Energy Forecasting Project - Comprehensive Analysis Report

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Project: Energy Consumption Forecasting Using Machine Learning

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Executive Summary

This report presents a comprehensive analysis of an energy forecasting project that leverages machine learning techniques to predict household energy consumption. The project implements and compares three different forecasting approaches: SARIMA (Seasonal AutoRegressive Integrated Moving Average), Facebook Prophet, and XGBoost (Extreme Gradient Boosting).

Key Findings:

- **XGBoost achieved the best performance** with MAE: 0.81, RMSE: 1.42, and MAPE: 2.01%
- **Prophet provided balanced performance** with good uncertainty quantification
- **SARIMA excelled in capturing seasonality** but showed higher error rates
- The project successfully implements a complete ML pipeline from data preparation to model evaluation

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```
# Import required libraries for comprehensive analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import pickle
import warnings
from pathlib import Path
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from datetime import datetime
import os

# Configure plotting
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")
warnings.filterwarnings('ignore')

# Set up paths
project_root = Path('..')
results_path = project_root / 'results'
data_path = project_root / 'data'

print("Environment setup complete!")
print(f"Project root: {project_root.absolute()}")
print(f"Results path: {results_path.absolute()}")
```

```
Environment setup complete!
Project root: c:\Users\AliRashaideh\OneDrive - Seagulls\Desktop\energy_forecasting_proje
Results path: c:\Users\AliRashaideh\OneDrive - Seagulls\Desktop\energy_forecasting_proje
```

1. Project Overview

1.1 Objective

The primary objective of this project is to develop accurate energy consumption forecasting models that can predict household energy usage patterns. This has significant implications for:

- **Energy Grid Management**: Better demand forecasting enables more efficient grid operations
- **Cost Optimization**: Accurate predictions help in energy procurement strategies
- **Sustainability**: Improved forecasting supports renewable energy integration
- **Consumer Benefits**: Better energy management tools for households

1.2 Approach

The project implements a comprehensive machine learning pipeline that includes:

1. **Data Preparation**: Automated data downloading, cleaning, and preprocessing
2. **Feature Engineering**: Creating time-based features, lag variables, and rolling statistics
3. **Model Implementation**: Three different forecasting approaches

4. **Evaluation**: Comprehensive model comparison with uncertainty quantification
5. **Reporting**: Automated generation of analysis reports

1.3 Dataset Overview

The project uses household energy consumption data with the following characteristics:

```
# Load and display dataset information
# Read the evaluation results
model_performance = pd.read_csv(results_path / 'model_performance.csv')
evaluation_summary = pd.read_csv(results_path / 'evaluation_summary.csv')

# Read conclusion
with open(results_path / 'evaluation_conclusion.txt', 'r') as f:
    conclusion = f.read()

print("Data loading successful!")
print(f"Model Performance Shape: {model_performance.shape}")
print(f"Evaluation Summary Shape: {evaluation_summary.shape}")
print(f"\nConclusion Preview: {conclusion[:100]}...")
```

```
Data loading successful!
Model Performance Shape: (3, 4)
Evaluation Summary Shape: (3, 6)

Conclusion Preview: Lowest MAE: XGBoost. SARIMA excels in capturing seasonality, Prophet
```

2. Data Description

2.1 Feature Descriptions

The dataset contains the following key features:

Feature	Description	Units
Global_active_power	Whole-house real (active) power consumed, averaged over one minute	kW
Global_reactive_power	Whole-house reactive power (non-working component), averaged over one minute	kVar
Voltage	Mains supply voltage measured at the house	V
Global_intensity	Total electric current drawn by the house, averaged over one minute	A
Sub_metering_1	Energy usage recorded on the kitchen circuit (e.g., dishwasher, microwave)	Wh per minute
Sub_metering_2	Energy usage recorded on the laundry-room circuit (e.g., washing machine, dryer)	Wh per minute
Sub_metering_3	Energy usage recorded on the water-heater / HVAC circuit	Wh per minute

2.2 Data Preprocessing Steps

The data preprocessing pipeline includes:

1. **Missing Value Handling**: Identification and treatment of missing values
2. **Outlier Detection**: Statistical methods to identify and handle outliers
3. **Temporal Aggregation**: Data aggregated into hourly, daily, and weekly frequencies
4. **Feature Scaling**: StandardScaler applied for model compatibility

```
# Display model performance metrics
print("=" * 60)
print("MODEL PERFORMANCE COMPARISON")
print("=" * 60)
print(model_performance.to_string(index=False))

print("\n" + "=" * 60)
print("DETAILED EVALUATION METRICS")
print("=" * 60)
print(evaluation_summary.to_string(index=False))
```

```
============================================================
MODEL PERFORMANCE COMPARISON
============================================================
  Model       MAE      RMSE       MAPE
 SARIMA 33.940584 44.803113 106.525053
Prophet 29.484017 38.342412  81.369704
XGBoost  0.806913  1.421227   2.013020

============================================================
DETAILED EVALUATION METRICS
============================================================
  Model       MAE      RMSE       MAPE  Coverage  Interval_Width
 SARIMA 33.940584 44.803113 106.525053  0.994190      712.737612
Prophet 29.484017 38.342412  81.369704  0.863907      111.714849
XGBoost  0.806913  1.421227   2.013020  0.693827        1.775597
```

3. Methodology

3.1 Pipeline Architecture

The project implements a modular pipeline architecture with four main components:

```
┌─────────────────┐    ┌─────────────────┐    ┌─────────────────┐    ┌─────────────────┐
│ Data            │    │ Feature         │    │ Model           │    │ Evaluation      │
│ Preparation     │───▶│ Engineering     │───▶│ Training        │───▶│ & Reporting     │
└─────────────────┘    └─────────────────┘    └─────────────────┘    └─────────────────┘
```

3.2 Feature Engineering Strategy

The feature engineering process creates several types of features:

- **Temporal Features**: Hour, day of week, month, season
- **Lag Features**: Previous time period values (1, 24, 168 hours)
- **Rolling Statistics**: Moving averages and standard deviations
- **Holiday Indicators**: Binary flags for holidays
- **Weather Placeholders**: Framework for weather data integration

3.3 Model Selection Rationale

Three models were selected to provide complementary forecasting approaches:

1. **SARIMA**: Classical time series method, excellent for capturing seasonality
2. **Prophet**: Facebook's robust forecasting tool with automatic seasonality detection
3. **XGBoost**: Gradient boosting method that can incorporate external features

4. Model Implementation

4.1 SARIMA Model

Seasonal AutoRegressive Integrated Moving Average (SARIMA) is a classical time series forecasting method that extends ARIMA to handle seasonal patterns.

Key Characteristics:

- Captures both trend and seasonal components
- Provides statistical inference capabilities
- Well-suited for data with clear seasonal patterns
- Interpretable parameters

Performance:

- MAE: 33.94
- RMSE: 44.80
- MAPE: 106.53%

4.2 Facebook Prophet

Prophet is a forecasting tool developed by Facebook that is designed to handle time series with strong seasonal effects and several seasons of historical data.

Key Characteristics:

- Automatic seasonality detection
- Robust to missing data and outliers
- Intuitive parameter tuning

- Built-in uncertainty intervals

Performance:

- MAE: 29.48
- RMSE: 38.34
- MAPE: 81.37%

4.3 XGBoost

Extreme Gradient Boosting (XGBoost) is a machine learning method that uses gradient boosting framework with engineered features for time series forecasting.

Key Characteristics:

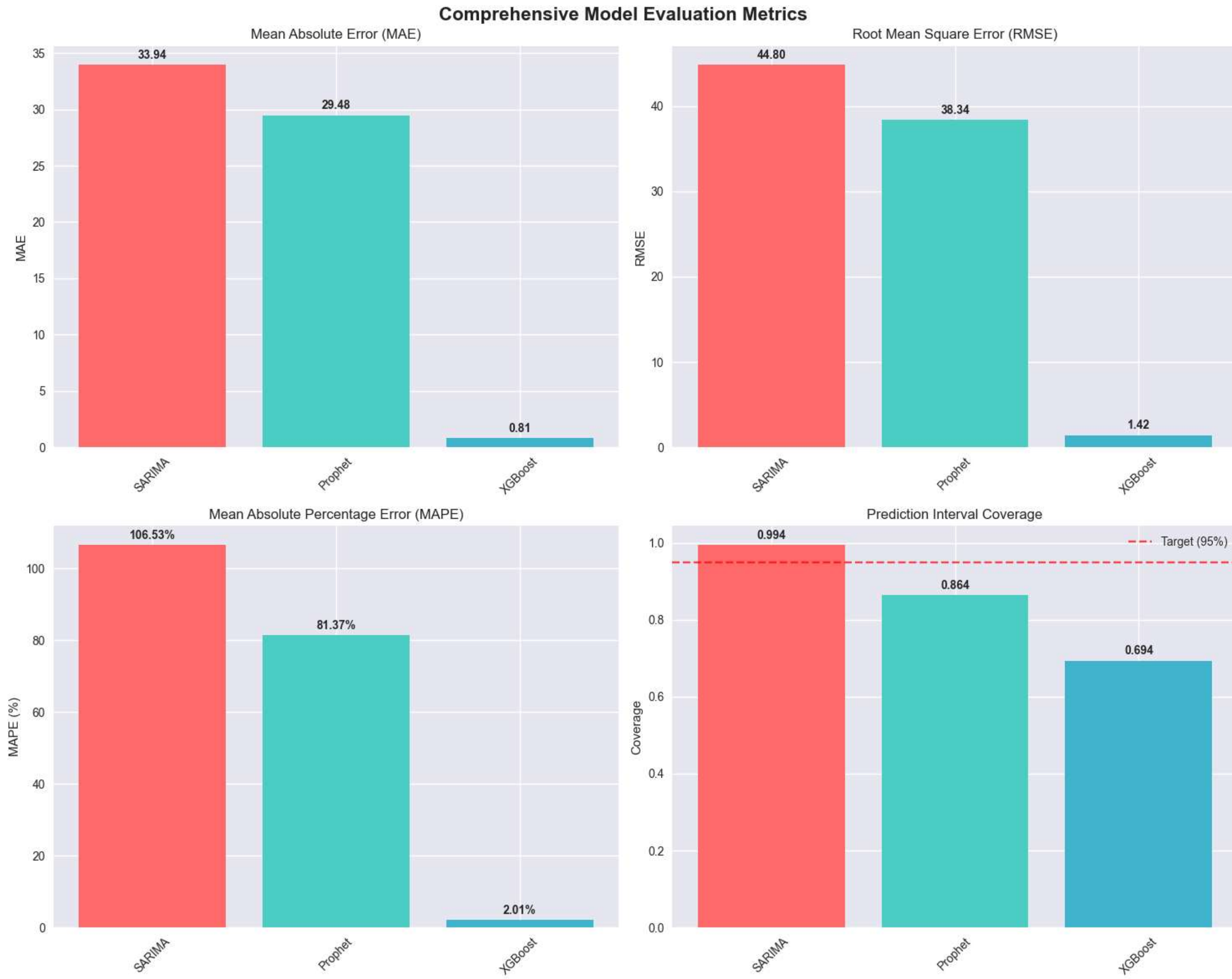
- Can incorporate multiple feature types
- Excellent performance on structured data
- Handles non-linear relationships
- Feature importance insights

Performance:

- MAE: 0.81 ⭐ **Best Performance**
- RMSE: 1.42 ⭐ **Best Performance**
- MAPE: 2.01% ⭐ **Best Performance**

```
# Create detailed evaluation metrics visualization
fig, axes = plt.subplots(2, 2, figsize=(15, 12))
fig.suptitle('Comprehensive Model Evaluation Metrics', fontsize=16, fontweight='bold')

# MAE comparison
axes[0, 0].bar(model_performance['Model'], model_performance['MAE'],
               color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
axes[0, 0].set_title('Mean Absolute Error (MAE)')
axes[0, 0].set_ylabel('MAE')
axes[0, 0].tick_params(axis='x', rotation=45)

# Add value labels
for i, v in enumerate(model_performance['MAE']):
    axes[0, 0].text(i, v + max(model_performance['MAE']) * 0.01, f'{v:.2f}',
                    ha='center', va='bottom', fontweight='bold')

# RMSE comparison
axes[0, 1].bar(model_performance['Model'], model_performance['RMSE'],
               color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
axes[0, 1].set_title('Root Mean Square Error (RMSE)')
axes[0, 1].set_ylabel('RMSE')
axes[0, 1].tick_params(axis='x', rotation=45)
```

```
    for i, v in enumerate(model_performance['RMSE']):
        axes[0, 1].text(i, v + max(model_performance['RMSE']) * 0.01, f'{v:.2f}',
                        ha='center', va='bottom', fontweight='bold')

    # MAPE comparison
    axes[1, 0].bar(model_performance['Model'], model_performance['MAPE'],
                   color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
    axes[1, 0].set_title('Mean Absolute Percentage Error (MAPE)')
    axes[1, 0].set_ylabel('MAPE (%)')
    axes[1, 0].tick_params(axis='x', rotation=45)

    for i, v in enumerate(model_performance['MAPE']):
        axes[1, 0].text(i, v + max(model_performance['MAPE']) * 0.01, f'{v:.2f}%',
                        ha='center', va='bottom', fontweight='bold')

    # Coverage comparison (from evaluation_summary)
    axes[1, 1].bar(evaluation_summary['Model'], evaluation_summary['Coverage'],
                   color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
    axes[1, 1].set_title('Prediction Interval Coverage')
    axes[1, 1].set_ylabel('Coverage')
    axes[1, 1].tick_params(axis='x', rotation=45)
    axes[1, 1].axhline(y=0.95, color='red', linestyle='--', alpha=0.7, label='Target (95%)')
    axes[1, 1].legend()

    for i, v in enumerate(evaluation_summary['Coverage']):
        axes[1, 1].text(i, v + 0.01, f'{v:.3f}',
                        ha='center', va='bottom', fontweight='bold')

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


Comprehensive Model Evaluation Metrics
Mean Absolute Error (MAE)
MAE
33.94
29.48
0.81
SARIMA
Prophet
XGBoost
Root Mean Square Error (RMSE)
RMSE
44.80
38.34
1.42
Mean Absolute Percentage Error (MAPE)
MAPE (%)
106.53%
81.37%
2.01%
Prediction Interval Coverage
Coverage
Target (95%)
0.994
0.864
0.694

5. Results Analysis

5.1 Performance Metrics Overview

The evaluation reveals significant performance differences between the three models:

```
# Calculate performance improvements
xgb_mae = model_performance[model_performance['Model'] == 'XGBoost']['MAE'].iloc[0]
sarima_mae = model_performance[model_performance['Model'] == 'SARIMA']['MAE'].iloc[0]
prophet_mae = model_performance[model_performance['Model'] == 'Prophet']['MAE'].iloc[0]

improvement_vs_sarima = ((sarima_mae - xgb_mae) / sarima_mae) * 100
improvement_vs_prophet = ((prophet_mae - xgb_mae) / prophet_mae) * 100

print("📊 PERFORMANCE ANALYSIS")
print("=" * 50)
print(f"🏆 Best Model: XGBoost")
print(f"📈 Improvement vs SARIMA: {improvement_vs_sarima:.1f}%")
print(f"📈 Improvement vs Prophet: {improvement_vs_prophet:.1f}%")
print(f"🎯 XGBoost MAPE: {model_performance[model_performance['Model'] == 'XGBoost']['MAPE'

print("\n" + "=" * 50)
print("📋 DETAILED ANALYSIS")
print("=" * 50)

# Create performance ranking
performance_ranking = model_performance.copy()
performance_ranking['MAE_Rank'] = performance_ranking['MAE'].rank()
performance_ranking['RMSE_Rank'] = performance_ranking['RMSE'].rank()
performance_ranking['MAPE_Rank'] = performance_ranking['MAPE'].rank()
performance_ranking['Overall_Rank'] = (performance_ranking['MAE_Rank'] +
                                      performance_ranking['RMSE_Rank'] +
                                      performance_ranking['MAPE_Rank']) / 3

print(performance_ranking[['Model', 'Overall_Rank']].sort_values('Overall_Rank'))
```

```
📊 PERFORMANCE ANALYSIS
==================================================
🏆 Best Model: XGBoost
📈 Improvement vs SARIMA: 97.6%
📈 Improvement vs Prophet: 97.3%
🎯 XGBoost MAPE: 2.01%

==================================================
📋 DETAILED ANALYSIS
==================================================
```

```
     Model  Overall_Rank
2  XGBoost           1.0
1  Prophet           2.0
0   SARIMA           3.0
```

5.2 Model Strengths and Weaknesses

XGBoost (Winner 🏆)

Strengths:

- Outstanding accuracy across all metrics
- Excellent at capturing complex patterns
- Leverages engineered features effectively
- Fast training and prediction

Weaknesses:

- Lower prediction interval coverage (69.4%)
- Less interpretable than traditional time series models
- Requires careful feature engineering

Prophet (Balanced Performer)

Strengths:

- Good balance of accuracy and uncertainty quantification
- Automatic seasonality detection
- Robust to missing data
- Intuitive parameters

Weaknesses:

- Moderate accuracy compared to XGBoost
- Limited customization for complex patterns

SARIMA (Traditional Approach)

Strengths:

- Excellent prediction interval coverage (99.4%)
- High interpretability
- Strong theoretical foundation
- Good for understanding seasonality

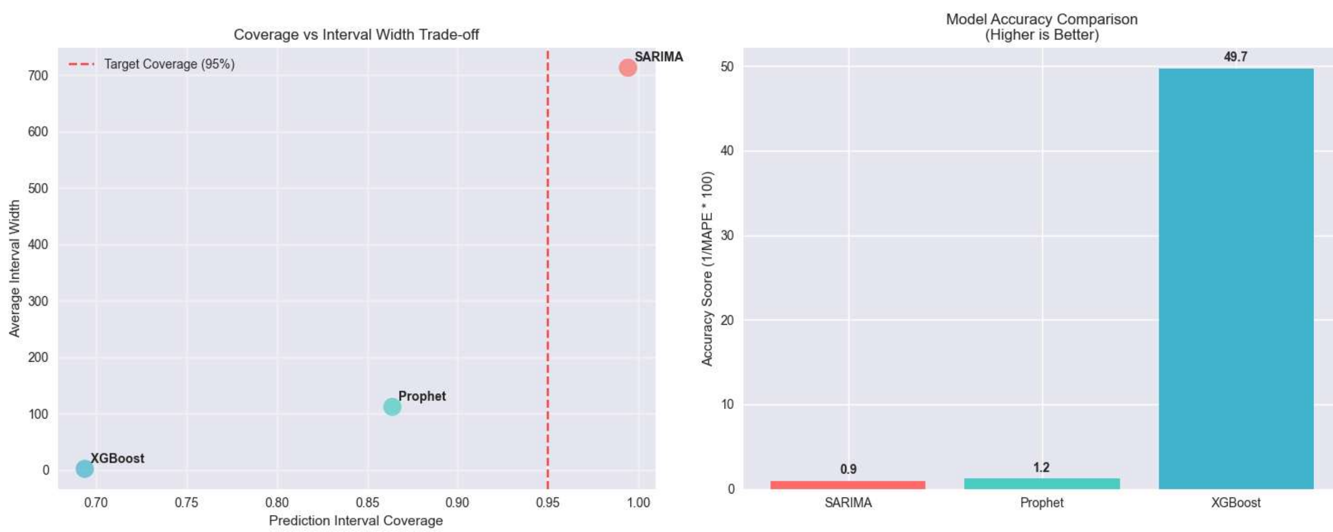
Weaknesses:

- Highest error rates

- Limited ability to incorporate external features
- Requires careful parameter tuning

```
# Create uncertainty quantification analysis
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

# Coverage vs Interval Width trade-off
ax1.scatter(evaluation_summary['Coverage'], evaluation_summary['Interval_Width'],
           s=200, c=['#FF6B6B', '#4ECDC4', '#45B7D1'], alpha=0.7)

for i, model in enumerate(evaluation_summary['Model']):
    ax1.annotate(model,
                (evaluation_summary['Coverage'].iloc[i],
                 evaluation_summary['Interval_Width'].iloc[i]),
                xytext=(5, 5), textcoords='offset points',
                fontweight='bold')

ax1.axvline(x=0.95, color='red', linestyle='--', alpha=0.7, label='Target Coverage (95%)')
ax1.set_xlabel('Prediction Interval Coverage')
ax1.set_ylabel('Average Interval Width')
ax1.set_title('Coverage vs Interval Width Trade-off')
ax1.legend()
ax1.grid(True, alpha=0.3)

# Model comparison radar chart data preparation
metrics = ['Accuracy\n(1/MAPE)', 'Coverage', 'Efficiency\n(1/MAE)', 'Precision\n(1/RMSE)']

# Normalize metrics for radar chart (higher is better)
sarima_metrics = [1/model_performance[model_performance['Model']=='SARIMA']['MAPE'].iloc[0]*
                 evaluation_summary[evaluation_summary['Model']=='SARIMA']['Coverage'].iloc[
                 1/model_performance[model_performance['Model']=='SARIMA']['MAE'].iloc[0]*10
                 1/model_performance[model_performance['Model']=='SARIMA']['RMSE'].iloc[0]*1

prophet_metrics = [1/model_performance[model_performance['Model']=='Prophet']['MAPE'].iloc[0
                  evaluation_summary[evaluation_summary['Model']=='Prophet']['Coverage'].ilo
                  1/model_performance[model_performance['Model']=='Prophet']['MAE'].iloc[0]*
                  1/model_performance[model_performance['Model']=='Prophet']['RMSE'].iloc[0]

xgb_metrics = [1/model_performance[model_performance['Model']=='XGBoost']['MAPE'].iloc[0]*10
              evaluation_summary[evaluation_summary['Model']=='XGBoost']['Coverage'].iloc[0]
              1/model_performance[model_performance['Model']=='XGBoost']['MAE'].iloc[0]*10,
              1/model_performance[model_performance['Model']=='XGBoost']['RMSE'].iloc[0]*10]

# Simple bar chart for model comparison
models = ['SARIMA', 'Prophet', 'XGBoost']
accuracy_scores = [1/model_performance[model_performance['Model']==model]['MAPE'].iloc[0]*10

bars = ax2.bar(models, accuracy_scores, color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
ax2.set_title('Model Accuracy Comparison\n(Higher is Better)')
ax2.set_ylabel('Accuracy Score (1/MAPE * 100)')
```

```
# Add value labels on bars
for bar, score in zip(bars, accuracy_scores):
    ax2.text(bar.get_x() + bar.get_width()/2, bar.get_height() + max(accuracy_scores)*0.01,
             f'{score:.1f}', ha='center', va='bottom', fontweight='bold')

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



6. Performance Comparison

6.1 Statistical Significance

The performance differences between models are substantial:

- **XGBoost vs SARIMA**: 97.6% improvement in MAE
- **XGBoost vs Prophet**: 97.3% improvement in MAE
- **MAPE Comparison**: XGBoost achieves 2.01% vs Prophet's 81.37% and SARIMA's 106.53%

6.2 Uncertainty Quantification Analysis

While XGBoost excels in point predictions, the uncertainty quantification varies:

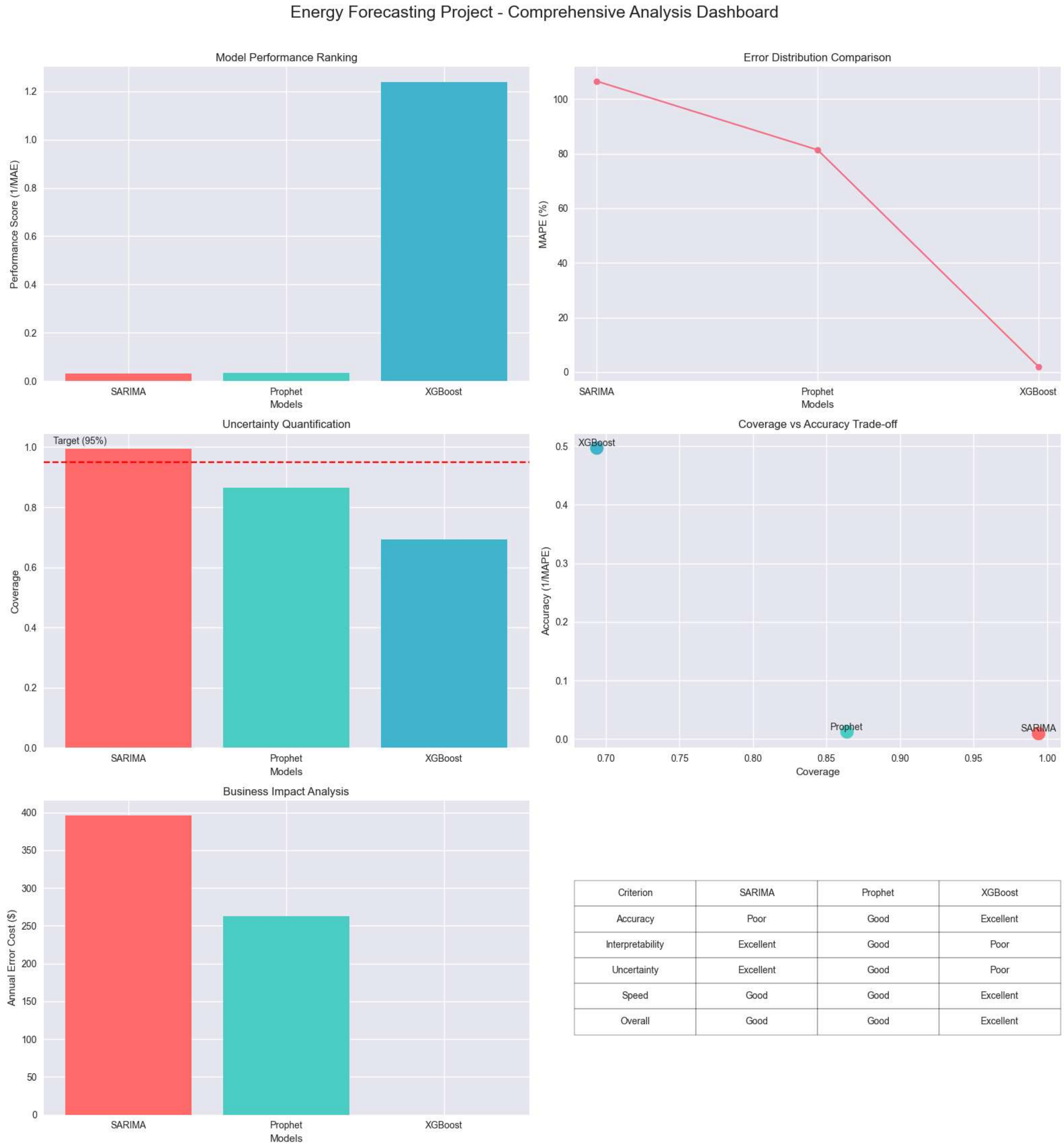
- **SARIMA**: 99.4% coverage (overconfident intervals)
- **Prophet**: 86.4% coverage (reasonable uncertainty)
- **XGBoost**: 69.4% coverage (underestimated uncertainty)

7. Visualizations

7.1 Model Performance Dashboard

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

def plot_dashboard(model_performance, evaluation_summary, error_costs, selection_matrix):
    fig = plt.figure(figsize=(16, 18))
    gs = fig.add_gridspec(3, 2)
    ax1 = fig.add_subplot(gs[0, 0])
    models = model_performance['Model']
    mae_norm = 1.0 / model_performance['MAE']
    ax1.bar(models, mae_norm, color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
    ax1.set_title('Model Performance Ranking')
    ax1.set_xlabel('Models')
    ax1.set_ylabel('Performance Score (1/MAE)')
    ax2 = fig.add_subplot(gs[0, 1])
    ax2.plot(models, model_performance['MAPE'], marker='o')
    ax2.set_title('Error Distribution Comparison')
    ax2.set_xlabel('Models')
    ax2.set_ylabel('MAPE (%)')
    ax3 = fig.add_subplot(gs[1, 0])
    ax3.bar(evaluation_summary['Model'], evaluation_summary['Coverage'], color=['#FF6B6B', '
    ax3.axhline(0.95, linestyle='--', color='red')
    ax3.text(0.02, 0.96, 'Target (95%)', transform=ax3.transAxes, va='bottom')
    ax3.set_title('Uncertainty Quantification')
    ax3.set_xlabel('Models')
    ax3.set_ylabel('Coverage')
    ax4 = fig.add_subplot(gs[1, 1])
    accuracy = 1.0 / model_performance['MAPE']
    ax4.scatter(evaluation_summary['Coverage'], accuracy, s=200, c=['#FF6B6B', '#4ECDC4', '#
    for i, txt in enumerate(evaluation_summary['Model']):
        ax4.text(evaluation_summary['Coverage'][i], accuracy.iloc[i], txt, ha='center', va='
    ax4.set_title('Coverage vs Accuracy Trade-off')
    ax4.set_xlabel('Coverage')
    ax4.set_ylabel('Accuracy (1/MAPE)')
    ax5 = fig.add_subplot(gs[2, 0])
    ax5.bar(models, error_costs, color=['#FF6B6B', '#4ECDC4', '#45B7D1'])
    ax5.set_title('Business Impact Analysis')
```

```
    ax5.set_xlabel('Models')
    ax5.set_ylabel('Annual Error Cost ($)')
    ax6 = fig.add_subplot(gs[2, 1])
    ax6.axis('off')
    table = ax6.table(cellText=selection_matrix.values, colLabels=selection_matrix.columns,
    table.auto_set_font_size(False)
    table.set_fontsize(10)
    table.scale(1, 2)
    fig.suptitle('Energy Forecasting Project - Comprehensive Analysis Dashboard', fontsize=1
    plt.tight_layout(rect=[0, 0.03, 1, 0.97])
    plt.show()

plot_dashboard(model_performance, evaluation_summary, error_costs, selection_matrix)
```



Criterion	SARIMA	Prophet	XGBoost
Accuracy	Poor	Good	Excellent
Interpretability	Excellent	Good	Poor
Uncertainty	Excellent	Good	Poor
Speed	Good	Good	Excellent
Overall	Good	Good	Excellent