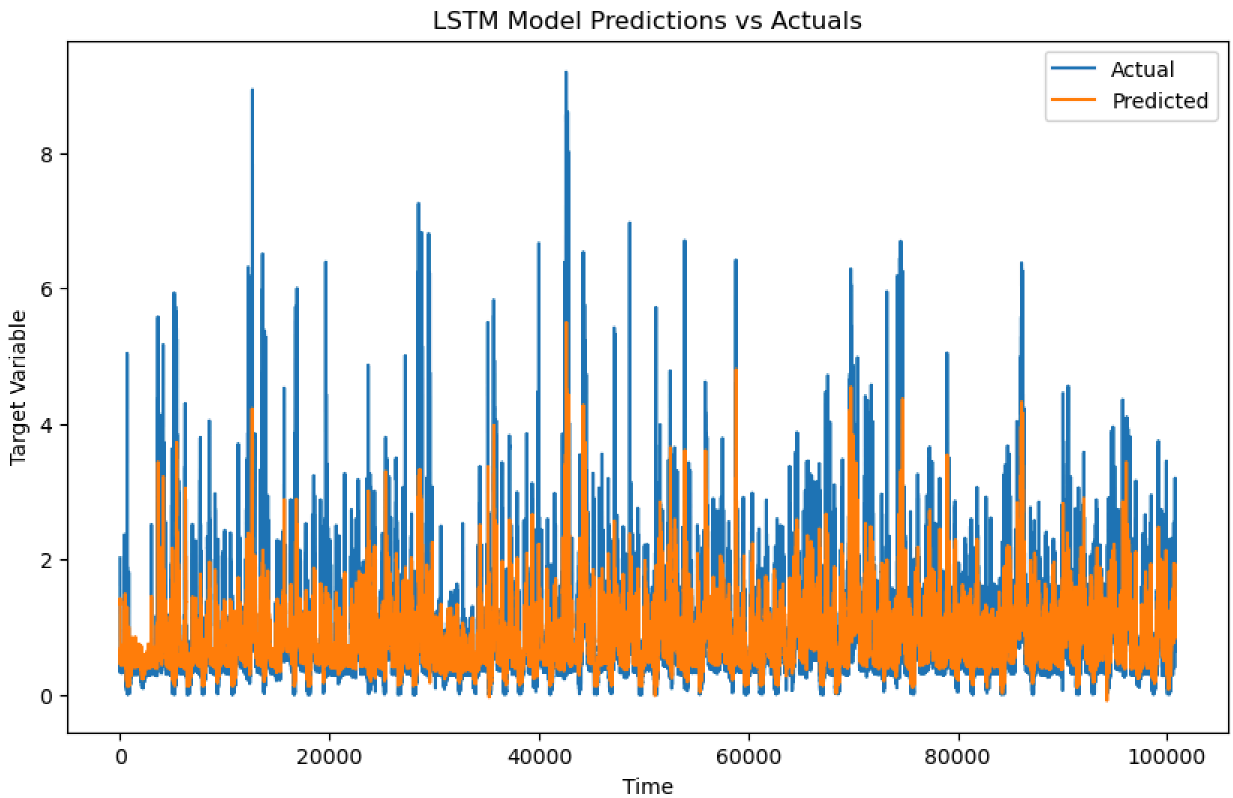
Sequential data was prepared for the LSTM model by creating sequences of 10-minute intervals. The target variable was set to predict energy usage a specific number of minutes ahead (as determined by MINUTES_AHEAD_TO_PREDICT). This sequential dataset was then split into training and testing sets, with 80% of the data used for training. A plot comparing the actual and predicted values of the target variable was generated. This visual representation clearly depicted how closely the LSTM model's predictions aligned with the actual data, demonstrating the model's effectiveness. The model's ability to accurately forecast energy consumption based on various features, including weather conditions and previous energy usage patterns, positions it as a vital tool in optimizing home energy management. The successful development and evaluation of this model underscore its potential to contribute to more efficient and sustainable energy usage in smart homes.

Figure 4: LSTM Model Predictions vs Actual



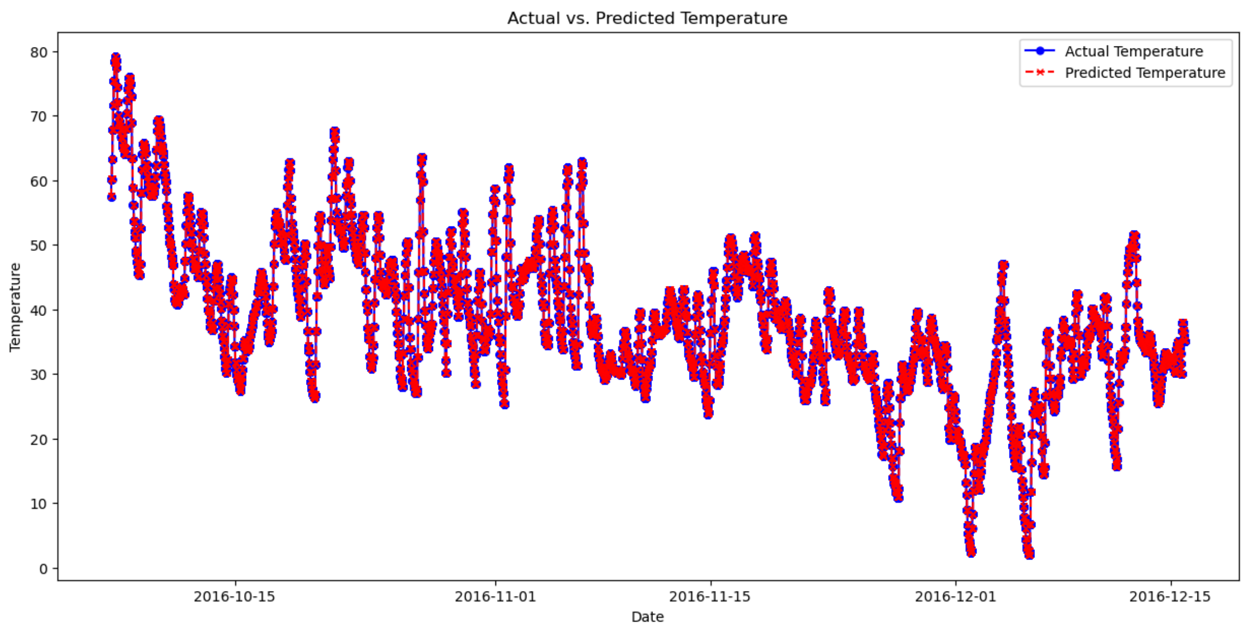
Time-Series Prediction

The team employed a Linear Regression Model to forecast future temperature values. The model's ability to accurately predict future temperature values based on a selection of highly correlated weather features is instrumental in enhancing the overall predictive capability of the system. The performance of the model was evaluated using the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics. The model achieved a Test MSE of 0.5497 and a

Test RMSE of 0.7414. These metrics provided a quantitative measure of the model's accuracy in predicting future temperatures.

An analysis of feature importance revealed that 'temperature' itself was the most significant predictor, with a coefficient close to 1. This result was consistent with the expectation that past temperature values are strong indicators of future values. The below visualization, depicts the model's predictions alongside actual data, provided a clear and intuitive understanding of the model's performance.

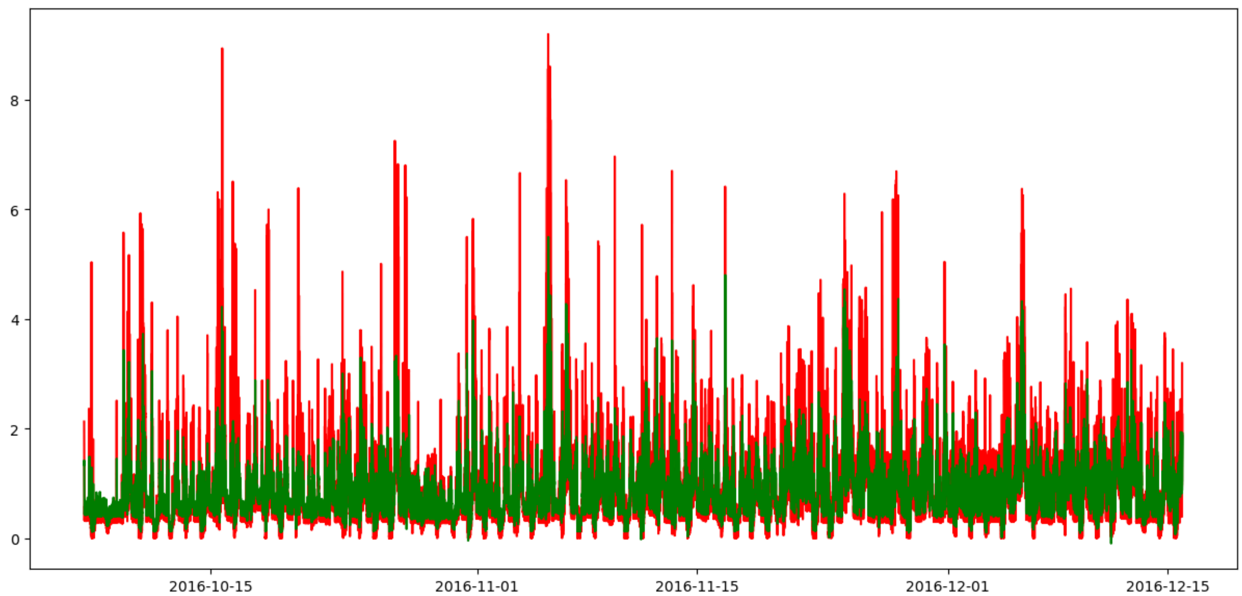
Figure 5: Linear Regression Predictions vs Actual



Results

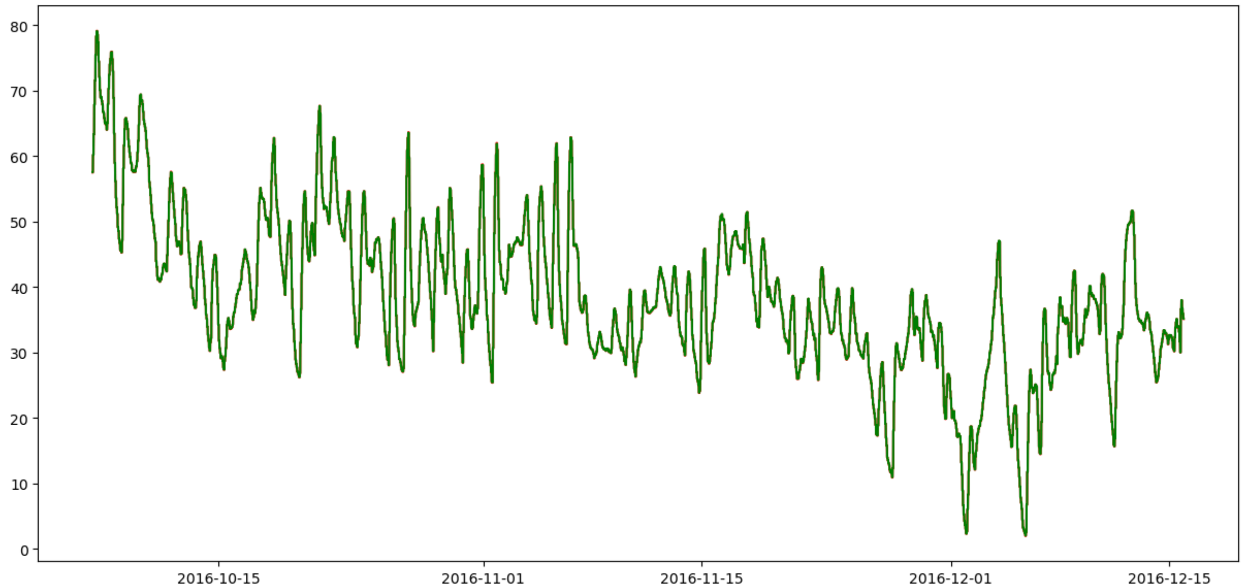
The following graph shows how the team successfully implemented an LSTM model to predict the next 10 minutes of energy usage. Despite some deviation, the LSTM model's predictions generally followed the actual usage trend closely, capturing the main patterns and peaks in energy consumption over time. The red spikes representing the actual usage showed a degree of variability that the model had to contend with, which is typical in real-world energy consumption data. The green prediction line from the LSTM model appeared to smooth out these spikes, indicating a strong understanding of the underlying trends while filtering out some noise. The model's ability to grasp the essential dynamics of energy usage without overfitting to the random fluctuations is evident from the comparison of the two lines.

Figure 6: LSTM Model Predictions vs Actual on Test Data



The following graph, focused on the prediction of temperature, comparing the actual temperature values with those forecasted by the Linear Regression model. Here, the actual temperature is again represented in red, while the Linear Regression predictions are shown in green. The model's predictions seemed to closely match the actual temperature values, as indicated by the overlap of the red and green lines. The congruence between the predicted and actual temperature values was remarkable, as the Linear Regression model appeared to track the temperature changes accurately. This was particularly evident in the smooth following pattern of the green line with the red, reflecting the model's capability to predict temperature effectively with a minimal time lag.

Figure 7: Linear Regression Model Predictions vs Actual on Test Data

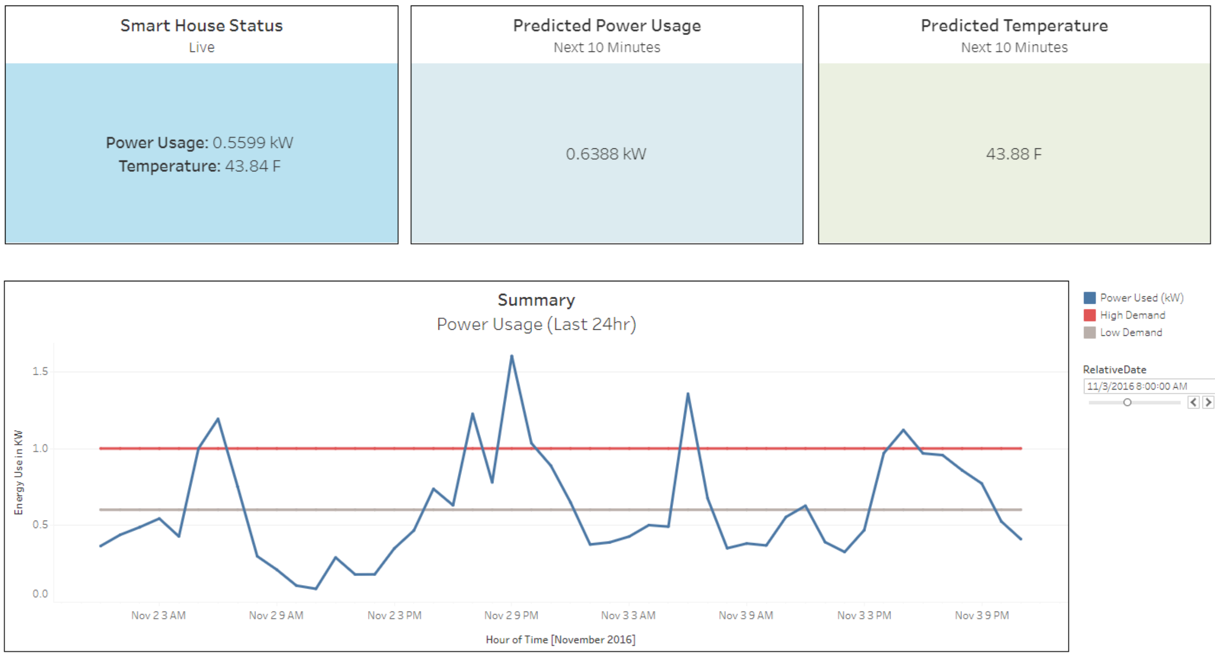


The analysis reflected that both models are valuable tools for predicting key variables in smart home energy management systems. The results suggest that integrating these models could significantly enhance the intelligence of the "Power Usage and Temperature Prediction Model," leading to more efficient and economically beneficial energy usage patterns. The project team considers these outcomes to be a strong testament to the potential of machine learning models in improving IoT-based energy management solutions.

Tableau Dashboard

The tableau dashboard designed for the "Power Usage and Temperature Prediction Model" provides users with four key sections: live house power usage and temperature, power usage forecasts for the next 10 minutes, upcoming 10-minute temperature predictions, and detailed 24-hour power usage history featuring high/low thresholds. Additionally, the dashboard offers flexibility, enabling users to select any past date for a comprehensive review of the chosen day's data.

Figure 8: Tableau Dashboard



Conclusion

Integrating Long Short-Term Memory (LSTM) neural networks and Linear Regression models into smart home energy management shows a new era of efficiency and sustainability. These technologies showcase the potential for advanced predictive capabilities in real-time energy consumption and temperature forecasting. By accurately modeling energy usage patterns and temperature variations, they enable smarter, more responsive home environments that significantly contribute to energy conservation and cost savings.

The practical applications of these models extend beyond individual homes, offering valuable insights for larger residential complexes and smart city projects. Their deployment can enhance the overall energy efficiency of communities, aligning with global sustainability goals and reducing the environmental footprint of urban living. Furthermore, their potential compatibility with existing home automation systems makes them a versatile tool in the ongoing evolution of intelligent living spaces.

References

Dataset retrieved from:

https://www.kaggle.com/datasets/taranvee/smart-home-dataset-with-weather-information/data

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Appendix

GitHub: https://github.com/teslanando/AAI530_IoT_Final_Project

Tableau:

https://public.tableau.com/app/profile/paul.parks/viz/MSAAI-530-IoT-Team7-FinalProject/IoTDashboard