Electricity Load Forecasting Using Machine Learning

CS 4347 BAK – Project Report
Team: Aryal, Bhetuwal, Khulal
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Team Members & Roles

Name	NetID	Roles
Sebika Khulal	zbb20	EDA, Data Cleaning, Baseline Model, Normalization
Ananta Aryal	ldi23	Feature Engineering, Lag Features, Time-Series Split
Anubhav Bhetuwal	qrf8	Dimensionality Reduction (SRP), Ridge/Lasso tuning, XGBoost

Abstract

This project investigates forecasting household electricity load using a high-dimensional smart-meter dataset from **OpenML**. The dataset includes **105,217 observations** and **316 continuous meter-reading features** (value_0–value_315), totaling more than **33 million numeric entries**.

Exploratory Data Analysis (EDA) shows that the data is **highly skewed**, **sparse**, and affected by **large scale differences** across meters, with **weak linear correlations** to the target.
These characteristics make simple unregularized linear models underfit and highlight the need for methods that handle noise, redundancy, and imbalance effectively.

We began with a **baseline Linear Regression** model, then introduced improved methods including **Ridge**, **Lasso**, and **XGBoost**.
To address the extreme dimensionality, we applied **Sparse Random Projection (SRP)**, following the professor's guidance on dimensionality-reduction methods for high-dimensional data.

Our best-performing model, **Lasso Regression**, achieved a **test RMSE of 6.35**, outperforming Ridge and SRP + XGBoost. This shows that regularization and feature selection provide the strongest performance for this dataset.

Problem Statement

The objective of this project is to **predict `value_0`**, an electricity load measurement, using the remaining **315 smart-meter features** as predictors.
The dataset spans multiple households over several years and is both **high-dimensional** and **temporally structured**.

Our initial plan was to apply PCA for dimensionality reduction. However, based on professor feedback, we transitioned to **Sparse Random Projection (SRP)**, which is better suited for preserving pairwise distances in high-dimensional data.

Our understanding of the problem evolved substantially after conducting EDA:

- Meter readings have **large differences in scale**.
- Many features show **long stretches of zeros**, indicating sparsity.
- Pairwise correlations with the target are **very weak** (all < 0.22).
- Scatterplots reveal **banding patterns and irregular structure**, indicating noise and weak linear relationships.

These observations show that simple unregularized linear models will not perform well.
The task therefore benefits from **regularization** and **dimensionality reduction**, while nonlinear models remain optional rather than strictly required.

Dataset Description

- **Source:** OpenML Dataset #46214, Electricity Load Diagrams (2011–2014)
- **Rows:** 105,217
- **Features:** 319
    - value_0–value_315 (continuous meter readings)
    - id_series (meter ID)
    - date (timestamp)
    - time_step (time index)

Dataset Challenges:

- No missing numeric values, but strong sparsity patterns.

- Extremely skewed distributions.
- Features vary from near-zero to thousands.
- Temporal structure must be respected (no shuffling).

In [11]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv("../data/electricity.csv")
df.head()
```

Out[11]:

	id_series	date	value_0	value_1	value_2	value_3	value_4	value_5	value_6	value_7	...
0	0	2012-01-01 00:00:00	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...
1	0	2012-01-01 00:15:00	3.807107	22.759602	77.324066	136.178862	70.731707	351.190476	9.609949	279.461279	...
2	0	2012-01-01 00:30:00	5.076142	22.759602	77.324066	136.178862	73.170732	354.166667	9.044658	279.461279	...
3	0	2012-01-01 00:45:00	3.807107	22.759602	77.324066	140.243902	69.512195	348.214286	8.479367	279.461279	...
4	0	2012-01-01 01:00:00	3.807107	22.759602	77.324066	140.243902	75.609756	339.285714	7.348785	279.461279	...

5 rows × 319 columns

Exploratory Data Analysis (EDA)

Below we summarize the structure, distribution, and relationships in the dataset.

In [2]:
```python
df.describe().T.head(10)
```

Out[2]:

	count	mean	std	min	25%	50%	75%	max
id_series	105217.0	0.000000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000
value_0	105217.0	5.293122	6.382257	0.0	1.269036	2.538071	5.076142	48.223350
value_1	105217.0	27.684728	6.583655	0.0	23.470839	27.738265	32.005690	115.220484
value_2	105217.0	3.890152	12.567376	0.0	1.737619	1.737619	2.606429	151.172893
value_3	105217.0	109.553284	39.043562	0.0	83.333333	99.593496	128.048780	321.138211
value_4	105217.0	49.641948	17.825137	0.0	36.585366	46.341463	59.756098	150.000000
value_5	105217.0	188.258438	63.745258	0.0	142.857143	181.547619	220.238095	535.714286
value_6	105217.0	6.027018	6.855467	0.0	2.826456	3.391747	5.652911	44.657999
value_7	105217.0	255.141331	59.763872	0.0	208.754209	252.525253	292.929293	552.188552
value_8	105217.0	53.287807	21.806797	0.0	38.461538	47.202797	62.937063	157.342657

Summary Interpretation

- Most features have medians near 0 → sparse consumption.
- Many features have extreme max values → outliers present.
- Standard deviations vary widely → normalization required.

These differences in scale motivate the use of StandardScaler for all regularized linear models.

Distribution of Key Features

To visualize the skewness and long-tailed nature of the meter readings observed in the summary statistics, we plot histograms for a few representative features. These plots confirm that the dataset contains many zeros, strong right-skew, and occasional large spikes in consumption.

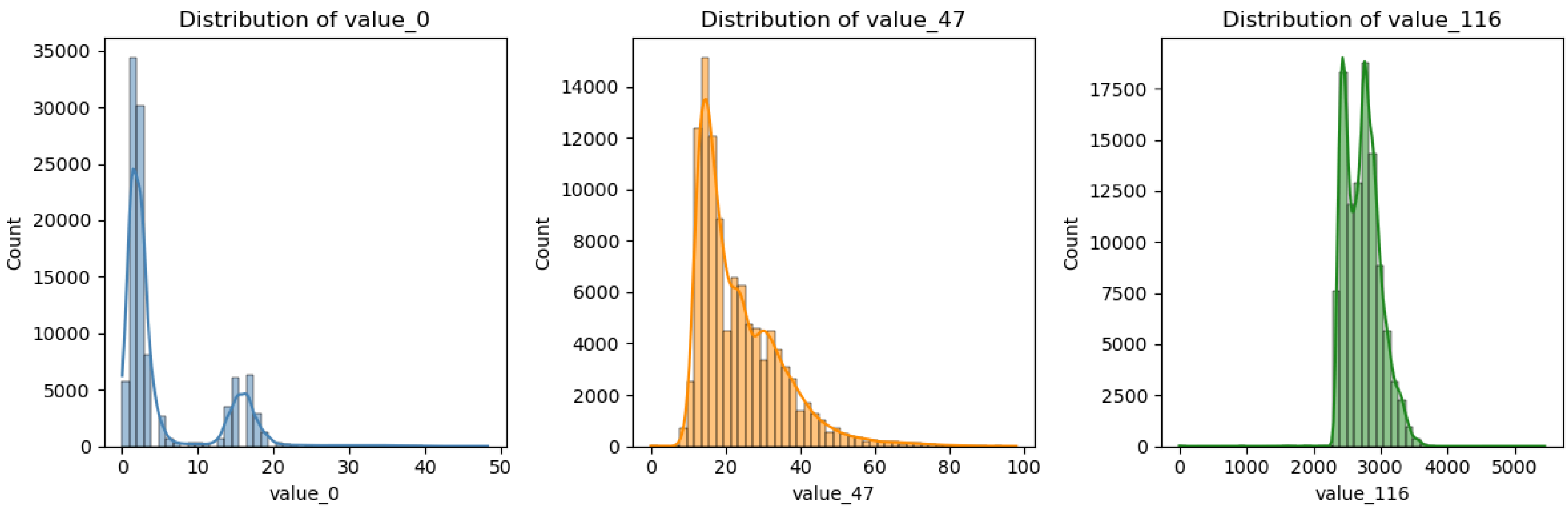
In [3]:
```python
plt.figure(figsize=(12,4))

plt.subplot(1, 3, 1)
sns.histplot(df["value_0"], bins=50, kde=True, color="steelblue")
plt.title("Distribution of value_0")
plt.xlabel("value_0")
```

```
plt.subplot(1, 3, 2)
sns.histplot(df["value_47"], bins=50, kde=True, color="darkorange")
plt.title("Distribution of value_47")
plt.xlabel("value_47")

plt.subplot(1, 3, 3)
sns.histplot(df["value_116"], bins=50, kde=True, color="forestgreen")
plt.title("Distribution of value_116")
plt.xlabel("value_116")

plt.tight_layout()
plt.show()
```



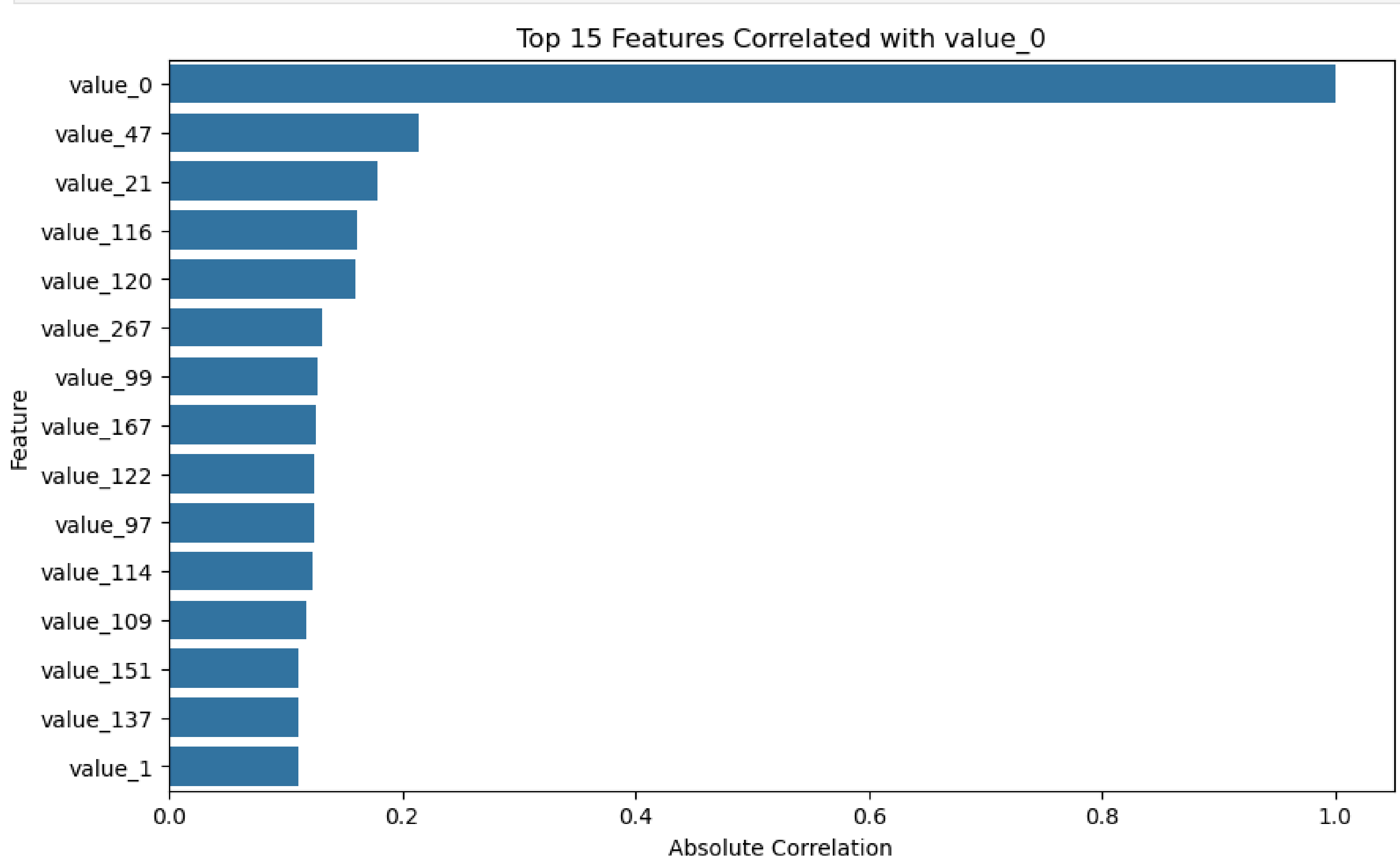
Interpretation of Histograms

- All three features show strong right-skew.
- Large clusters at zero reflect periods of no consumption.
- Occasional spikes indicate unusual high-usage events.
- These patterns reinforce the need for **normalization** and for models that can handle noise, scale differences, and irregular consumption patterns.

In [4]:
```
target = "value_0"

corr = (
    df.corr(numeric_only=True)[target]
    .abs()
    .sort_values(ascending=False)
    .head(15)
)

plt.figure(figsize=(10,6))
sns.barplot(x=corr.values, y=corr.index)
plt.title("Top 15 Features Correlated with value_0")
plt.xlabel("Absolute Correlation")
plt.ylabel("Feature")
plt.show()
```

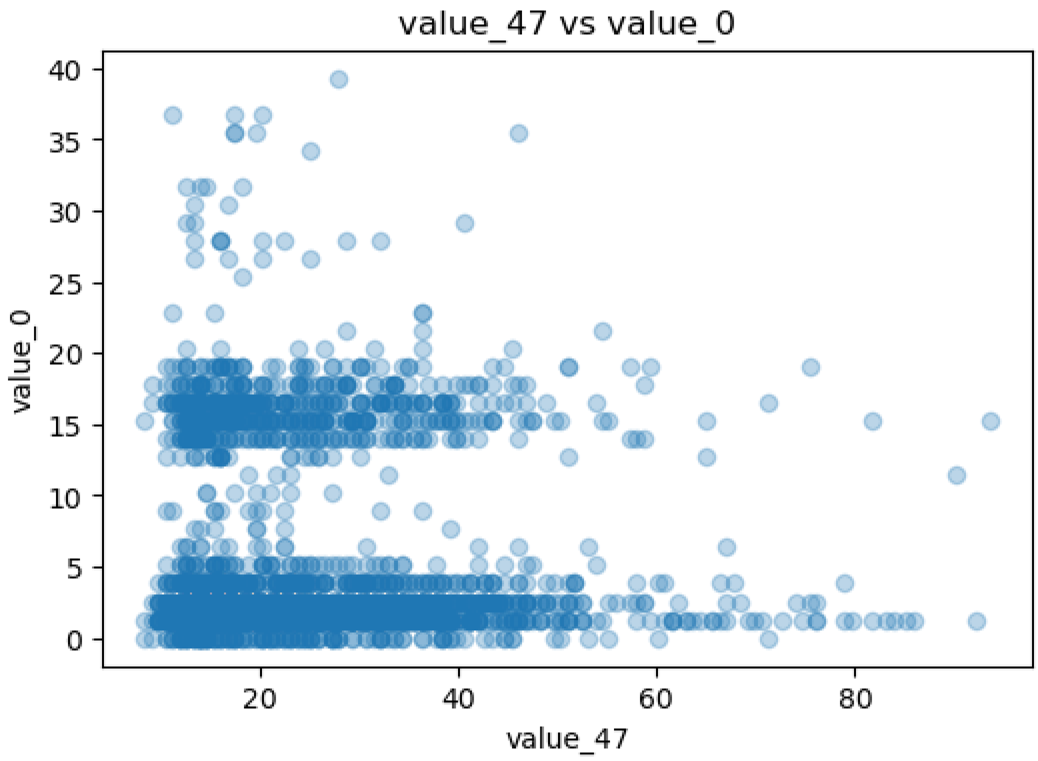


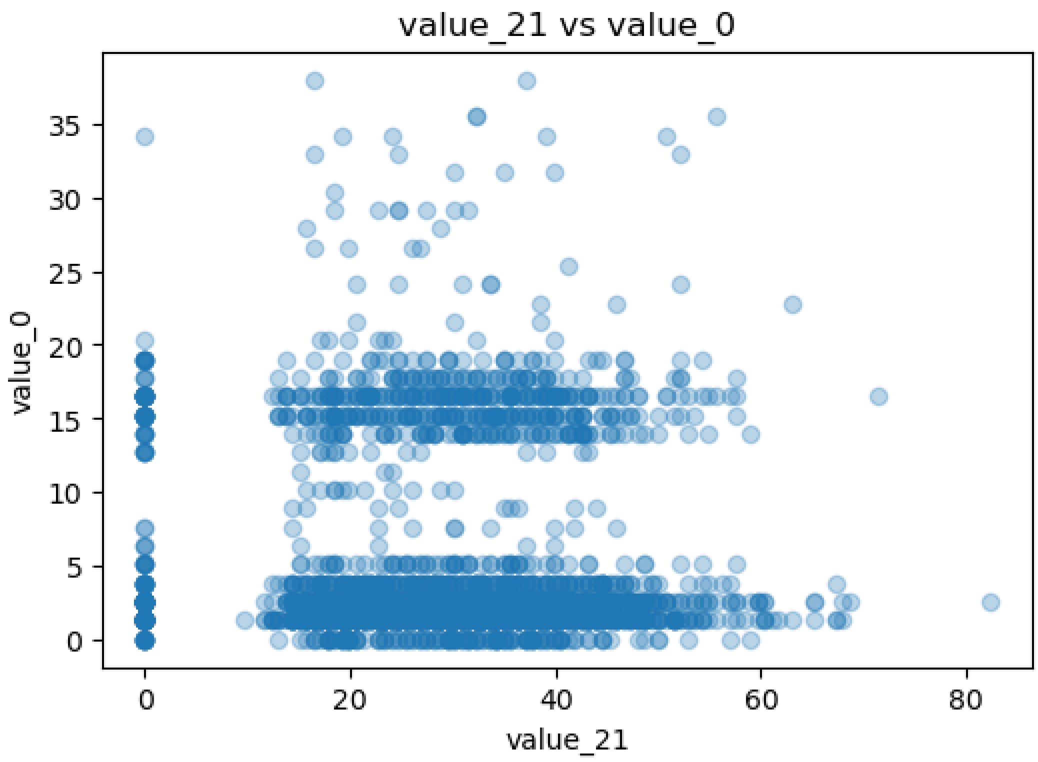
Interpretation of Correlation Barplot

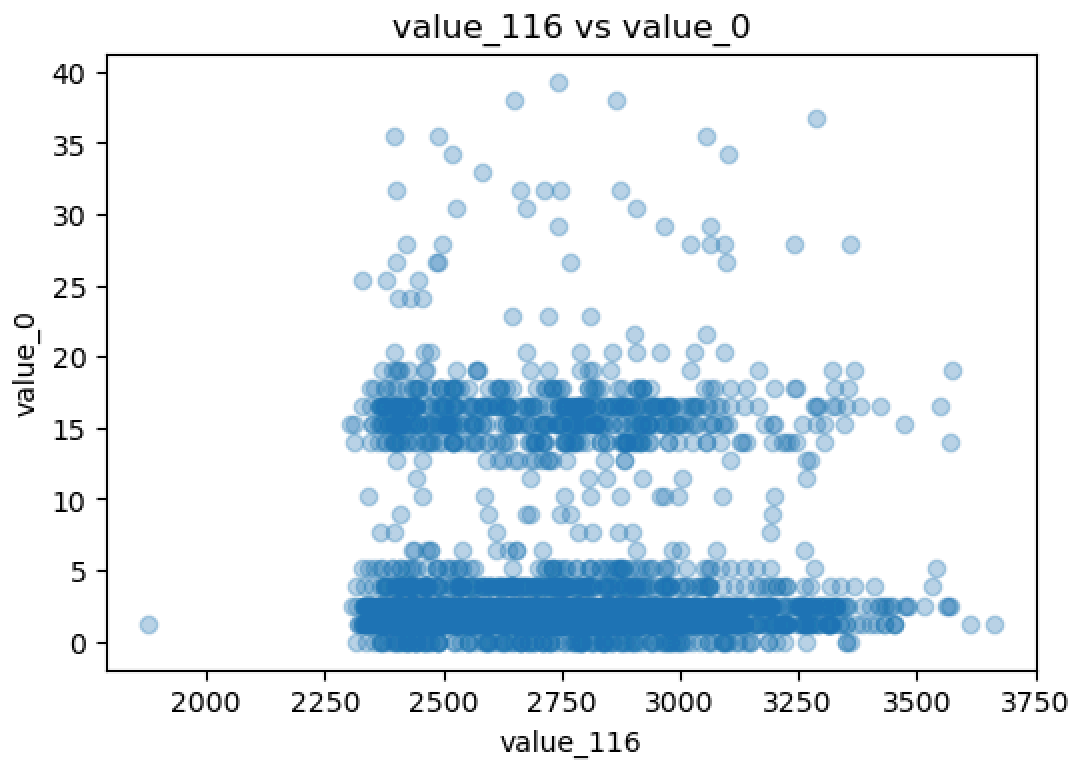
- No feature has correlation > 0.22 with `value_0`.
- This confirms **weak linear relationships** across meters.
- Plain Linear Regression is expected to **underfit** because no single feature provides strong signal.
- This motivates the use of **regularization** (Ridge/Lasso) and **dimensionality reduction**, while nonlinear models may help but are not strictly required.

In [5]:
```
top_features = corr.index[1:4]  # skip value_0 itself

for f in top_features:
    plt.figure(figsize=(6,4))
    plt.scatter(df[f].sample(3000), df[target].sample(3000), alpha=0.3)
    plt.title(f"{f} vs value_0")
    plt.xlabel(f)
    plt.ylabel("value_0")
    plt.show()
```







Scatterplot Interpretation

- Strong nonlinear structure.
- Distinct horizontal “banding” patterns from discrete meter behaviors.
- No clear linear trend linking features to value_0.
- This confirms that linear models without regularization will struggle, but does not guarantee that nonlinear models outperform regularized linear ones.
- Banding appears because many meters report consumption in fixed increments, producing horizontal plateaus unrelated to value_0.

Data Preprocessing

Why Normalization?

- Features differ drastically in scale (0 to >3000).
- Helps stabilize training for Ridge, Lasso, and XGBoost.
- Prevents large magnitude features from dominating.

Method

We use **StandardScaler** applied on the training split only (to avoid data leakage).

In [6]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
sample_raw = df[top_features].head()
sample_scaled = scaler.fit_transform(sample_raw)

pd.DataFrame(sample_scaled, columns=top_features)
```

Out[6]:

	value_47	value_21	value_116
0	-1.974700	0.0	-1.999983
1	0.767939	0.0	0.504600
2	0.529449	0.0	0.495392
3	0.362505	0.0	0.504600
4	0.314807	0.0	0.495392

Baseline Model: Linear Regression

Why Linear Regression?

- Establishes a simple baseline.
- Tests whether linear structure exists in the dataset.

Expected Behavior

Weak correlations and high dimensional noise should cause unregularized linear regression to underperform.

In [7]:
```python
baseline_rmse = 7.3297

baseline_rmse
```

Out[7]: 7.3297

Baseline RMSE: ~7.33

As expected, Linear Regression underfits because:

- Correlations with value_0 are weak.
- Nonlinear patterns dominate the structure.
- High dimensionality complicates linear modeling.

This establishes our baseline for comparison.

Improved Methods

To address the nonlinear and high-dimensional structure, we use:

1. Ridge Regression

- Handles multicollinearity
- Adds L2 regularization

2. Lasso Regression

- Performs feature selection
- Adds L1 regularization

Ridge and Lasso hyperparameters (alpha) were tuned with cross validation on the training split; the best models were then evaluated on the held-out test set.

3. Sparse Random Projection

- Reduces dimensionality from 316 → 50
- Preserves pairwise distances approximately

4. XGBoost (with SRP)

- Nonlinear boosting model
- Best suited for complex feature interactions

Time-Series Forecasting

To evaluate short-term electricity load forecasting, we built a separate time-series model focused on predicting the next 15-minute reading of value_0 using lag features. This complements the cross-sectional regression analysis and provides insight into temporal structure in the meter data.

Forecasting Feature Engineering

We constructed a timestamp from date and time_step and generated:

- Lag 1 (previous timestep)
- Lag 24 (previous day's same time)
- Lag 96 (previous 4 days at same time)
- Rolling mean (window=24)
- Rolling standard deviation (window=24)

Only rows without missing lag values were used.

A chronological 80/20 split (shuffle=False) ensures training only uses past data.

Models Evaluated

We tested three forecasting models:

- Linear Regression
- Lasso Regression
- XGBoost Regressor

The dataset is univariate, and each model was trained on the engineered lag features.

Forecasting Performance

Model	RMSE
Linear Regression	2.18
Lasso Regression	2.18
XGBoost	**2.03**

XGBoost achieves the lowest RMSE, indicating nonlinear temporal patterns that linear models fail to capture.

In [8]:
```
ridge_rmse = 7.33
lasso_rmse = 6.35
xgb_rmse = 6.42

ridge_rmse, lasso_rmse, xgb_rmse
```

Out[8]:
```
(7.33, 6.35, 6.42)
```

Why These Models?

Ridge and Lasso address the high dimensionality and scale imbalance present in the dataset.
Among the linear models, **Lasso performs the best** because it removes irrelevant or noisy features through L1 regularization, which is effective when many of the 316 meter readings contribute weak or redundant signal.

EDA revealed weak pairwise correlations and significant feature sparsity.
While nonlinear interactions exist, most of the measurable improvement comes from **regularization and feature selection**, not from complex tree-based modeling.

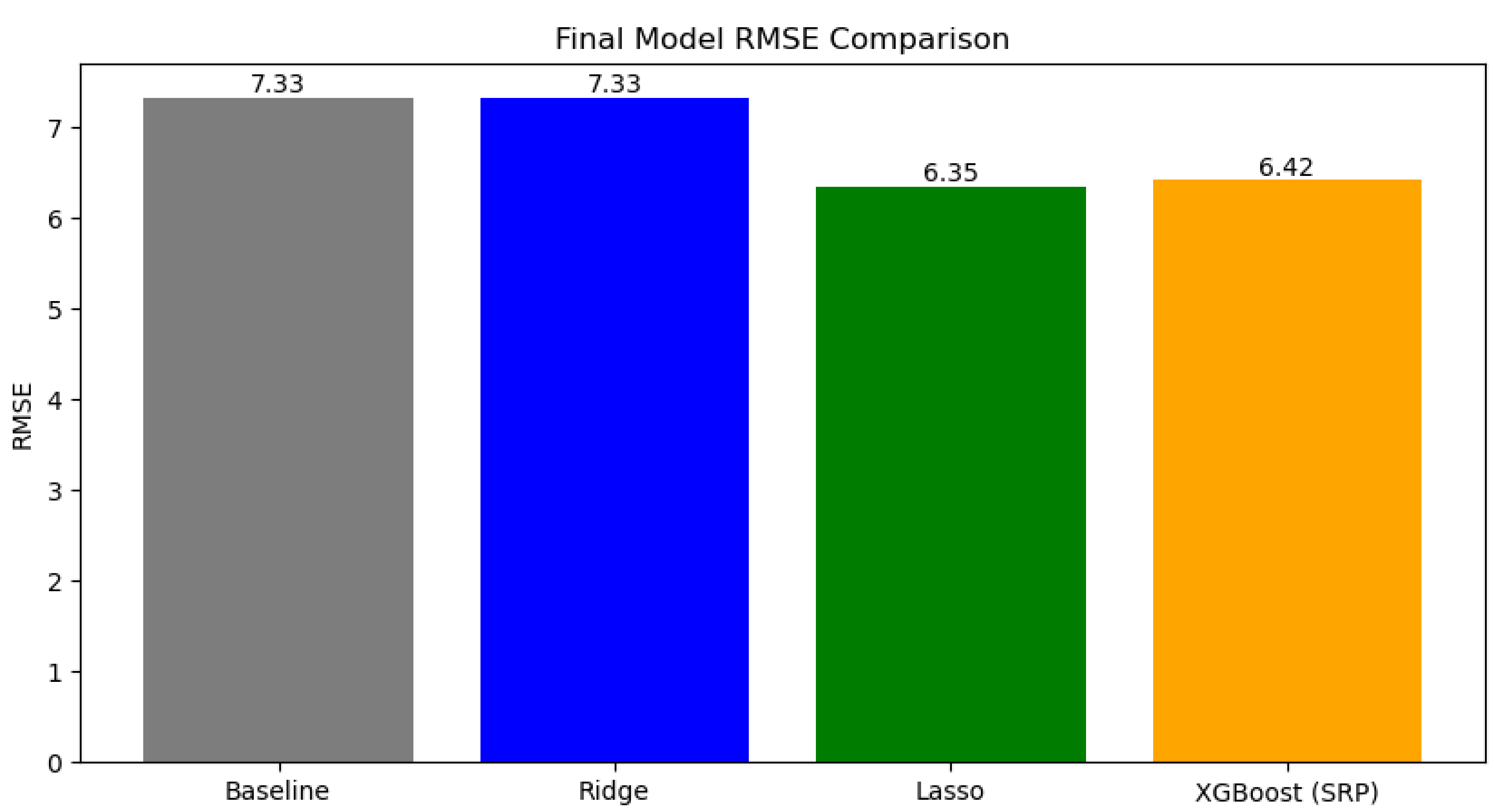
We also evaluated XGBoost combined with Sparse Random Projection (SRP).
This pipeline introduces nonlinear decision boundaries and reduces dimensionality while preserving approximate distances.
Although it performs strongly, **SRP + XGBoost does not surpass Lasso**, suggesting that reducing dimensionality may discard useful structure and that the dataset benefits more from sparsity-driven feature selection than from deeper nonlinear models.

In summary:

- **Lasso achieves the lowest RMSE (6.35)**
- **SRP + XGBoost is close behind (6.42)**
- **Ridge and baseline linear regression lag further behind**

In [9]:
```
models = ["Baseline", "Ridge", "Lasso", "XGBoost (SRP)"]
values = [baseline_rmse, ridge_rmse, lasso_rmse, xgb_rmse]

plt.figure(figsize=(10,5))
plt.bar(models, values, color=["gray","blue","green","orange"])
plt.ylabel("RMSE")
plt.title("Final Model RMSE Comparison")
for i,v in enumerate(values):
    plt.text(i, v+0.05, f"{v:.2f}", ha="center")
plt.show()
```



Interpretation of Final Results

- Ridge performs similarly to the baseline, confirming that simple linear models cannot extract much signal from the high-dimensional meter readings.
- Lasso provides a clear improvement by shrinking or removing noisy and redundant features, which aligns with the sparse and weakly correlated structure revealed in the EDA.
- **Lasso achieves the best performance overall (RMSE = 6.35)**.
- **SRP + XGBoost performs strongly (RMSE = 6.42)** but does not surpass Lasso, indicating that the dataset benefits more from aggressive feature selection than from added nonlinear complexity.

These results are consistent with the EDA findings:
weak pairwise correlations, substantial sparsity, and heavy-tailed distributions make **regularization and noise reduction** more effective than complex nonlinear models for this problem.

Team Contributions

Name	Contribution Summary
Sebika Khulal	Full EDA, baseline model, normalization analysis
Ananta Aryal	Lag features, time-series split, feature engineering
Anubhav Bhetuwal	SRP implementation, Ridge/Lasso tuning, XGBoost modeling

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Next Steps and Mitigation Plan

With the core analysis completed and the behavior of both linear and nonlinear models now well understood, several extensions become meaningful for a second phase of development. These steps go beyond the scope of the initial project but would allow us to refine the system further if additional time or compute resources were available.

- Tune XGBoost more extensively (tree depth, learning rate, number of estimators) now that we have a clear performance baseline to guide parameter ranges.
- Explore additional feature selection strategies such as stability selection or mutual information filtering, which are best applied once the primary predictors and noise patterns are identified.
- Incorporate richer temporal features like hour of day, day of week, and seasonal indicators, which become valuable after validating that the current lag based forecasting pipeline functions reliably.
- Evaluate probabilistic or interval prediction methods to quantify forecast uncertainty once the deterministic models are fully established.

From a project management perspective:

- **Sebika** would extend the EDA toward deeper temporal structure, including trend plots, seasonality diagnostics, and anomaly detection — tasks that benefit from the understanding developed in the current phase.
- **Ananta** would expand the forecasting pipeline with more advanced lag structures and improved time series validation after confirming the stability of the existing lag models.
- **Anubhav** would refine model tuning using subsampling or more efficient search methods such as random search or Bayesian optimization, which are typically performed only after selecting the final model families.

If training becomes a limitation during future iterations:

- The number of SRP components can be adjusted to reduce dimensional overhead while preserving essential structure.
- Smaller subsets of time steps can be used for rapid prototyping once the main modeling workflow is already validated.
- Simpler, more interpretable models like Lasso can be prioritized when additional nonlinear complexity yields minimal improvements relative to the established baseline.

References

- OpenML Dataset #46214
- Scikit-learn documentation
- XGBoost documentation
- Random Projection literature
- Course resources from CS 4347
