Conformal Prediction for Energy Price Forecasting

01617 Deep Learning: Project 3 - Synopsis

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1 Motivation

Conformal prediction is appealing because it produces prediction intervals with guaranteed coverage. We can be, say, 90% confident that the true outcome falls within our predicted range. This is particularly valuable in financial contexts where uncertainty quantification matters for risk management and decision making. We want to explore how conformal prediction can be applied to energy price forecasting, specifically looking at Danish electricity spot prices where accurate uncertainty estimates could inform trading strategies.

The challenge is that energy markets are volatile and exhibit distribution shifts. Summer versus winter demand patterns, sudden weather events, and policy changes all create instability. We're interested in whether recent advances in conformal methods can handle these shifts better than earlier approaches.

2 Background

Standard conformal prediction assumes data is exchangeable, meaning observations are roughly independent and identically distributed. This assumption breaks down for time series data, where tomorrow's price depends on today's, and the underlying distribution can shift over time.

Several methods have tried to address this. Adaptive Conformal Inference (ACI) and Online Gradient Descent (OGD) approaches update prediction intervals dynamically based on recent coverage errors. These methods work by adjusting interval widths using binary feedback: did we cover the true value or not?

A recent paper from ICLR 2025 [2] proposes Error-Quantified Conformal Inference (ECI), which extends this idea by incorporating *how far off* the prediction was, not just whether it failed. The intuition is that missing by €100/MWh should trigger a different correction than missing by €5/MWh. The method adds an error quantification term to the standard update rule:

$$q_{t+1} = q_t + \eta[(\mathrm{err}_t - \alpha) + (s_t - q_t)\nabla f(s_t - q_t)]$$

We want to investigate whether this approach yields tighter, more adaptive prediction intervals on real energy data, particularly during distribution shifts like the 2022 European energy crisis.

3 Milestones

- **Week 1:** Understand the ECI paper and related work on online conformal prediction. Set up Danish energy data (2022 hourly spot prices with weather and generation features). Build initial forecasting models, likely a classical time series model (ARMA or similar) and a deep learning model (LSTM or similar).
- **Week 2:** Implement baseline conformal methods (ACI, OGD) to establish comparison points. Set up evaluation metrics: coverage rates, interval widths, and possibly adaptation speed during known distribution shifts.
- **Week 3:** Implement ECI and experiment with it. Compare against baselines across different forecasting models. Explore hyperparameter sensitivity and potentially test variants like ECI-cutoff or ECI-integral if time permits.

- **Week 4:** Analyze when and why ECI performs differently than baselines. Create visualizations showing coverage and interval width over time, especially during volatile periods. Write up findings in the final report.

References

[1] Anastasios N. Angelopoulos and Stephen Bates. *A Gentle Introduction to Conformal Prediction and Distribution-Free Uncertainty Quantification*. 2022. arXiv: `2107.07511 [cs.LG]`. URL: `https://arxiv.org/abs/2107.07511`.

[2] Junxi Wu et al. *Error-quantified Conformal Inference for Time Series*. 2025. arXiv: `2502.00818 [stat.ML]`. URL: `https://arxiv.org/abs/2502.00818`.