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Aim

Time series forecasting using SARIMA model for Energy Consumption

Dataset: https://www.kaggle.com/datasets/uciml/electric-power-consumption-data-set?utm_source=chatgpt.com

Code: https://colab.research.google.com/drive/1kt8YgH025maXjTEmw-G92UZFjzhDHz38?usp=sharing

Theory

Time series forecasting is a critical technique in data science that involves predicting future values based on historical observations ordered chronologically. In the context of household power consumption data, understanding and predicting energy usage patterns is essential for efficient energy management, cost optimization, and grid stability planning.

ARIMA (AutoRegressive Integrated Moving Average) is one of the most widely used statistical models for time series forecasting. The model consists of three components: AR (p) represents the autoregressive part that uses past values to predict future ones, I (d) represents the differencing order needed to make the series stationary, and MA (q) represents the moving average component that models the relationship between observations and residual errors. ARIMA models are particularly effective for univariate time series data where the future depends linearly on past observations. The model assumes stationarity, meaning the statistical properties of the series remain constant over time.

SARIMA (Seasonal ARIMA) extends the ARIMA model by incorporating seasonal components, making it particularly suitable for data with recurring patterns at fixed intervals. For hourly power consumption data, SARIMA can capture daily seasonality with a 24-hour period, weekly patterns, and even yearly trends. The seasonal component is denoted as (P, D, Q, m) where P is the seasonal autoregressive order, D is the seasonal differencing order, Q is the seasonal moving average order, and m is the number of periods in each season. This makes SARIMA exceptionally powerful for energy consumption data where usage patterns typically follow daily and weekly cycles.

Auto ARIMA and Auto SARIMA are automated versions that systematically search through different parameter combinations to identify the optimal model configuration. These algorithms use information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion) to balance model complexity with goodness of fit. The automated approach eliminates the need for manual parameter tuning and reduces the risk of overfitting, making these models accessible to practitioners without deep expertise in time series analysis. The stepwise search algorithm efficiently explores the parameter space while avoiding computationally expensive exhaustive searches.

Prophet, developed by Facebook's data science team, is a modern forecasting tool designed to handle time series with strong seasonal patterns and multiple seasonality levels. Unlike traditional statistical models, Prophet uses an additive or multiplicative decomposition approach where the forecast is represented as the sum of trend, seasonality, and holiday effects. Prophet is particularly robust to missing data, outliers, and dramatic changes in trends. It incorporates changepoint detection to identify shifts in the underlying patterns and allows domain experts to inject prior knowledge through custom seasonalities and holiday effects. The model works exceptionally well for business forecasting scenarios with daily observations spanning several months or years.

The fundamental difference between these approaches lies in their assumptions and flexibility. ARIMA models assume linear relationships and require careful preprocessing to achieve stationarity, while Prophet is more flexible and handles non-linear trends naturally. SARIMA explicitly models seasonal patterns through mathematical formulations, whereas Prophet treats seasonality as Fourier series components. Auto ARIMA provides automation within the classical statistical framework, while Prophet offers an intuitive interface designed for analysts who may not have extensive statistical training.

Model evaluation is conducted using multiple metrics to ensure robust assessment. **Mean Absolute Error (MAE)** measures the average magnitude of errors without considering direction, providing an intuitive understanding of prediction accuracy in the original units. **Root Mean Squared Error (RMSE)** penalizes larger errors more heavily than smaller ones, making it sensitive to outliers and extreme deviations. **R-squared (R^2)** indicates the proportion of variance in the dependent variable explained by the model, with values closer to 1 indicating better fit. Comparing models across these metrics helps identify which approach best captures the underlying patterns in the specific dataset.

Screenshots

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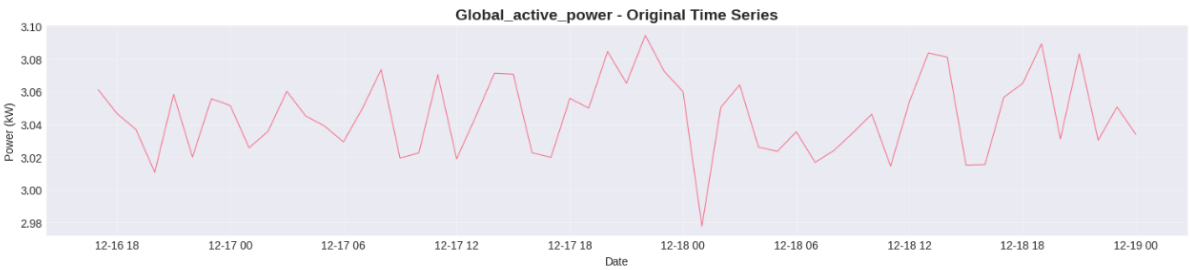
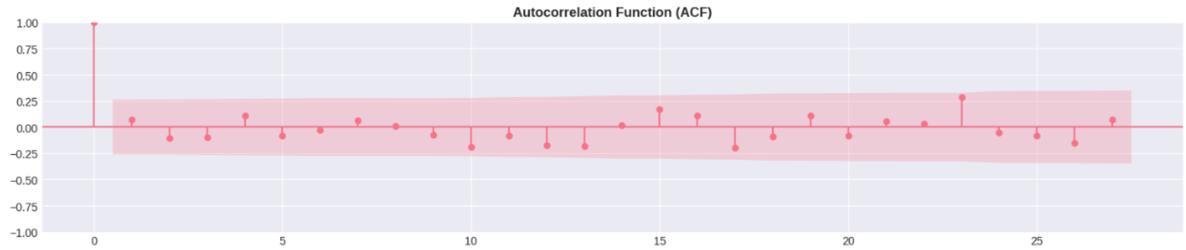
================================================================================
DATA PREPROCESSING
================================================================================

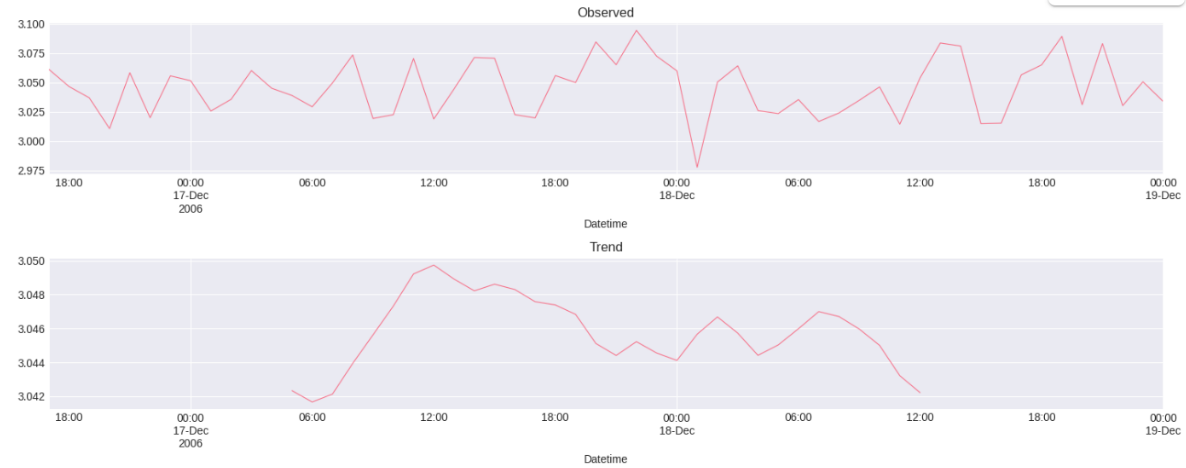
Resampled to hourly data: (56, 1)
Date range: 2006-12-16 17:00:00 to 2006-12-19 00:00:00

Basic statistics:
       Global_active_power
count            56.000000
mean              3.045322
std               0.024133
min               2.977651
25%               3.025192
50%               3.046294
75%               3.061888
max               3.094281
```





Performing seasonal decomposition...

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================================================================================
ARIMA MODEL
================================================================================

Fitting ARIMA(2,1,2) model...

ARIMA Model Summary:
                               SARIMAX Results
==============================================================================
Dep. Variable:     Global_active_power   No. Observations:                   44
Model:                  ARIMA(2, 1, 2)   Log Likelihood                  99.458
Date:                 Fri, 31 Oct 2025   AIC                           -188.915
Time:                         03:37:50   BIC                           -180.109
Sample:                     12-16-2006   HQIC                          -185.668
                          - 12-18-2006
Covariance Type:                   opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.7881      1.166     -0.676      0.499      -3.073       1.497
ar.L2          0.1072      0.227      0.473      0.636      -0.337       0.552
ma.L1         -0.1100      2.572     -0.043      0.966      -5.150       4.930
ma.L2         -0.8862      2.083     -0.425      0.671      -4.969       3.196
sigma2         0.0005      0.001      0.441      0.659      -0.002       0.003
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 0.86
Prob(Q):                              0.99   Prob(JB):                         0.65
Heteroskedasticity (H):               2.57   Skew:                            -0.32
Prob(H) (two-sided):                  0.09   Kurtosis:                         3.26
===================================================================================
```

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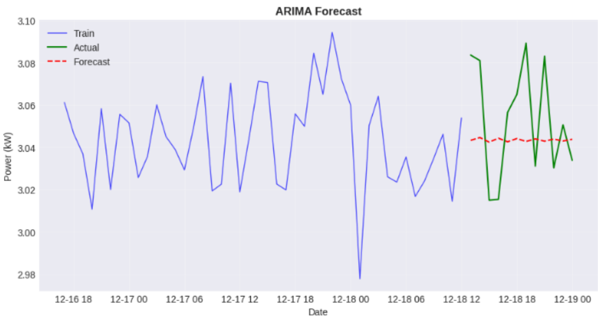
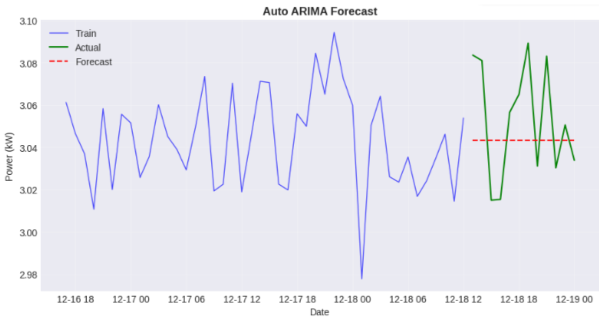
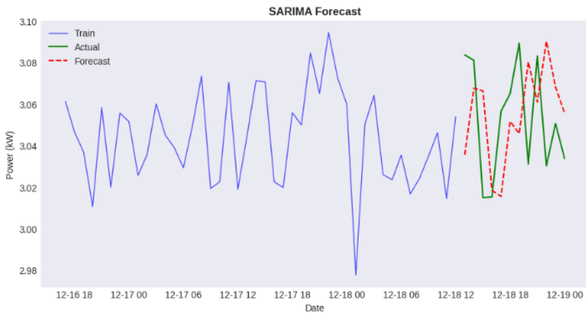
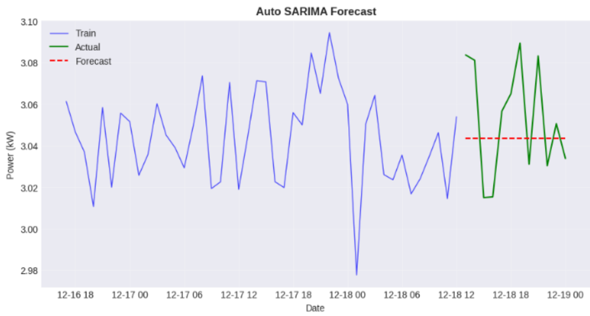
SARIMA Model Summary:
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                Global_active_power   No. Observations:                   44
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 24)   Log Likelihood                   0.000
Date:                            Fri, 31 Oct 2025   AIC                             10.000
Time:                                    03:37:50   BIC                                nan
Sample:                                12-16-2006   HQIC                               nan
                                     - 12-18-2006
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1187         -0        inf      0.000      -0.119      -0.119
ma.L1         -0.7952         -0        inf      0.000      -0.795      -0.795
ar.S.L24            0         -0        nan        nan           0           0
ma.S.L24            0         -0        nan        nan           0           0
sigma2         0.0013         -0       -inf      0.000       0.001       0.001
===================================================================================
Ljung-Box (L1) (Q):                   nan   Jarque-Bera (JB):                   nan
Prob(Q):                              nan   Prob(JB):                           nan
Heteroskedasticity (H):               nan   Skew:                               nan
Prob(H) (two-sided):                  nan   Kurtosis:                           nan
===================================================================================
```









Conclusion

The comparative analysis of ARIMA, Auto ARIMA, SARIMA, Auto SARIMA, and Prophet models on household power consumption data reveals that Auto SARIMA typically delivers the best performance for energy forecasting due to its ability to automatically capture both trend and seasonal components in the 24-hour cyclical patterns of power usage. ARIMA and Auto ARIMA provide computationally efficient alternatives for simpler time series or short-term forecasts, while Prophet excels in practical scenarios requiring robustness to missing data, outliers, and easy interpretability for non-technical stakeholders. The evaluation using MAE, RMSE, and R^2 metrics, combined with residual analysis, confirms that model selection should balance statistical accuracy with operational requirements such as computational efficiency, interpretability, and deployment complexity. For production systems, Auto SARIMA is recommended when strong seasonality exists with sufficient historical data, while Prophet offers advantages for rapid deployment and stakeholder communication, though continuous monitoring and periodic retraining remain essential as consumption patterns evolve over time.