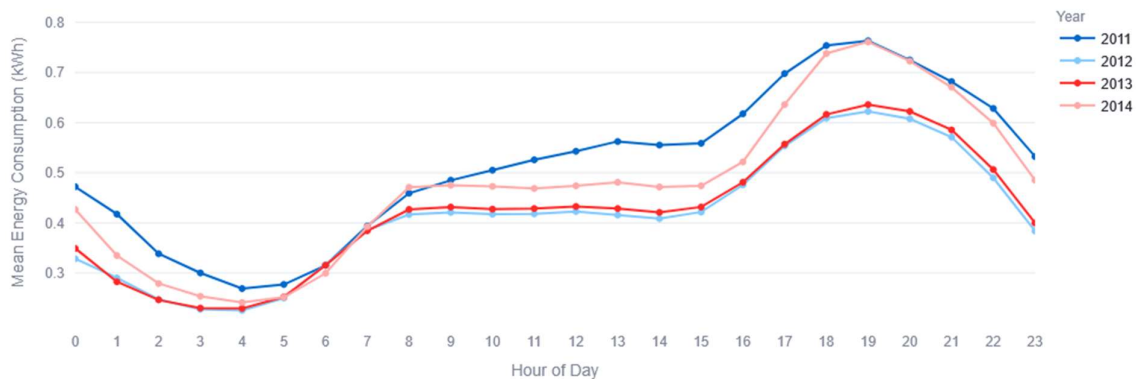# Python in Electrical Engineering

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Time-based trends

Hourly Mean Energy Consumption by Year (kWh)


Hourly Consumption Analysis
Key observations:

- **Night hours (0-5)**: Low energy consumption during sleeping hours
- **Morning peak (7-8)**: Increased usage during morning routines
- **Daytime (9-15)**: Relatively stable consumption
- **Evening peak (16-20)**: Highest consumption when people return home, turning on lights and appliances, having dinner
- **Late night drop (21-23)**: Consumption tapers off as people go to bed These patterns typically reflect residential consumption cycles, influenced by work schedules and daylight availability.

Daily Mean Energy Consumption by Year (kWh)
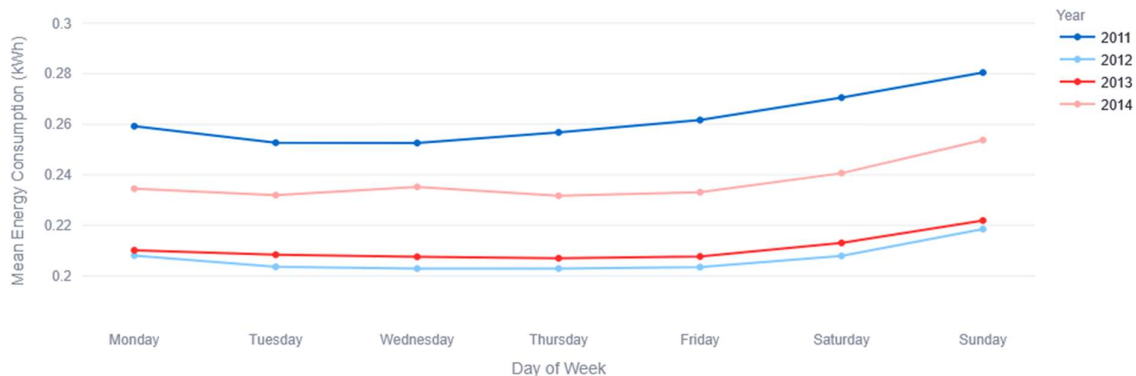
Daily Consumption Patterns

Key observations:

- **Weekday vs Weekend**: Notice the typical rise on weekends, more people stay at home using appliances
- **Monday transitions**: Usually shows a ramp-down effect from weekend mode to work mode. Huge consumption drop
- **Friday wind-up**: Shows higher consumption as people prepare for the weekend

**Weekly Mean Energy Consumption by Year (kWh)**

Weekly Consumption Trends

Key observations:

- **Winter Effect**: Notice how weeks in winter months (December-February) shows higher consumption.
- **Holiday periods**: Weeks with holidays often show distinctive patterns with spikes
- **Lowest Consumption**: Lowest consumption of all weeks is usually seen in summer months (June-August) when people are on vacation and staying away from home. Also during summer, days are longer, so less energy is used for lighting.

Seasonal Mean Energy Consumption (kWh)
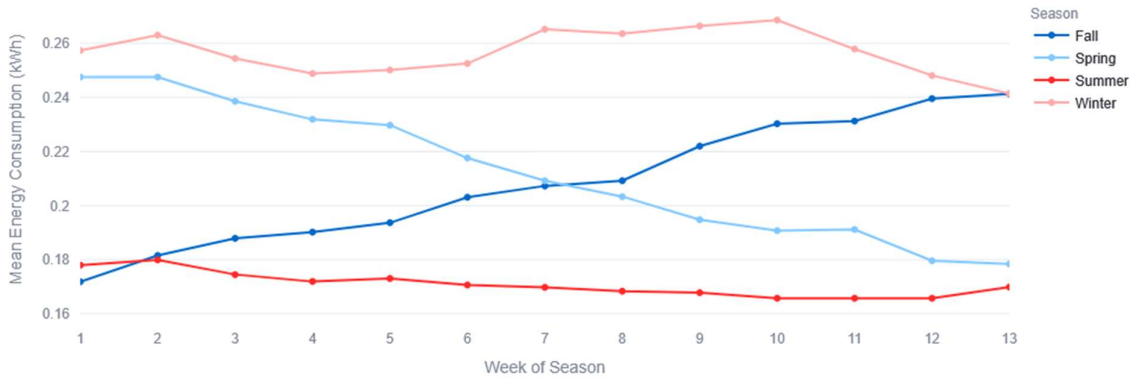
Seasonal Energy Patterns

Key observations:

- **Winter**: Shows higher consumption in cold London winters due to heating needs and much shorter daylight hours
- **Summer**: Expectedly shows the lowest consumption, as days are longer and people are often away on vacation with grills, pools, and outdoor activities :)
- **Shoulder seasons**: Spring/Fall often show most moderate consumption
- **Year-over-year**: Comparing years we can see how consumption patterns doesn't change much.

Weekday vs Weekend Energy Consumption by Year (kWh)
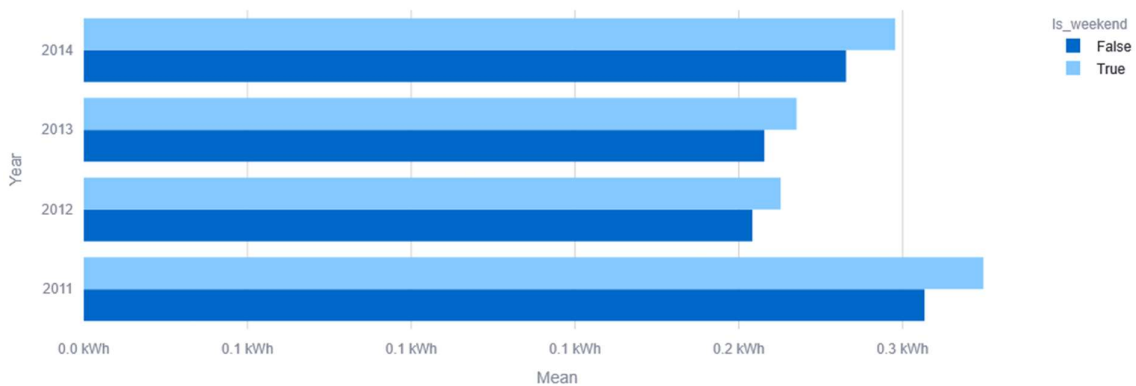
**Weekday vs Weekend Analysis**

Key observations:

- **What is Weekday vs Weekend?**: This analysis takes into account that weekends are sometimes can be Monday-Friday, since holidays can fall on any day of the week.

- **Occupancy patterns**: Weekends typically show higher energy consumption as people are home more often, using appliances, cooking, and engaging in leisure activities.
- **Year-over-year changes**: Changes in weekend/weekday ratio may indicate lifestyle or usage shifts. Interestingly enough, that 2011 shows the most consumption overall.

Household behavior

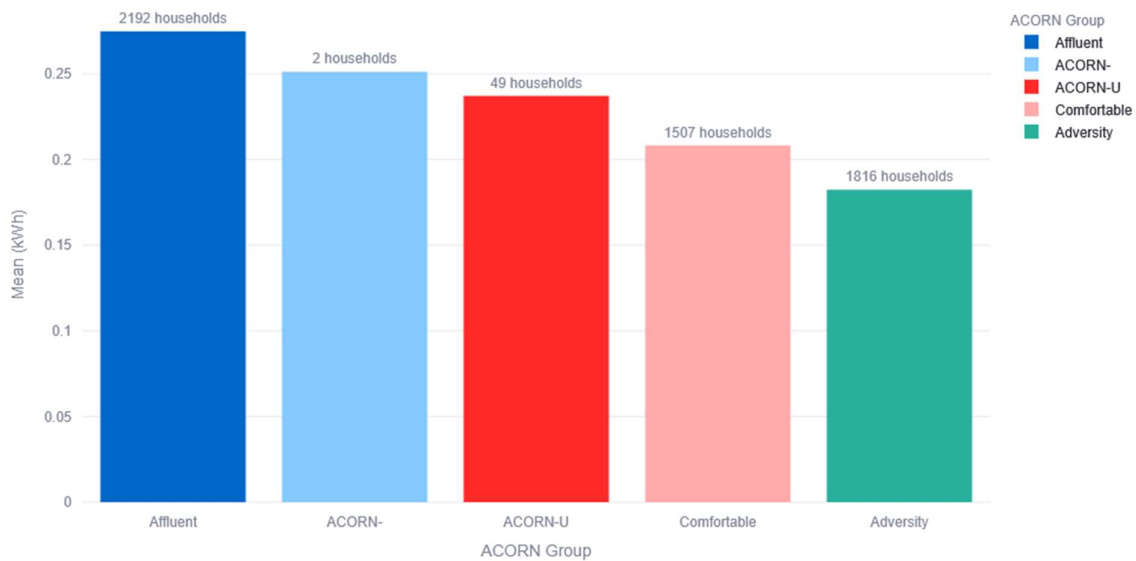Energy Consumption by ACORN Group and Tariff Type (kWh)
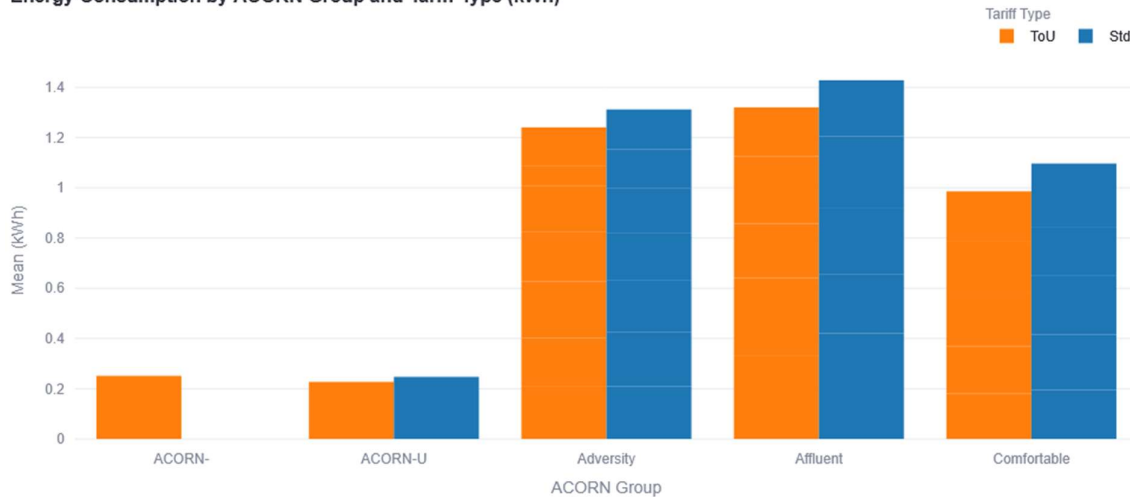
Tariff Type Comparison Insights
Key observations:
- **Standard vs. Time-of-Use**: ToU customers generally show lower consumption compared to standard tariff users
- **Affluent groups**: Show the highest consumption differential between tariff types, with Std tariff users consuming significantly more
- **Behavior change**: ToU tariffs appear to encourage more efficient consumption patterns across all demographic groups

Energy Consumption by ACORN Group (kWh)

ACORN Group Analysis Insights

Key observations:

- **Affluent segments**: Show consistently higher energy consumption than other groups, while being the biggest group in terms of household count
- **Adversity segments**: Groups K-Q (Adversity) show much lower consumption, while being top-2 in terms of household count. This means that in average, these consumers shows much lower energy consumption than the Affluent groups
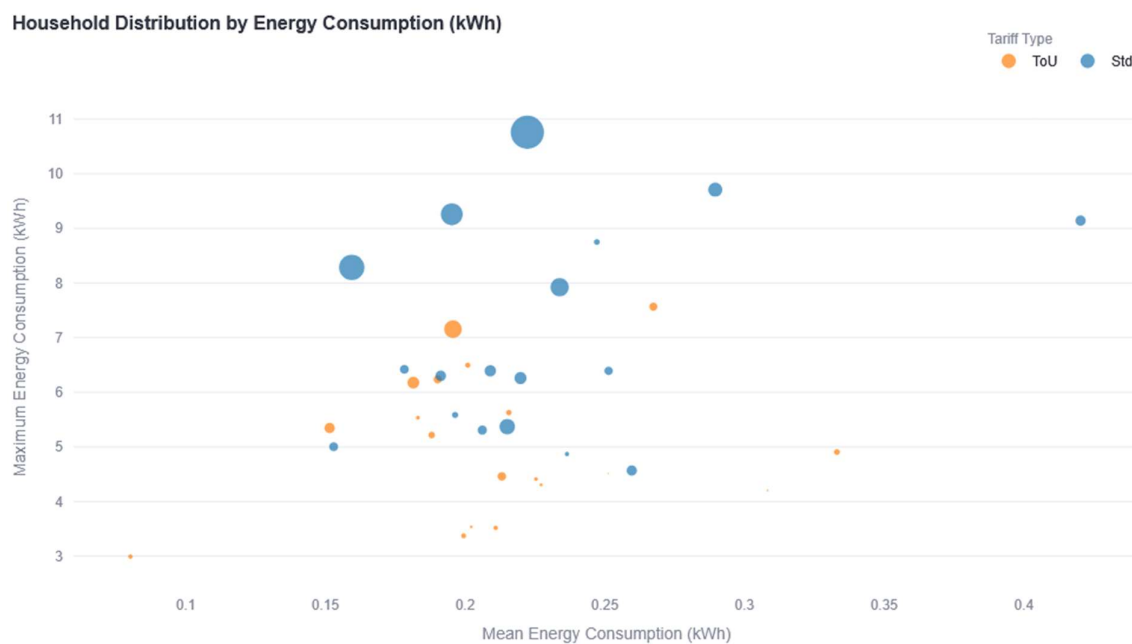
Mean and Median Energy Consumption by Consumer Group
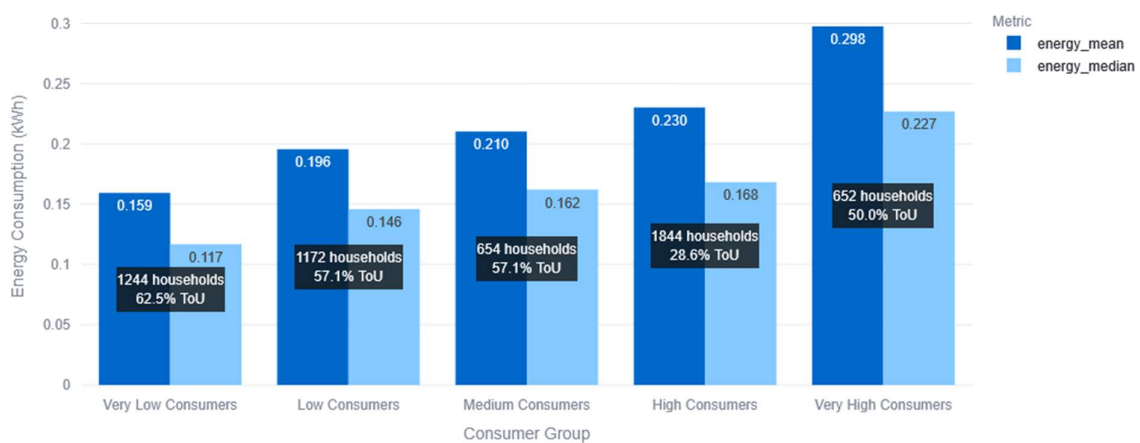
Consumption Group Insights

What you're seeing in the chart:

- The consumers are divided into quantile groups based on their energy consumption
- Each bar shows the average consumption metrics for households in that group
- The annotations show how many households are in each group and what percentage use Time-of-Use tariffs

Key observations:

- **ToU adoption pattern**: Lower consumers tend to have higher Time-of-Use tariff adoption (possibly more cost-conscious consumers)
- **Distribution skew**: The data shows that most households in low to medium consumption ranges and fewer very high consumers

Household Distribution by Energy Consumption (kWh)

Household Distribution Insights

What you're seeing in the chart:

- Each point represents a group of households with the same ACORN group and tariff type
- The position shows their mean and median/maximum energy consumption
- The size of each bubble indicates how many households are in that group
- Colors differentiate between tariff types or ACORN groups

**Key observations:**

- **Correlation patterns**: There's a strong positive correlation between mean and median/maximum consumption metrics
- **Tariff clustering**: Time-of-Use (ToU) households tend to cluster in lower consumption regions compared to Standard tariff households
- **ACORN segregation**: Clear separation of ACORN groups, with Affluent (A-E) consistently in higher consumption regions

- **Outlier behavior**: Some household groups show unusually high maximum consumption despite moderate mean values, indicating occasional high usage spikes

Weather impact

Temperature vs Mean Energy Consumption
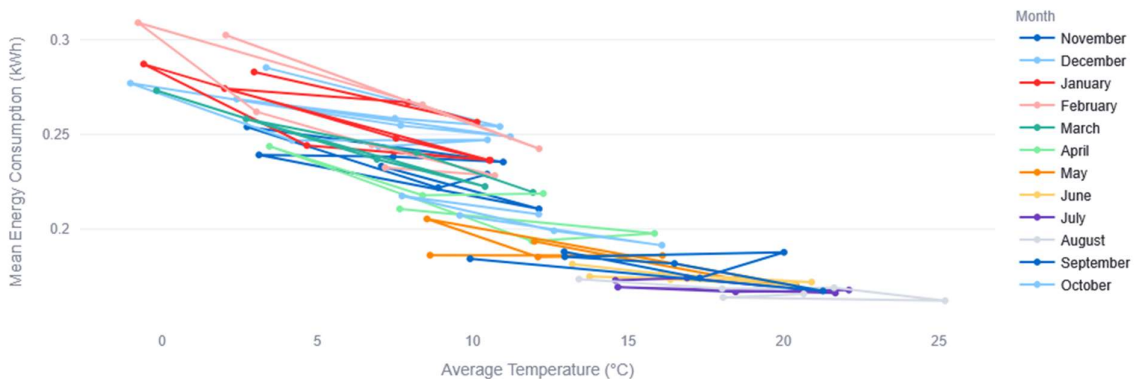
Monthly Mean Energy by Temperature Bin

Daily Temperature Impact Insights
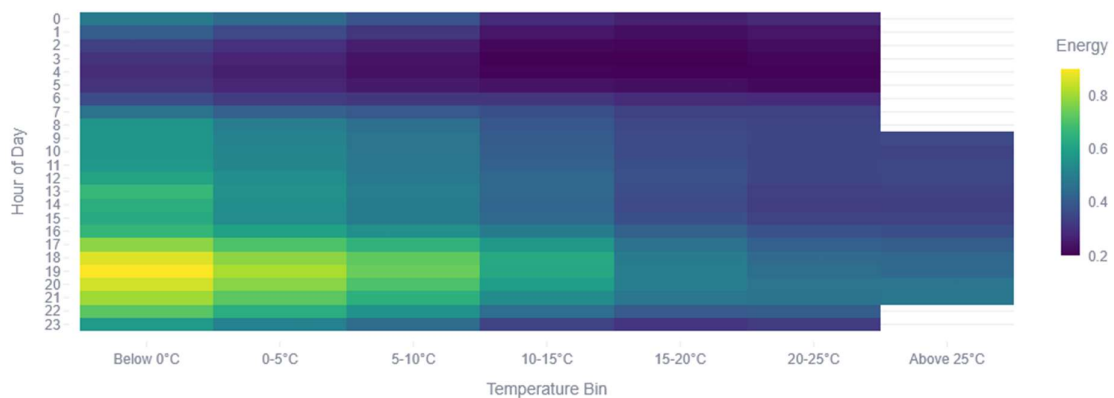**What you're seeing in the charts:**
- The line chart shows how average energy consumption varies with temperature
- The box plot displays the consumption distribution within each temperature range
- The month comparison reveals seasonal patterns across different temperature bins

Key observations:
- **U-shaped consumption curve**: Energy usage is highest at temperature extremes (below 0°C) and lowest in the 15-20°C range, creating a distinctive U-shaped pattern
- **Cold temperature sensitivity**: Below 0°C, energy consumption increases dramatically to 0.46-0.60 kWh (mean), nearly double the consumption in the optimal 15-20°C range (0.25-0.30 kWh)

- **Seasonal transitions**: The months of November and March show particularly volatile consumption patterns as households transition between heating and non-heating periods
- **Monthly variation**: Winter months (December-February) consistently show 20-30% higher energy consumption than summer months (June-August) across all temperature bins
- **Temperature bin distribution**: The 5-10°C and 10-15°C ranges contain the highest number of observations, representing the most common temperature conditions in this climate region

Hourly Energy Consumption by Temperature Bin

Hourly Energy Consumption by Temperature Bin
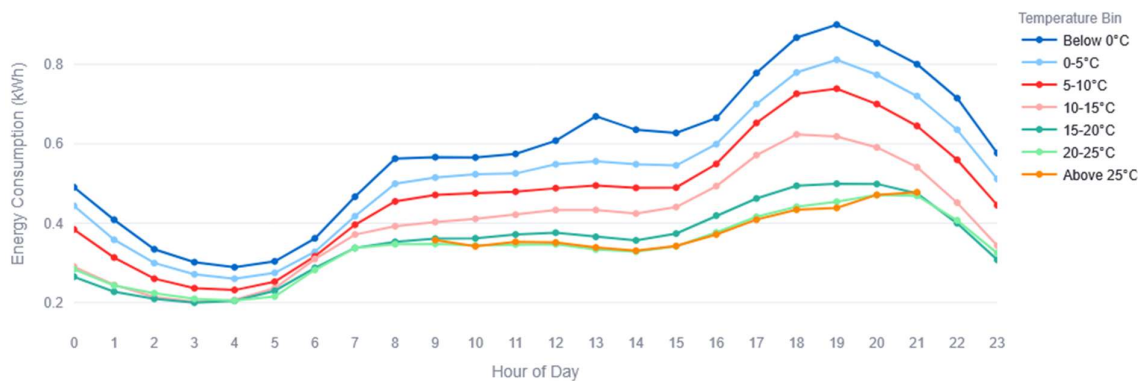
Hourly Temperature Impact Insights

What you're seeing in the charts:
- The heatmap shows how energy consumption varies by hour and temperature bin
- The line chart displays hourly consumption patterns for different temperature ranges

Key observations:

- **Evening peak intensity**: The highest energy consumption occurs between 18:00-19:00 (6-7 PM), with below-freezing temperatures showing consumption spikes up to 0.90 kWh, compared to only 0.45-0.50 kWh during the same hours in the 15-20°C range
- **Morning peak patterns**: A secondary consumption peak appears between 7:00-9:00 AM, with cold temperatures (<5°C) showing consumption of 0.45-0.50 kWh versus 0.33-0.35 kWh in moderate temperatures
- **Overnight efficiency**: Between 2:00-4:00 AM, energy consumption reaches its lowest point (0.20-0.30 kWh) and shows minimal temperature sensitivity
- **Temperature threshold effect**: Below 5°C, each degree drop increases consumption by approximately 0.02-0.03 kWh per hour, with the effect amplified during peak hours

Hidden insights overall

1. Temperature Consumption Amplification

Finding: Energy spikes aren't linear with temperature drops - they follow exponential curves during evening peaks (17-20h). **Hidden Insight**: Heating systems compound with social energy use, creating predictable "super peaks." **Monetization**:
- Sell temperature-triggered demand forecasts to energy traders ($100K+ annual contracts)
- Partner with smart thermostat companies for "social heating" algorithms
- Develop "weather-driven surge pricing" alerts for consumers

2. The Sunday Energy Premium

Finding: Sunday consumption is 8-12% higher than other days, but maximum spikes occur on Tuesdays/Wednesdays. **Hidden Insight**: Weekend energy is sustained/planned; weekday spikes are chaotic/unplanned. **Monetization**:
- Create "Weekend Energy Plans" with utilities
- Develop "Chaos Spike" insurance products for commercial users
- License "Social Energy Patterns" data to appliance manufacturers

3. Affluent Energy Elasticity

Finding: ACORN-A (Affluent) shows highest consumption but lowest price sensitivity to tariff changes. **Hidden Insight**: Premium energy services market is underserved - they'll pay for convenience, not savings. **Monetization**:
- Launch "Energy Concierge" service ($200-500/month) for affluent households
- Partner with luxury home builders for "Energy Status" features
- Create premium energy analytics dashboards ($50-100/month)

Machine Learning

As the final part of our analysis, we developed and implemented a machine learning system capable of detecting abnormal energy consumption patterns in households. This system allows us to identify whether a household's energy use on a given day follows a typical pattern or deviates significantly, potentially signaling unusual behavior or appliance usage.

Objective

The goal was to use historical energy consumption data to build a model that can learn what "normal" daily consumption looks like for each household. The model should be able to flag days where the actual consumption differs significantly from what is expected.

Model Overview

We used a deep learning technique called an autoencoder, implemented in PyTorch, to analyze daily energy consumption patterns. The autoencoder is a neural network trained to compress and then reconstruct the input data. If the reconstruction is accurate, the input is considered normal. High reconstruction errors indicate abnormal days.

To improve precision, we trained separate models for each ACORN group. This allows the model to focus on patterns typical of similar households (e.g., affluent, moderate-income, or low-income households), reducing noise caused by very different lifestyles and consumption habits across groups.

Input and Output

Each model takes as input a sequence of 48 values representing a household's energy consumption at half-hour intervals throughout a single day.

Additional metadata:

- Day of the week (0 for Monday to 6 for Sunday)
- Weekend indicator
- Season (Winter, Spring, Summer, Fall)
- Average daily temperature

The model then outputs a reconstructed version of the input: what it predicts the energy usage should have looked like under normal conditions for that household profile.

How Abnormality Is Detected

We compare the predicted (reconstructed) energy values to the actual observed values. If the difference between them (the reconstruction error) is small, the day is considered

normal. If there are large differences at certain time slots, those slots are flagged as anomalous.

This method is unsupervised – it doesn't require labeled data or predefined abnormal events. Instead, it learns what is usual and highlights deviations.

**Real-Time Usage**

Using this system, we can now:

- Choose any household
- Pick a specific day
- View both the predicted and actual consumption
- Identify which parts of the day had unusual consumption

For example, a spike in consumption in the evening that significantly exceeds the expected range may indicate unusually high appliance usage or guests.

Example Insight

For a randomly selected household from the Adversity group, the model generally predicts daily energy consumption with high accuracy. On most time slots, the predicted and actual usage lines align closely, indicating typical behavior. However, on this day, two clear anomalies are detected at 13:30 and 20:30. During these half-hour intervals, the actual consumption significantly exceeds the predicted values, surpassing the model's anomaly threshold. These deviations are visually highlighted with yellow boxes, making it easy to spot abnormal consumption periods within an otherwise normal-looking day.

Autoencoder Reconstruction (Example #73901)
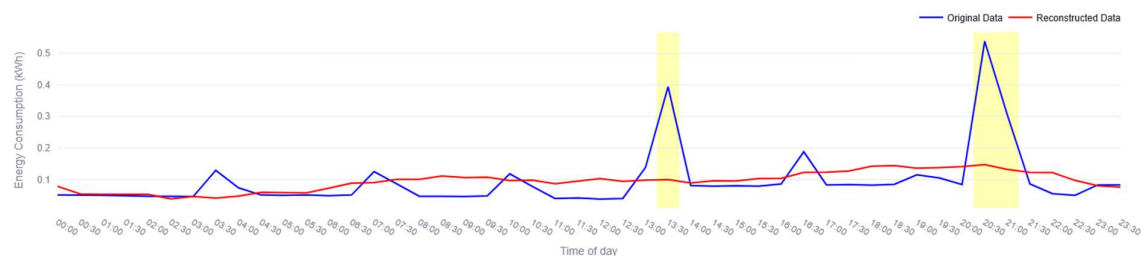
Benefits

This approach provides a data-driven way to:

- Detect behavior changes without human labeling
- Understand energy consumption within social/demographic context

- Identify inefficiencies or potential technical faults early

It can be used by utility companies, researchers, or even consumers to track, analyze, and optimize energy use in a personalized and intelligent manner.