PROBABILISTIC FORECASTING FOR POWER SYSTEM OPERATIONS

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Overview

- **Objectives**
  - Develop *scalable probabilistic forecasting and system simulation* tools for real-time market operations.

- **Applications**
  - Provide market participants locational price distributions for integrating flexible demand and distributed energy resources
  - Provide operator short-term forecast of LMP distribution, power flow distribution, and probability distributions of discrete events such as congestions and contingencies.
  - *Multi-area interchange scheduling under uncertainty*
Outline

- A scalable forecasting and system simulation tool
  - Real-time operation models
  - Geometry of parametric DC OPF
  - Online learning via dynamic critical region generation
  - Complexity and performance: numerical results

- Multi-area interchange scheduling under uncertainty
  - Multi-area and multi-interface models
  - Stochastic interchange scheduling
  - Numerical results

- Conclusions and future work
Load vs. LMP forecasting

- Load are physical processes
- a variety of techniques on both point and probabilistic forecasting
- accuracy typically at 1–3% mean absolute percentage error (MAPE)

- LMPs are solutions of OPF
- Many black-box techniques on (point) LMP forecasting.
- Limited accuracy (10–20% in MAPE)
A real time LMP model

\[
\min_g \quad C(g) \\
\text{subject to} \quad 1^T(g - d_t) = 0 \quad (\lambda_{t-1}) \quad \text{power balance} \\
S(g - d_t) \leq F \quad (\mu_{t-1}) \quad \text{transmission limit} \\
g \leq G \\
g \leq \hat{g}_{t-1} + \Delta.
\]

\[
\pi_t = \lambda_{t-1} 1 + S^T \mu_{t-1}.
\]
Real time LMP model with reserve co-optimization

\[
\begin{align*}
\min_{g,r,s} & \quad \sum_i \left( c^g_i g_i + \sum_j c^r_i r_{i,j} \right) + \sum_u c^p_u s^l_u + \sum_v c^p_v s^s_v \\
\text{subject to} & \quad \sum_i (g_i - d_i) = 0, \\
& \quad \sum_i S_{ik}(g_i - d_i) \leq F_k, \\
& \quad \sum_i \sum_j d^u_{i,j} r_{i,j} + \left( I^+_u - I_u \right) + s^l_u \geq Q^l_u, \\
& \quad I_u = \sum_i \sum_j \sum_{k \in I_u} A_{ik}(g_i - d_i), \\
& \quad \sum_i \sum_j d^v_{i,j} r_{i,j} + s^s_v \geq Q^s_v, \\
& \quad g_i + \sum_j r_{i,j} \leq g^+_i, \\
& \quad \hat{g}_i - \Delta^-_i \leq g_i \leq \hat{g}_i + \Delta^+_i, \\
& \quad 0 \leq r_{i,j} \leq r^+_i, \\
& \quad g_i \geq g^-_i, \\
& \quad s^l_u, s^s_v \geq 0.
\end{align*}
\]

energy balance, transmission constraint \( k \), locational reserve \( u \), interface flow, system reserve \( v \), generator capacity \( i \), generation ramp \( i \), reserve ramp \( i, j \), generation capacity \( i \),
Seams in multi-area operations

\[
\begin{align*}
\min_{q, g_1, g_2} & \quad C_1(g_1) + C_2(g_2) \\
\text{subject to} & \quad 1^T(d_1 - g_1) + q = 0 \quad (\lambda_1) \\
& \quad 1^T(d_2 - g_2) - q = 0 \quad (\lambda_2) \\
& \quad S_1(d_1 - g_1) + T_1 q \leq F_1 \quad (\mu_1) \\
& \quad S_2(d_2 - g_2) + T_2 q \leq F_2 \quad (\mu_2) \\
& \quad g_1 \in \mathcal{G}_1, g_2 \in \mathcal{G}_2.
\end{align*}
\]
Simulation of large stochastic power networks

Characteristics:
- Random generation and load
- Probabilistic contingencies
- Multiperiod security constrained economic dispatch (SCED) with ramp constraints

Features:
- Joint and marginal distributions of nodal prices
- Joint and marginal distributions of power flows
- Joint and marginal distribution of generation dispatch and reserve
- ...........
Probabilistic forecasting and simulation

- **Generic Monte Carlo**
  - Generate sample paths of random generation, demand, contingency scenarios
  - Simulate real-time dispatch (OPF)
  - Complexity: \( \#\text{OPF}=MT \)

- **Online Learning via Dynamic Critical Region Generation**
  - Exploit structures of OPF solution
  - Online learning of solution dictionary
  - Complexity: \( \#\text{OPF}=10^{\{-x\}}MT \)
\[
\min_x \quad z(x) \\
\text{subject to} \quad Ax \leq b + E\theta \\
\]

\[y\]
DCRG: Dynamic Critical Region Generation

Algorithm 1 Dynamic Critical Region Generation
1: Input: load distribution and the mean trajectory \( d_t, t = 1, \cdots, T \).
2: Initialization: compute the initial critical region dictionary \( C_0 \) from \( d_t \).
3: for \( m = 1, \cdots, M \) do
4:   Generate a sample path \( \{d^1_t, d^2_t, \cdots, d^M_t\} \) from load distribution.
5:   for \( t = 1, \cdots, T \) do
6:     Search \( C_{t-1}^m \) for critical region \( C(d^m_t) \).
7:     if \( C(d^m_t) \not\in C_{t-1}^m \) then
8:       Compute the critical region \( C(d^m_t) \) and update \( C_t^m = C_{t-1}^m \cup \{C(d^m_t)\} \).
9:     end if
10:   end for
11: end for
12: Output: The critical region dictionary \( C_T^M \).
The Polish Network

- 3120 buses, 3693 branches
- 505 thermal units with ramp constraints
- 30 wind farms (Gaussian)
- 10 constrained transmission lines
- 10,000 Monte Carlo runs
- 24 hour simulation horizon

- 505 decision variables
- 2041 constraints
- ~3M OPFs
Computation cost comparison
Critical region distribution

3000 critical region observed in 3M samples

There are $\sim 2^{HT}$ typical sequences

$$H = - \sum_i (p_i \times \log_2 p_i)$$
The IEEE 118 system

- 118 buses in three areas
- 10 capacity constraints
- 91 stochastic loads (Gaussian)
- 54 thermal generators
- 1000 Monte Carlo runs
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- Conclusions and future work
Two-area single-interface proxy model
Two-area single-interface interchange

- Each ISO has a simplified model of the neighboring area with a proxy bus.
- Market participants submit offers/bids for external transactions at proxy buses.
- Export/import quantity is scheduled ahead of time.
- Each ISO schedules its own operations with fixed interchange.

- FERC approves coordinated transaction scheduling (CTS) for PJM & NYISO, March 2014.
- Estimated cost saving: 9M~26M per year.
- Versions of CTS are being implemented for MISO-PJM, NYISO-ISONE.
Tie optimization (TO)

\[
\begin{align*}
\min_{q, g_1, g_2} & \quad C_1(g_1) + C_2(g_2) \\
\text{subject to} & \quad \text{power balance constraints for Area 1 and 2} \\
& \quad \text{transmission constraints for Area 1 and 2} \\
& \quad \text{generator constraints for Area 1 and 2} \\
& \quad \text{interface capacity constraint}
\end{align*}
\]
Coordinated Transmission Scheduling (CTS)

\[
\min_{g_1, g_2, q} \quad C_1(g_1) + C_2(g_2) + C_{\text{bid}}(q)
\]

subject to
- power balance constraints for Area 1 and 2
- transmission constraints for Area 1 and 2
- generator constraints for Area 1 and 2
- interface capacity constraint
Stochastic Coordinated Transmission Scheduling (SCTS)

\((P_1)\) \(\min_{q \leq Q} \sum_{i=1}^{2} E_{d_i} [C_i(g_i^*(q, d_i))]

\((P_{2i})\) \(\min_{g_i \in S_i} C_i(g_i)

subject to \(1^T(d_i - g_i) \pm q = 0, \quad (\lambda_i)
\)
\(S_i(d_i - g_i) \pm T_i q \leq F_i. \quad (\mu_i)
\)
\(\pi_i(q, d_i) \triangleq \lambda_i(q, d_i) + (T_i)^T \mu_i(q, d_i)\)

**Theorem 1**

The optimal interchange is given by the solution \(q^*\) of

\[ \pi_1(q) = \pi_2(q) \]

if \(q^* < Q\) and \(Q\) otherwise.
The multi-interface interchange problem

Two-stage stochastic optimization:

$$\begin{align*}
(P_3) \min_{q \leq Q} & \sum_{i=1}^{N} E_i \left[ C_i(g_i(q_i, d_i)) \right] \\
(P_{4i}) \min_{g_i \in G_i} & C_i(g_i) \\
\text{subject to} & \quad 1^T(d_i - g_i) + 1^T q_i = 0, \quad (\lambda_i) \\
& \quad S_i(d_i - g_i) + T_i q_i \leq F_i. \quad (\mu_i)
\end{align*}$$

Interface-by-Interface Scheduling (IBIS):

1. Initialize $q^{(0)} = 0$.
2. For iteration $k$, solve each interface flow sequentially with fixed flows on the other interfaces.
3. If $\|q^{(k-1)} - q^{(k)}\|_2 \leq \epsilon$, terminate; otherwise, go to Step (2) for iteration $k + 1$. 

**Theorem 2**

*Interface-by-Interface Scheduling (IBIS) Algorithm* generates a sequence $\{q^{(k)}\}_{k=0}^{\infty}$ that converges to the global optimal solution.
- 3 areas, 2 interfaces, and 12 wind generators
- Case 1: renewable penetration level 22%
- Case 2: renewable penetration level 33%
*Renewable penetration = $\frac{E[\text{wind}]}{\text{total load}}$
Scenario 1: 20% renewables

- Diagram showing interface flows and expected overall costs.
- Area 1: \( \pi_1^{CE} = 37.73 \) vs. \( \pi_1^{IBIS} = 36.57 \)
- Area 2: \( \pi_2^{CE} = 38.25 \) vs. \( \pi_2^{IBIS} = 36.57 \)
- Area 3: \( \pi_3^{CE} = 33.26 \) vs. \( \pi_3^{IBIS} = 36.57 \)
Scenario 2: 30% renewables
Summary of results

- Real-time LMP models
  - Energy and energy-reserve markets
  - Deterministic and probabilistic contingencies

- Forecasting methodologies
  - Multiparametric programming approach to
  - Deterministic and probabilistic contingencies
  - Forecast methods and applications
    - An online learning approach of to forecasting of LMP and power flow distributions.
    - A Markov chain approach for ex ante and ex post LMPs
    - Multi-area interchange scheduling under uncertainties
Related publications
