The Role of Forecasting and AI/ML in Grid Optimization

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Grid Planning and Operation: An Optimization Perspective

Power system studies at various time horizons

- 1 year to 10 years: power system planning
- 1 week to 1 year: maintenance scheduling (operational planning)
- Minutes to 1 week: power system operation (unit commitment, economic dispatch and optimal power flow, automatic generation control)
- Milliseconds to seconds: power system dynamics
- Nanoseconds to microseconds: power system transients

- In the form of optimization, long-term planning and short-term operation share similar structures, though the modeling granularity can vary

$$\begin{aligned} \text{Planning:} \quad & \text{minimize} \quad && \text{investment cost} + \text{operation cost} \\ & \text{subject to} \quad && \text{(flow, bus, unit, \ldots) constraints} \end{aligned}$$

$$\begin{aligned} \text{Operation:} \quad & \text{minimize} \quad && \text{commitment cost} + \text{dispatch cost} \\ & \text{subject to} \quad && \text{(flow, bus, unit, \ldots) constraints} \end{aligned}$$

Challenges in Grid Optimization

- Even if everything is deterministic, the resulting optimization problems can be large-scale, multi-period, mixed-integer (NP-hard), and non-convex (NP-hard), which are generally solved through approximation/relaxation techniques and heuristics
- With the increasing penetration of inverter-based resources toward the net-zero carbon emissions goal, such optimization can be even more challenging
- The optimization paradigm depends on how to model uncertainty: the forecast form
- Example: two-stage stochastic programming given probability distributions

$$\begin{aligned} \underset{\boldsymbol{x}}{\text{minimize}} \quad & \boldsymbol{c}^T\boldsymbol{x} + \mathrm{E}_\omega[Q(\boldsymbol{x},\omega)] \\ \text{subject to} \quad & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\ & \boldsymbol{x} \in \boldsymbol{X} \end{aligned}$$

$\boldsymbol{x}$: here-and-now decisions

ω: random outcome realized after $\boldsymbol{x}$

where $Q(\boldsymbol{x},\omega)$ is the optimal value of the second-stage problem

$$\begin{aligned} \underset{\boldsymbol{y}}{\text{minimize}} \quad & \boldsymbol{q}(\omega)^T\boldsymbol{y} \\ \text{subject to} \quad & \boldsymbol{T}(\omega)\boldsymbol{x} + \boldsymbol{W}(\omega)\boldsymbol{y} = \boldsymbol{h}(\omega) \\ & \boldsymbol{y} \in \boldsymbol{Y} \end{aligned}$$

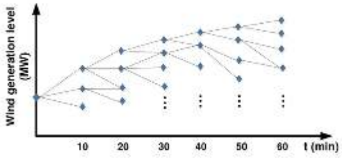
$\boldsymbol{y}(\boldsymbol{x},\omega)$: wait-and-see decisions

The Role of Forecasting

Types of energy forecasting, based on the forecast . . .

- Variable: (net) load, solar irradiance, solar power, . . .
- Horizon: long-term (for planning), medium-term, short-term (for operation), . . .
- Form: point (single estimate), probabilistic (quantile), scenario tree, scenario set, . . .

- Example: scenario tree (suitable for dynamic programming) vs. scenario set (suitable for sample average approximation)



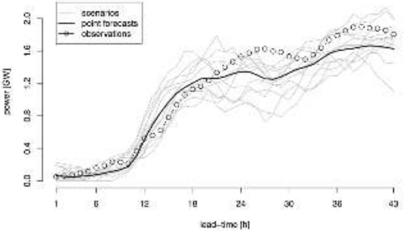


Figure: (left) scenario tree [Hedayati-Mehdiabadi et al. '15]; (right) scenario set [Morales et al. '14]

The Role of Forecasting

- Example: probabilistic forecasting can capture uncertainty

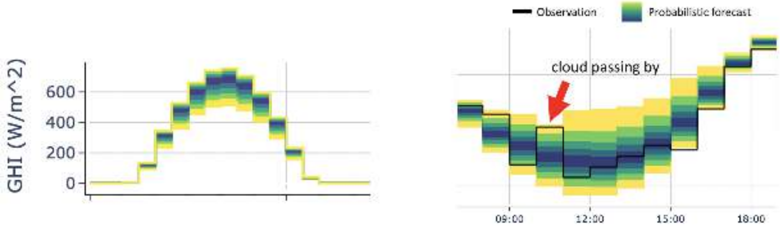


Figure: Probabilistic forecasts at 0%, 10%, . . . , 90%, 100% of (left) solar irradiance; (right) net load (`https://www.herox.com/net-load-forecasting`)

- In contrast, point forecasting induces deterministic optimization which is rough but simple to solve: there are always trade-offs in selecting the forecast form
- Even for a given forecast form, different forecasting methods can have different performance: trade-offs exist between accuracy and (training and inference) time

The Role of AI/ML

- Improving forecasting performance, especially during the grid's transformation
- Generative AI: generating representative scenarios (sample paths) into the future
- Inducing new solution methods for complex optimization problems

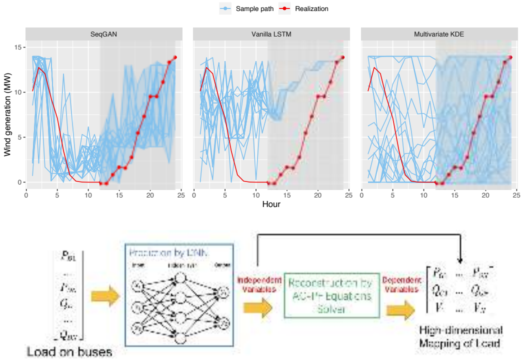


Figure: (top) scenario generation of wind power generation; (bottom) deep OPF [Pan et al. '23]

DE-EE0009357: Net-Load Forecasting

Methods

- Thrust I: a fuzzy system based gradient boosting model (Model I) for small data sets
- Thrust II: a Transformer based neural network model (Model II) for large data sets
- Thrust III: multi-target forecasting of net load and demand response (DR) potential

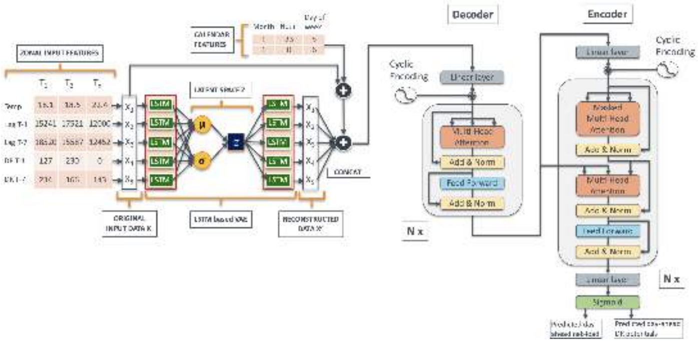


Figure: architecture of the extended Model II for multi-target forecasting of net load and DR potential

DE-EE0009357: Net-Load Forecasting

Key milestones

- Cleaned 5 small (less than 3 years) and 5 large data sets
- Web-based data visualization platform
- Point forecasting (mean absolute percentage error): 4% for Model I, 2% for Model II
- Probabilistic forecasting (continuous ranked probability score): 20% reduction
- Training and inference time: targets are met
- Methodology of quantifying DR potential
- The extended models will achieve similar target performance for DR potential

Conclusion

- The developed algorithms outperform the legacy algorithms, especially under the increasing penetration of behind-the-meter solar
- The public accessibility of the cleaned data sets and source code for the developed tools will benefit stakeholders from academia to industry
- As we unleash the power of AI/ML in power systems, we are looking forward to deeper collaboration with the industry: data is the fuel to the AI/ML engine