The Role of Forecasting and AI/ML in Grid Optimization

Wenyuan Tang
Department of Electrical and Computer Engineering
North Carolina State University

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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

Planning: minimize \( \text{investment cost} + \text{operation cost} \)
subject to \( \text{(flow, bus, unit, \ldots)} \) constraints

Operation: minimize \( \text{commitment cost} + \text{dispatch cost} \)
subject to \( \text{(flow, bus, unit, \ldots)} \) constraints
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:

  $$\begin{align*}
  \text{minimize} \quad & c^T x + E_\omega \left[ Q(x, \omega) \right] \\
  \text{subject to} \quad & Ax = b \\
  \quad & x \in X
  \end{align*}$$

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

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

  $y(x, \omega)$: 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
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