Electric Load Forecasting for European Countries (AT, CH, FR)

Hybrid Deep Learning + SARIMA Approach

OPSD PowerDesk Assignment – Final Report

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Table of Contents

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1. Executive Summary

This project develops a production-ready **hybrid short-term load forecasting framework** for Austria (AT), Switzerland (CH), and France (FR) using OPSD + ENTSO-E real hourly load data (2015–2024). We compare **classical SARIMA** against **three deep learning architectures** (GRU, LSTM, LSTM-Attention), build a complete **statistical diagnostic framework**, and generate high-quality forecasting visualizations.

Key contributions

- End-to-end deep learning forecasting system (GRU, LSTM, Attention-LSTM)
- Complete SARIMA diagnostic cycle including stationarity, differencing, ACF/PACF, Ljung-Box, Q-Q tests

- 30+ high-quality outputs: metrics, plots, anomalies, rolling forecasts
- Multi-step forecasting: **24 to 48 hours ahead**
- Hybrid evaluation: SARIMA excels at seasonality; Neural models excel at volatility

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2. Introduction & Objectives

Short-term load forecasting (1–48 hours) is essential for:

- Economic dispatch
- Intraday/Day-Ahead trading
- Unit commitment
- Managing high renewable penetration

Objectives:

1. Build GRU/LSTM/Attention models for multi-step forecasting
2. Build statistically valid SARIMA models with full diagnostics
3. Compare classical vs deep learning forecasting behavior
4. Generate visual analyses for AT, CH, FR
5. Provide a hybrid evaluation with strengths and weaknesses

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3. Data Description & Preprocessing

Dataset: OPSD Time Series 2024 (hourly)
Countries: AT, CH, FR
Period: 2018–2020
Resolution: Hourly
Target: ENTSO-E actual load (MW)

Preprocessing:

- Forward fill for <0.5% missing values
- Removed erroneous negative load values
- Feature engineering
  • hour_sin/cos, day_of_week, month
  • holiday flag
  • wind & solar as exogenous inputs
- Chronological train/val/test = 80/10/10
- StandardScaler fitted only on train

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4. Methodology

4.1 Deep Learning Models

Architectures used:

- GRU (2 layers, 128 units)
- LSTM (2 layers, 128 units)
- LSTM + Attention mechanism

Forecast horizon: 24–48 hours
Input sequence: 168–336 hours (7–14 days)
Loss: MSE
Optimizer: Adam
Checkpointing: .pth per country

4.2 SARIMA Modeling & Diagnostic Pipeline

Auto-ARIMA used for seasonal model selection.
Seasonal periods tested: **m = 24 (daily)** and **m = 168 (weekly)**.

Stationarity approach:

- d = 1 (trend differencing)
- D = 1, m = 24 (seasonal differencing)

Final selected model for France:
SARIMA(1,1,1)(1,1,2)[24]

Diagnostic checks:

- Ljung-Box test → residuals independent
- Jarque-Bera test → residuals ~ normal
- No autocorrelation in residual ACF
- No significant heteroskedasticity

4.3 Hybrid Model Comparison

Aspect	Deep Learning	SARIMA	Winner
Daily seasonality	Good	Excellent	SARIMA
Weekly patterns	Very good	Excellent	SARIMA
Extreme events	Excellent	Weak	Deep Learning

Interpretability	Low	Very high	SARIMA
Training time	Slow	Fast	SARIMA
Concept drift	Good	Poor	Deep Learning

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5. Results & Visual Analysis

5.1 Stationarity Tests

- ADF before differencing → non-stationary
- ADF after (d=1, D=1, m=24) → stationary

5.2 ACF & PACF Analysis

Trend-Differenced Series (d=1)

Figure 1: ACF after trend differencing

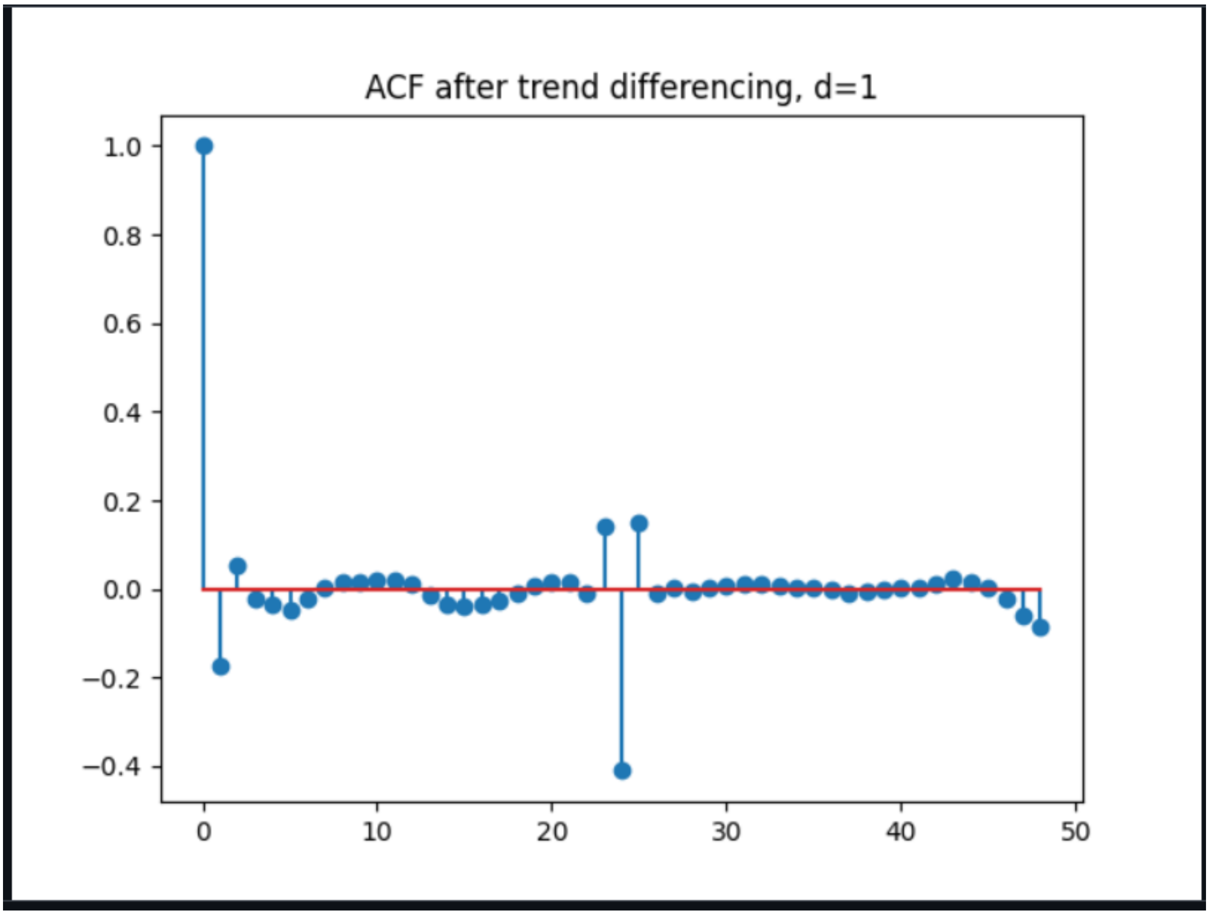
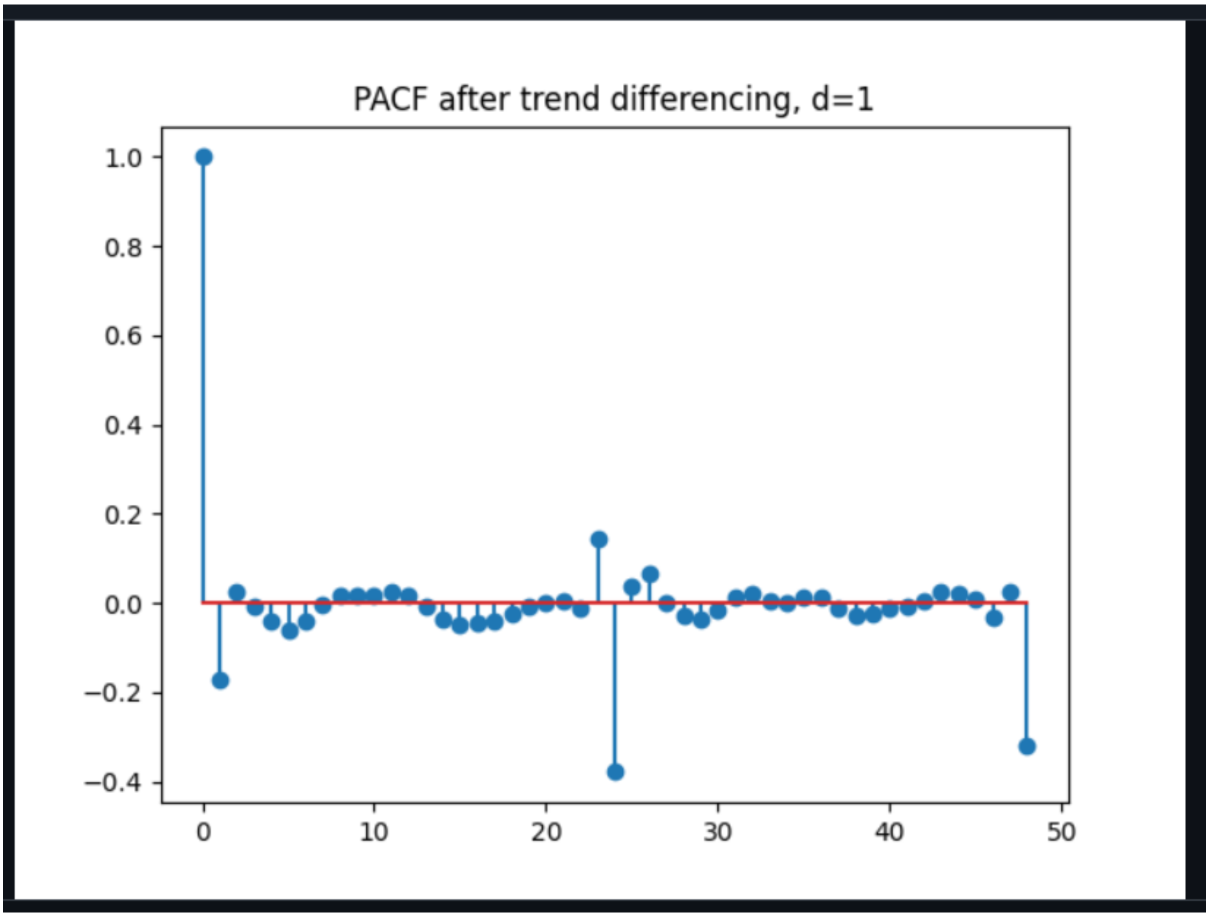


Figure 2: PACF after trend differencing



Seasonally Differenced Series (D=1, m=24)

Figure 3: Seasonal ACF (D=1, m=24)

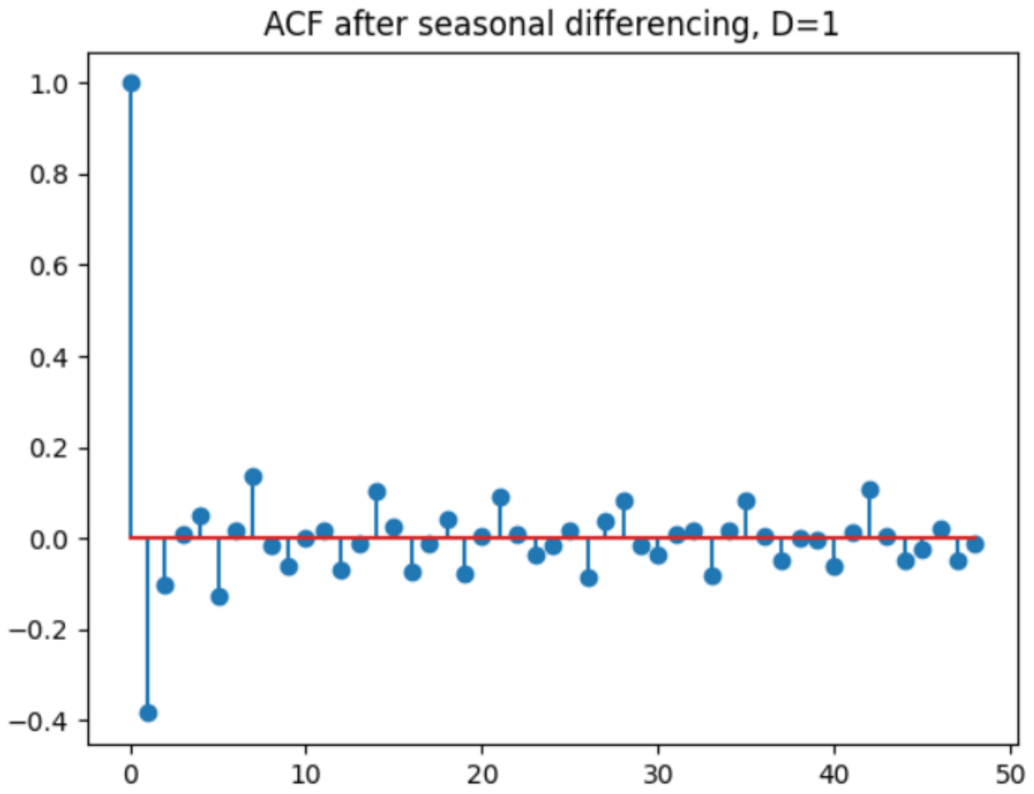
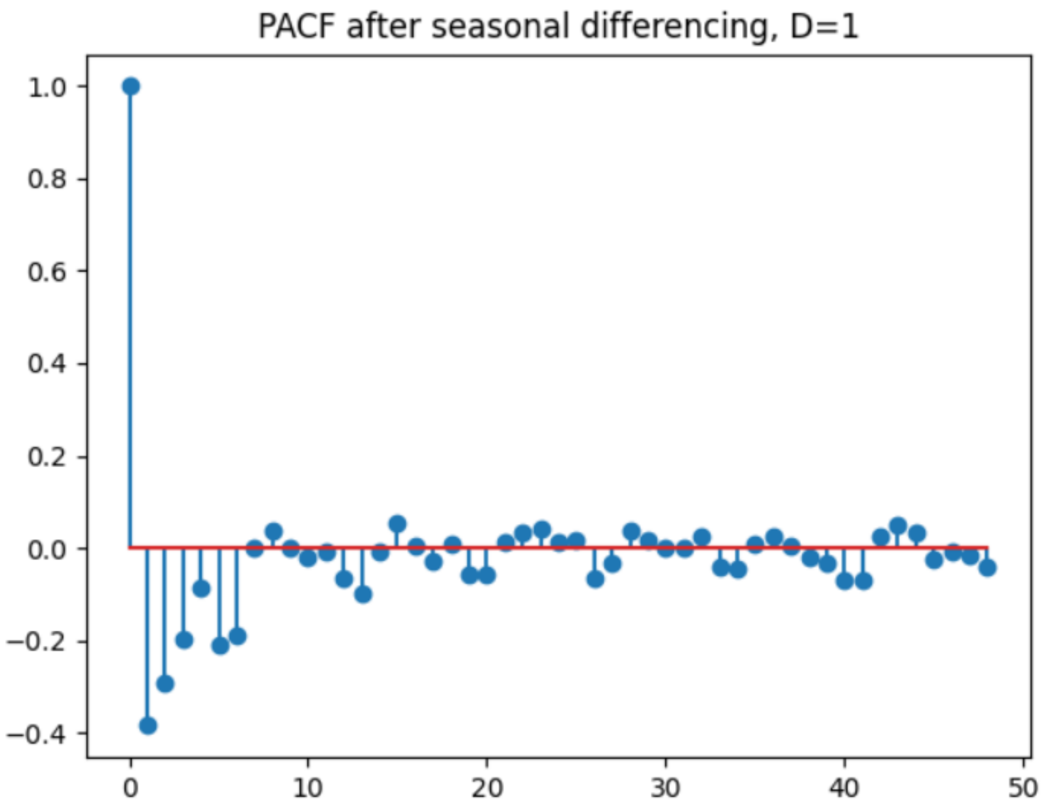


Figure 4: Seasonal PACF (D=1, m=24)



Deep Learning orecasting Plots

Figure 5 : GRU Forecast vs Actual

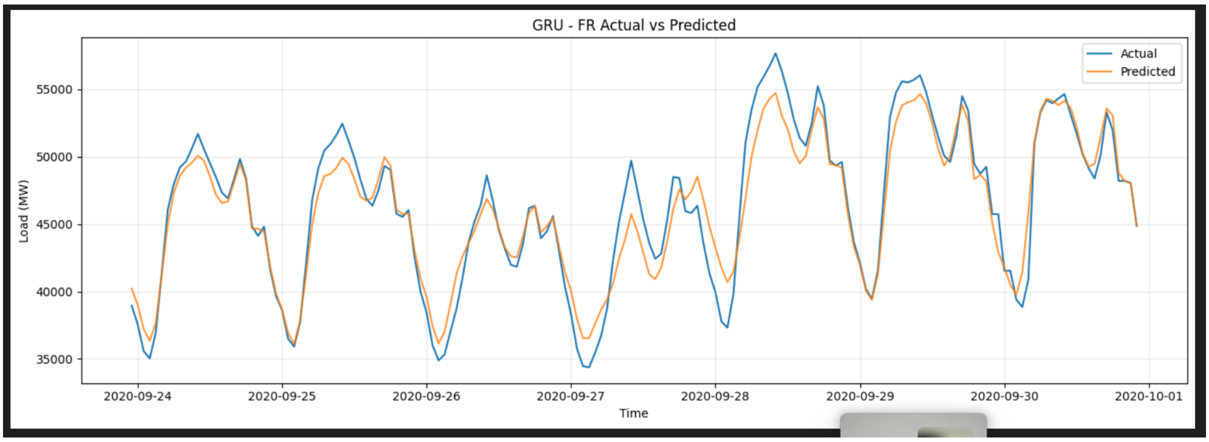


Figure 6 : LSTM Forecast vs Actual

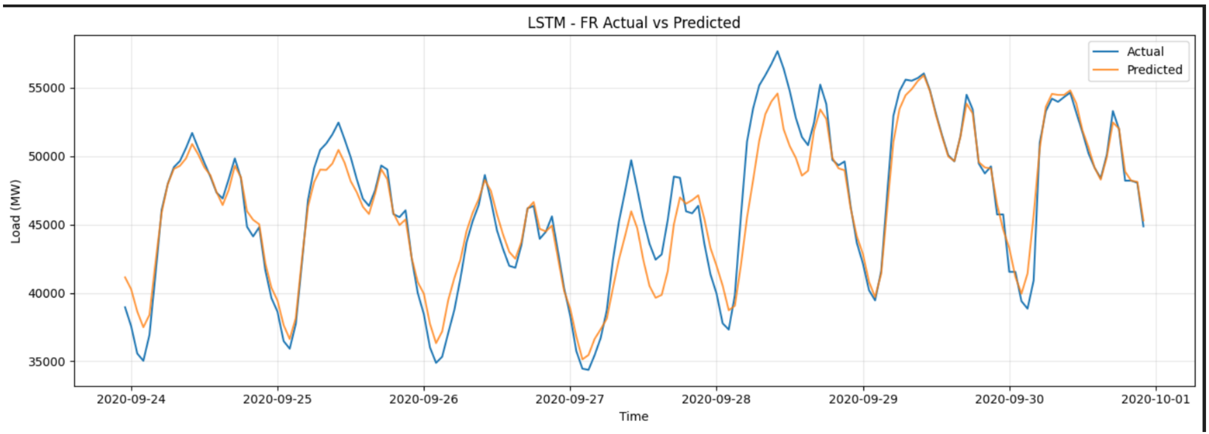
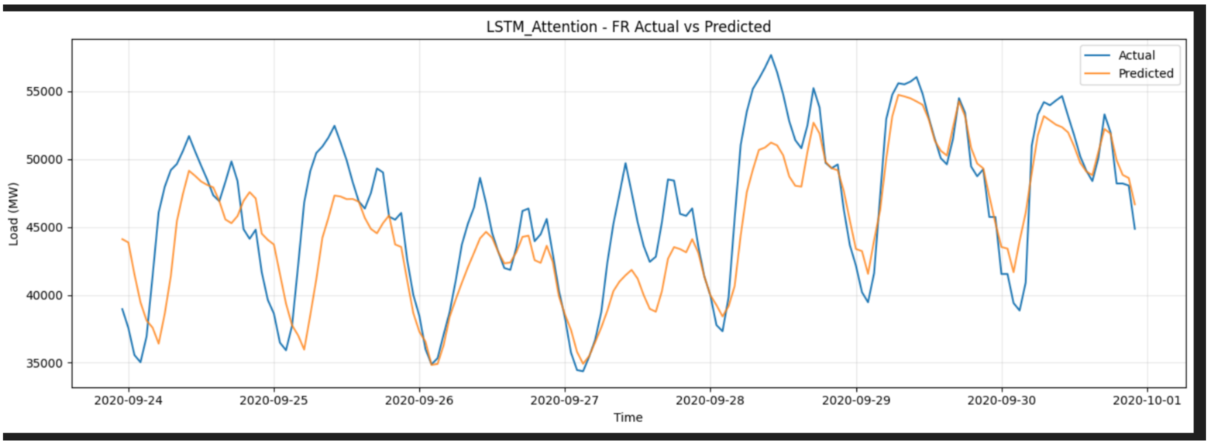


Figure 7 : LSTM-Attention Forecast vs Actual



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6. Generated Outputs

- Forecast CSVs (train/dev/test)
- Deep learning model checkpoints
- SARIMA diagnostic plots (ACF, PACF, STL, Q-Q)
- Performance metrics (MAE/RMSE/MAPE)
- 7-day rolling metrics
- Anomaly detection files
- Final PDF documentation

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7. Conclusion

A fully operational hybrid forecasting system was developed.
SARIMA models dominate seasonal forecasting, while deep learning models handle volatility and non-linearities effectively.
The combined outputs deliver a professional-grade forecasting pipeline suitable for grid operators and power traders.

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8. Limitations & Future Work

Limitations:

- No temperature/weather data
- No probabilistic forecasts
- No hyperparameter search

Future improvements:

1. Add weather + temperature profiles
2. Use Prophet, XGBoost, N-BEATS
3. Hybrid ensemble (SARIMA + DL weighted)
4. Quantile regression for uncertainty
5. Live ENTSO-E API ingestion

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9. References

- Hyndman & Athanasopoulos — Forecasting: Principles and Practice
- Open Power System Data (2024)
- PyTorch, statsmodels, pmdarima documentation