Faculty of Electrical Engineering
Warsaw University of Technology

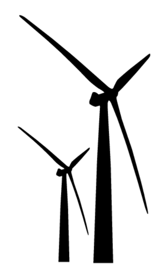
Comparative Analysis of Machine Learning and Statistical Models for Short-Term Energy Production Forecasting in Poland

Author: **Inż. Jakub Karpiński**

Affiliation
Faculty of Eletrical Engineering
Warsaw University of Technology
Warsaw, Polan
Jakub.karpinski4.stud@pw.edu.pl

Accurate forecasts of hourly energy production are essential for maintaining grid stability, optimizing dispatch, and integrating variable renewables. In Poland's rapidly changing energy mix—where renewable penetration and regulatory shifts introduce new uncertainties—small forecast errors can translate into significant operational and economic risks. This work compares three forecasting approaches (ARIMA, LightGBM, LSTM) and provides a basic exploration of ensemble methods for short-term energy production prediction.

Benefits:

- Grid Stability and Reliability 
- Economic dispatch and Optimization 
- Renewable energy integration and Sustainability 

Data

Energy production data were obtained from the ENTSO-E transparency platform, spanning January 2015 through February 2025 at an hourly granularity. The dataset reports total generation disaggregated by source—lignite, hard coal, natural gas, oil, biomass, onshore wind, solar PV, hydro (reservoir, run-of-river, pumped storage), and other renewables—enabling the models to capture seasonal cycles, diurnal load patterns, weekday/weekend variations, and public holiday effects. For model development, the data were split into a training set covering January 2015 through December 2022, and an independent test set from January 2023 to February 2025.

Models:

- LightGBM
- ARIMA
- LSTM
- Naive - benchmark

Optimized function: Mean Absolute Error (MAE)

Results

Model	MAE	MAPE
LightGBM	44,32	0,245
ARIMA	455,12	2,528
Naive	643,28	3,573
LSTM	2603,17	14,454

Table presents each model's overall average error (in MW) alongside its corresponding percentage error. LightGBM achieves the lowest error at 44.32 MW (0.245 %), substantially outperforming ARIMA (455.12 MW, 2.528 %) and the naive persistence forecast (643.28 MW, 3.573 %). In contrast, the LSTM model records the highest error of 2603.17 MW (14.454 %), highlighting its difficulty in accurately capturing the full range of hourly production variability under the current setup.

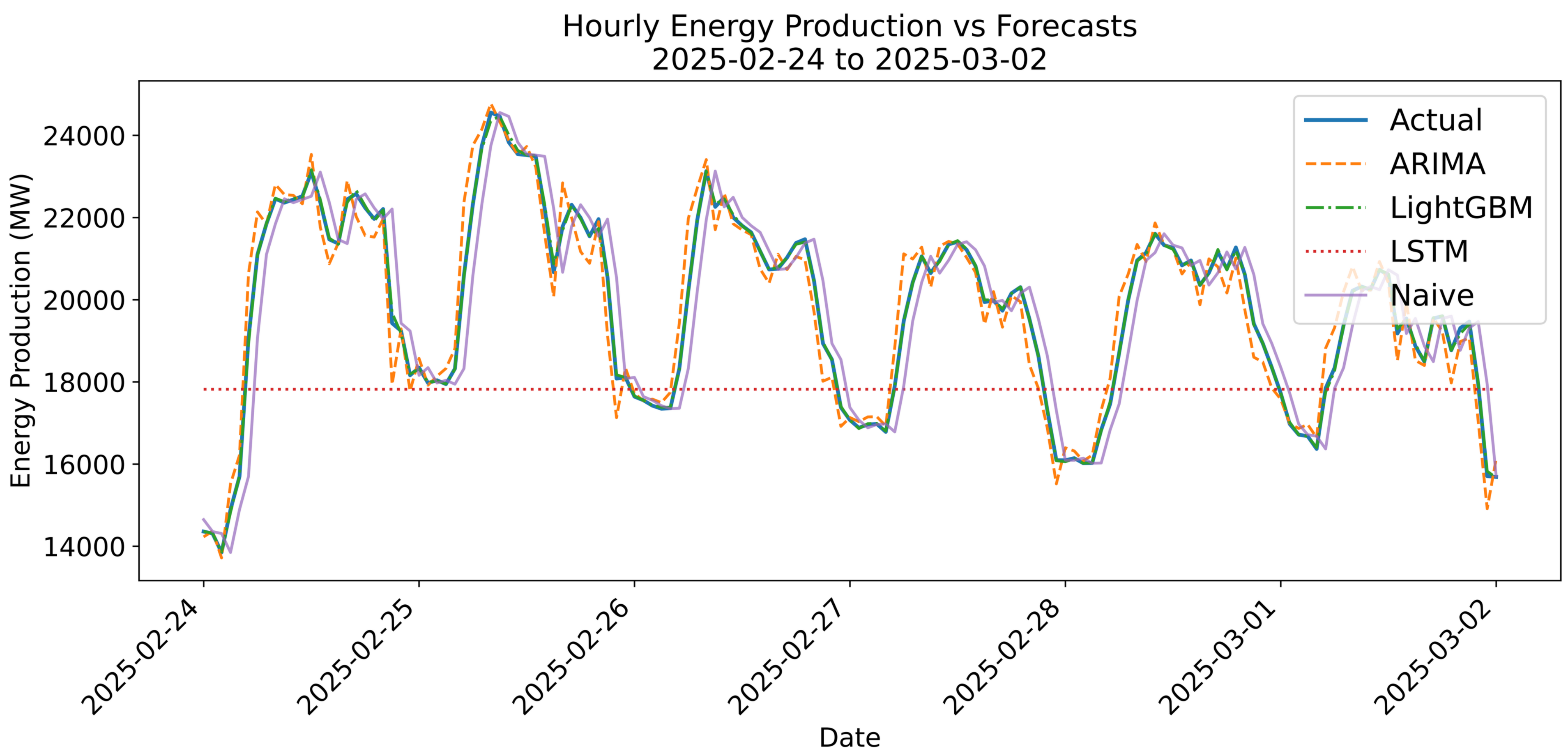
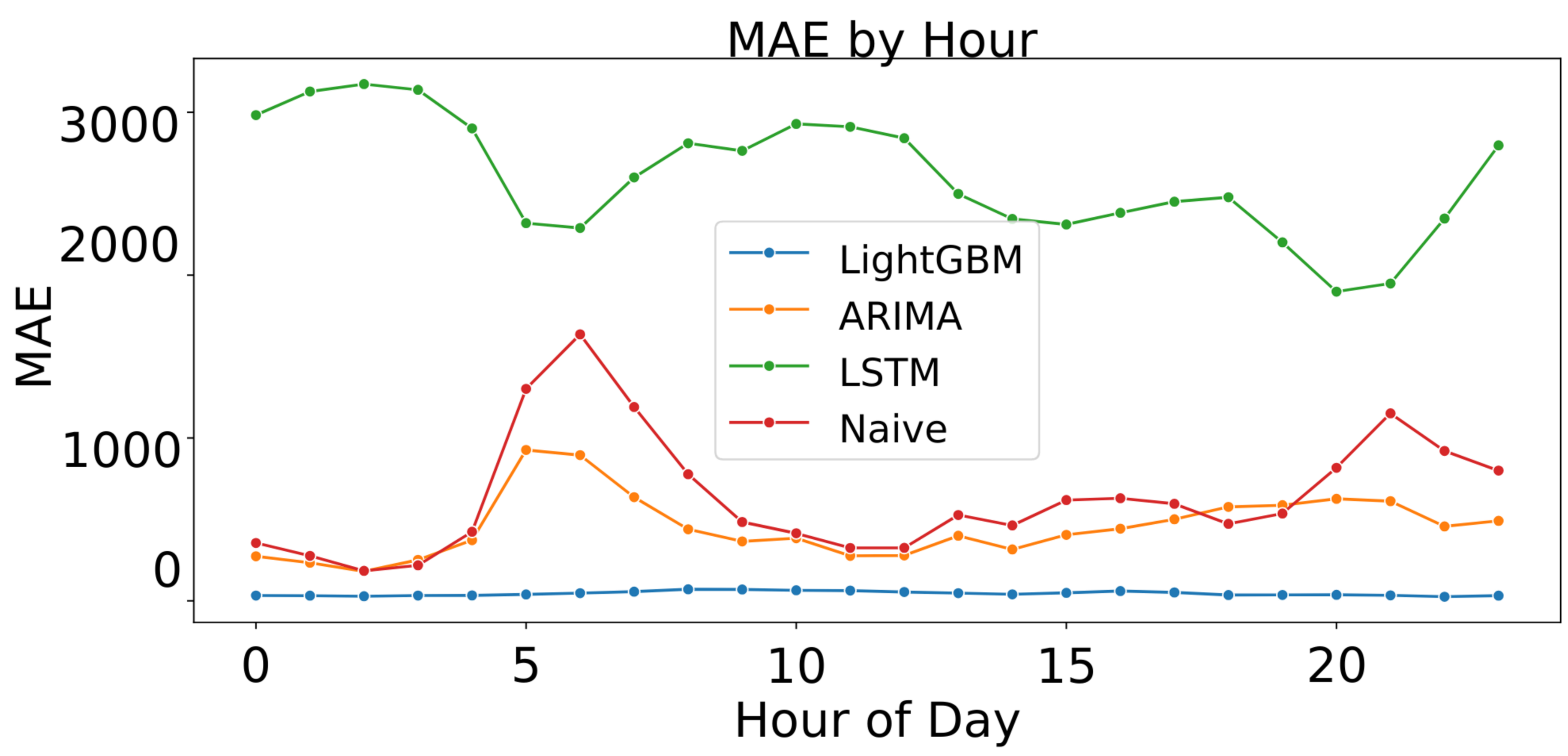


Figure above overlays the actual hourly energy production for the last full week with forecasts from ARIMA, LightGBM, LSTM, and the naive persistence model. Overall, LightGBM tracks the observed series most closely, capturing both the morning ramp-up and evening decline with minimal lag and deviation. ARIMA generally follows the trend but exhibits noticeable underestimation during rapid load increases, while the naive forecast reproduces yesterday's pattern but fails to adapt to daily shifts. The LSTM model shows the largest discrepancies, particularly under-predicting midday peaks and over-predicting late-night lows. It struggles to capture rapid fluctuations, often overshooting the true values by predicting changes that are too large. These patterns reinforce LightGBM's superior short-term accuracy and highlight areas—such as nonlinear ramp events—where the other models could be improved.



This plot highlights the challenge of forecasting the morning production ramp. LightGBM delivers consistent accuracy throughout the day, while ARIMA and the naive approach falter during these rapid changes. In contrast, the LSTM model adapts most effectively to the sharp increases in morning output.
Ensemble Evaluation: A preliminary weighted ensemble (AAE 79.4 MW) was tested but underperformed compared to LightGBM, indicating the need for more sophisticated blending strategies.

Conclusions

- **LightGBM** as Baseline: Delivers the lowest error (44 MW, 0.25 %), proving highly effective for 24 h forecasting in Poland.
- **LSTM** & **ARIMA** Insights: LSTM requires deeper tuning to handle rapid ramps; ARIMA struggles with non-linear spikes.
- **Operational Impact**: Reliable short-term forecasts enable better dispatch decisions, reduce imbalance costs, and support renewable integration.
- **Next Steps**: Explore advanced ensemble techniques, enrich feature sets (weather, market data), and prototype a real-time forecasting platform.