Peer Review: Group 23 – Forecasting Energy Prices

Overall Assessment

Group 23 delivered a solid presentation and piece of research. The work demonstrates a good understanding of time series modeling, appropriate methodological choices, and strong structure. There is clear effort in diagnostics and model comparison, which contributes positively to the quality of the analysis and makes it more interpretable for the reader/listener as well. The report also outlines weaknesses of the research and possible areas of improvement, further strengthening the notion that the group has familiarized itself with most aspects of energy price forecasting through statistical models. These areas of improvement, along with a couple of others, were discussed during the presentation, and are summarized in this document.

Strengths of report and presentation

- **Report and presentation structure**: Clear, logical, and easy to follow. Points were communicated directly and clearly to the listener.
- **Methodology**: Good use of standard time series models including ARIMA, SARIMA, and GARCH. Models are properly explained, and the theoretical foundation is strong.
- **Diagnostics**: Proper stationarity tests, i.e. Augmented Dickey-Fuller and KPSS, and model selection criteria (AIC, BIC, HQIC) were applied. The group uses these findings to difference the data and thus achieves more accurate results.
- **Results and interpretation**: Results of the models are properly discussed, and the group shows high understanding and ability to interpret results. Results are discussed both from a statistical and economic/financial perspective, which yields more interpretable results for the reader/listener.
- **Model comparison**: Inclusion of a naïve benchmark and model evaluation shows good modeling practice and gives the reader a better understanding of the complexity of energy forecasting.
- **Reflection**: Thoughtful discussion around model complexity and selection, particularly in relation to lag order from ACF and model fit. The group also reflects well around the model comparison to the naïve benchmark, and how results that are slightly more significant than the naïve benchmark has significant economic value.

Suggestions for Improvement

Data transformation and preprocessing

- The data source and structure could have been described in greater detail. It would be interesting to see the sources of energy in the grid, to more accurately explain and model the variations in price. For example, more renewables in the energy mix should contribute to higher heteroskedasticity. Additionally, it would be interesting to highlight the energy source that determines the marginal price.
- The non-normal distribution of the data was flagged by high Jarque-Bera statistic. This violates the assumptions of the ARIMA/SARIMA model and could lead to weaker results. Could the group transform the data to be normally distributed, for example by applying log returns or other transformations?

Seasonality & Volatility

- Interesting seasonal behavior was detected (e.g., strong seasonality at 130 trading days / 0.5 years), but the seasonal structure could have been analyzed in more depth and higher frequency (e.g., hourly, daily, or weekly effects).
- SARIMA with a 65-day season capturing a 130 trading day pattern with high statistical significance, raises questions which possibly could be explored further. The group did, however, answer thoughtfully and reflected well about this upon request.
- Volatility modeling was included (i.e., GARCH), but consider testing explicitly for heteroskedasticity, particularly given the influence of renewables and weather variability.

Interpretation & Communication

- Consider further discussion around transition periods, regime shifts, or unexpected events (e.g., what happened in 2018?). As prof. Risstad pointed out, using one SARIMA model for the entire time series is probably not sufficient, as the input variables to the system is changing through time. The group also reflected well upon this when asked about it.

Points to Explore Further

- **Preprocessing**: Consider preprocessing the data to better fit a normal distribution, e.g. through applying a log transformation.

- **Exogenous Variables**: Consider ARIMAX or SARIMAX models with additional variables such as temperature, marginal production cost of the energy system (e.g. the economic cost of petro-based energy sources such as heating fuel), or renewable energy supply.
- **Seasonal Variation**: Explore hourly, daily or weekly effects and variation within seasonal patterns.
- **Model Extensions**: Consider fractional differencing (with $0 < d < 1$) or regime-switching models (modelling the sample with more SARIMA models) to handle more complex dynamics.
- **Machine Learning**: ML models may better capture non-linear relationships and allow better handling of correlated or high-dimensional external variables. This is outside the scope of this course but could be an interesting addition to the project.

Final Thought

This is a thoughtful and well-executed project with a solid application of time series models. With more detailed communication of assumptions, preprocessing, and interpretation, plus potential expansion into multivariate or non-linear modeling, the project could be further strengthened.

Overall, a very good report and presentation that deserves credit.