Final Report — Electricity Consumption Forecasting Study

Project Summary

This project presents a comparative study of naive persistence, moving-average, ARIMA, SARIMA, Prophet, and LSTM models for short-term hourly electricity consumption forecasting. The study was conducted in Google Colab using the Household Power Consumption dataset.

Methodology

Data preprocessing included timestamp construction, numeric validation, hourly aggregation, interpolation of missing hours, and a time-aware 80/20 split. All models were trained on the same window and evaluated using a unified metric framework to ensure experimental consistency.

Key Findings

Naive persistence proved to be a strong benchmark. SARIMA improved upon ARIMA by modeling daily recurrence. Prophet struggled with highly variable, appliance-driven load behavior. The LSTM model achieved the best overall accuracy by capturing nonlinear temporal dynamics.

Model	MAE	RMSE	MAPE (in %)	sMAPE (in %)
LSTM Model Performance (Hourly)	0.3556	0.5335	55.24	41.38
Naive Forecast Results	0.3755	0.6237	41.54	
Moving Average (3h)	0.4752	0.7414	59.9789	
Moving Average (24h)	0.5559	0.7827	85.7468	
Moving Average (12h)	0.5627	0.7984	86.2114	
Moving Average (6h)	0.5748	0.8341	83.1101	
SARIMA Model Performance (Hourly)	0.6018	0.8229	120.65	64.46
ARIMA Model Performance (Hourly)	0.6819	0.9086	122.07	76.54
Prophet Model Performance (Hourly)	0.7375	0.9772	123.99	102.4

Conclusions

Short-term residential load is primarily persistence-driven, with limited dominant seasonality but meaningful nonlinear behavior. Deep learning provides measurable benefits when temporal context and nonlinear effects are important, while naive forecasting remains competitive and computationally efficient.

Future Work

Future extensions may include GRU and CNN-LSTM architectures, integration of sub-metering and voltage features, probabilistic forecasting, multi-step prediction horizons, and interpretability analysis of learned temporal patterns.