Improving Day-Ahead Energy Forecasts for Power System Operations with Open-Source Data and Machine Learning

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Net Demand Forecasting Errors are Growing

- ➤ Weather-dependent demand and generation is increasing net demand **variability**.
- ➤ This increase in net demand variability is causing **forecasting errors** to grow.

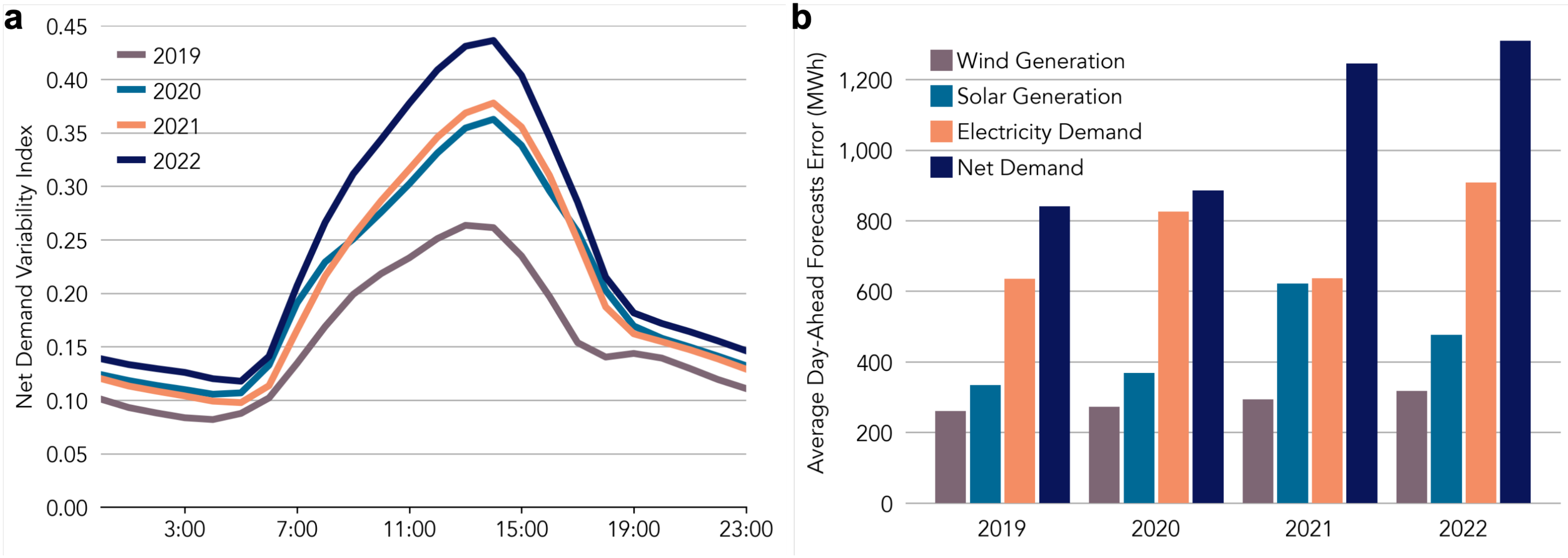

Figure 1: CAISO's net electricity demand variability index (a), and average forecasting errors (b) from 2019 to 2022*;* Source: www.caiso.com

Increasing Reserve Requirements and Imbalances

Figure 2: CAISO's operating reserves requirements (a), reserves costs and trend (b), and imports and exports (c); Source: www.caiso.com

- Growth in **forecasting errors** has led to an increase in:
  - **imports** and **exports** from the imbalance market,
  - **operating reserves** procured in the ancillary services market and their associated **costs**.

Electricity Demand and Supply Uncertainty

- **Demand** from the largest customer-serving utilities in California (PG&E, SDGE, and SCE).
- **Solar** at the northern (NP15), southern (SP15), and central (ZP26) trading hubs.
- **Wind** at NP15 and SP15 trading hubs.

Figure 3: 2022 CAISO's demand (a, b, c), solar (d, e, f) and wind (g, h) generation (95% confidence interval and seasonal averages), trading hubs (i) and utility (j) areas; Source: www.oasis.caiso.com

Forecast Operational Characteristics

- The proposed model assimilates:
  - **11 weather features** in operational day (d),
  - from High-Resolution Rapid Refresh (**HRRR)** Numerical Weather Prediction (NWP) **forecast** from NOAA at 16:00 ($t = 16$ interval),
  - to forecast hourly **demand, solar, and wind generation** in operational day (d).
- We used NWPs from Jun 2019 to May 2022 for **training** and from Jun 2022 to Mar 2023 for **testing**.

Figure 4: The proposed day-ahead forecast characteristics are $l = 8$ hours (lead time), $h = 24$ hours (horizon), and $t = 1$ hour (granularity).

Joint Day-Ahead Probabilistic Energy Forecast

1. **Open-source** Numerical Weather Forecast (NWF).
2. **Asset-level spatial filtering** to reduce dimensionality.
3. **Sparse learning** to select the weather features.
4. **Bayesian learning** to quantify uncertainty and generate scenarios.
5. **Chain of Models** to generate realistic scenarios.

Figure 5: Workflow.

Sparse Learning

Weather feature selection:

- **Lasso**: L_1 −norm regularization.
- **Orthogonal Matching Pursuit** (OMP): L_0 −norm.
- **Elastic Net** (EN): L_1 −norm and L_2 −norm.
- **Group Lasso** (GL): L_0 −norm and L_1 −norm.

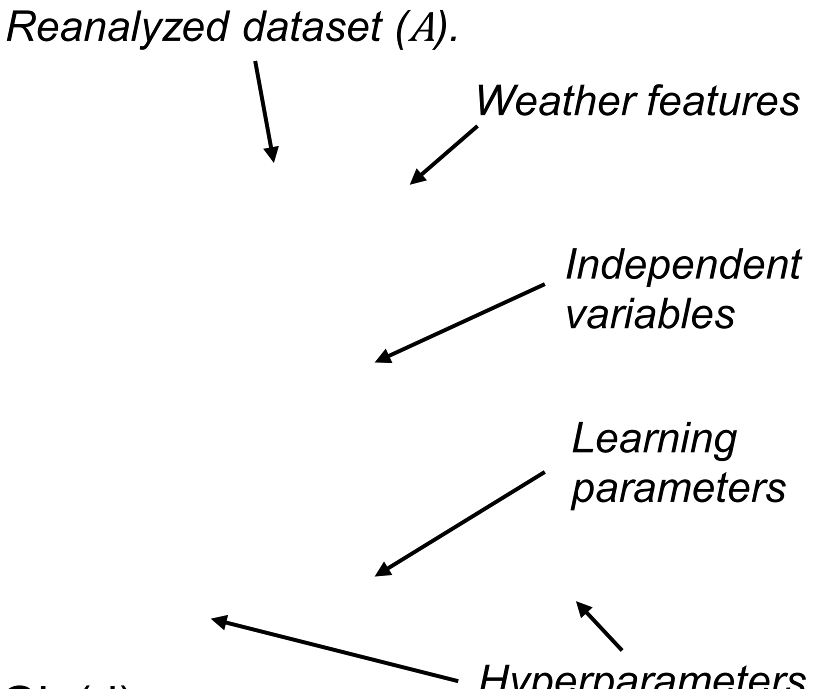

Figure 6: Lasso (a), OMP (b), EN (c), and GL (d).

Bayesian Learning

- **Bayesian Linear Regression**[1] (BLR): Independent models.
- **Relevance Vector Machine**[2] (RVM): BLR with automatic relevance determination.
- **Gaussian Process for Regression**[1] (GPR): Non-linear independent models ("kernel trick").
- **Multi-Task GPR**[3] (MTGPR): GPR joint at system-level (SLGPR), or at nodal-level (NLGPR).

[1]Rasmussen et al., Gaussian processes for machine learning (2006).
[2]Tipping, Sparse Bayesian learning and the relevance vector machine (2001).
[3]García-Hinde et al., A conditional one-output likelihood formulation for multitask Gaussian processes (2022).

Figure 7: Bayesian inference: (a) BLR, (b) RVM, (c) GPR, and (d) MTGPR.

Probabilistic Energy Forecasts are Competitive

Figure 8: Baseline system-level forecast errors (a) and Skill Scores (SS) for independent (b) and joint (c) forecasts. Baseline nodal-level forecast errors (d) and SS for independent (e) and joint (f) net-demand forecasts.

- The proposed model **improve upon** point-wise forecasts from **baseline (CAISO).**
- Joint forecasts **perform better than** independent forecasts at the **system-level.**
- Independent forecasts **perform better than** joint forecasts at the **nodal-level.**

Multiple Criteria for Model Selection

- Multivariate **proper scoring rules**[4]:
- **Energy Score** (ES).
- **Variogram Score** (VS).
- **Interval Score** (IS) - 60%, 80%, 90%, 95% and 97.5%.
- Each **proper scoring rules** evaluates a different **property!**

Figure 9: An accurate model (a and d, ↓ ES and ↑ SS_{RMSE}) that generates realistic scenarios (b, ↓ VS) from a calibrated predictive distribution (c, ↓ IS) with low computational cost (e, ↓ time) requires looking at multiple scores.

[4] Gneiting et al., Strictly proper scoring rules, prediction, and estimation (2007).

Robust Day-Ahead Forecast on Extreme Events

- **Joint** energy forecast at **nodal-level** (NP15).
- Extreme net demand forecasting error on **May 29, 2022**.

Figure 10: Joint day-ahead energy (demand, solar and wind generation) forecast density and scenarios. A joint scenario is highlighted.

Dynamic Reserves Allocation Reduces Imbalances

- Allocation (from **Jun 2022** to **Mar 2023**) based on **predictive distribution:**
  - by finding the **confidence level** containing a target reserve capacity,
  - **reduces imports,** slightly increasing exports.
- Model selection based on **interval score reduces imbalances**.

Figure 11: The proposed reserve allocation adapts to the uncertainty in the day-ahead net demand forecast.

Conclusions

Challenges:

- Quantify the **benefits** of a probabilistic forecast to incentivize adoption.
- Provide a **workflow** to incorporate a probabilistic forecast into electricity market operation.
- Assign **risk** to forecast scenarios based on their probability.

Take Aways:

A probabilistic day-ahead forecast based on **open-source** data:

- reach **similar accuracy** than ISOs' forecast baseline.
- has the potential to **dynamically** allocates reserves **more efficiently** in response to the uncertainty.

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