Cost Estimation in Unit Commitment Problems Using Simulation-Based Inference

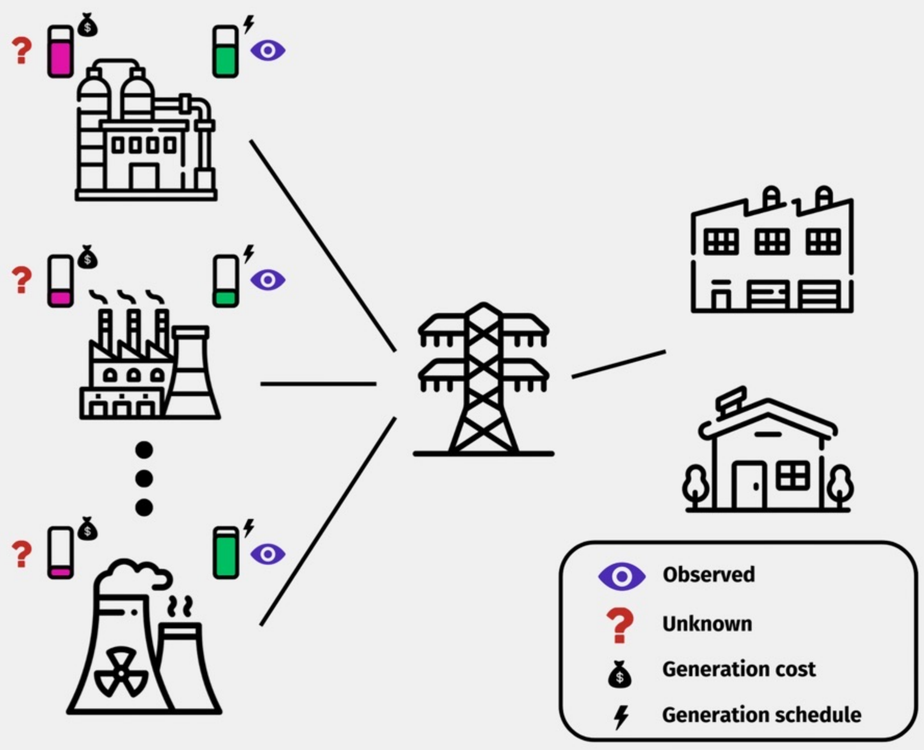
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Context

- Unit Commitment (UC): optimizes power plant production over time to meet demand, minimizing costs and satisfying constraints.
- Generation schedule: published production schedules – UC's output.
- Generation cost: non-public fuel and startup costs, crucial UC parameters for accurate cost modeling and generation scheduling.

Challenge

- Infer **unknown generation costs** using **observed generation schedules** and demand scenarios.
- Traditional methods are computationally intensive in inference and may not capture the full uncertainty.



Contributions

- Simulation-based inference (SBI) allows estimation of unknown cost parameters in UC problems.
- Neural Posterior Estimation (NPE) effectively approximates the posterior distribution.
- Fast inference through amortized inference VS traditional methods.

Problem formulation

UC problem solution: $\boldsymbol{G} = f(\boldsymbol{\psi}, \boldsymbol{\theta}, \boldsymbol{\delta})$, where:

- $\boldsymbol{G}$: generation schedule (observations).
- $\boldsymbol{\psi}$: known physical characteristics (generation limits, ramp rates, etc.).
- $\boldsymbol{\theta}$: unknown generation cost parameters to be estimated.
- $\boldsymbol{\delta}$: demand scenarios.
- f: optimization model (simulator).

Methodology

Simulation-Based Inference

By simulating the UC model with different $\boldsymbol{\theta}$ and $\boldsymbol{\delta}$, we generate synthetic observations.

Neural Posterior Estimation

$$\phi^* = \arg\max_{\phi} \mathbb{E}_{p(\boldsymbol{G},\boldsymbol{\theta},\boldsymbol{\delta})} \left[\log q_{\boldsymbol{\phi}}(\boldsymbol{\theta} \mid \boldsymbol{G}, \boldsymbol{\delta}) \right]$$

Train neural surrogate (e.g., normalizing flow) to approximate the posterior $q_{\boldsymbol{\phi}}(\boldsymbol{\theta} \mid \boldsymbol{G}, \boldsymbol{\delta})$ by maximizing the expected log-likelihood over synthetic observations.

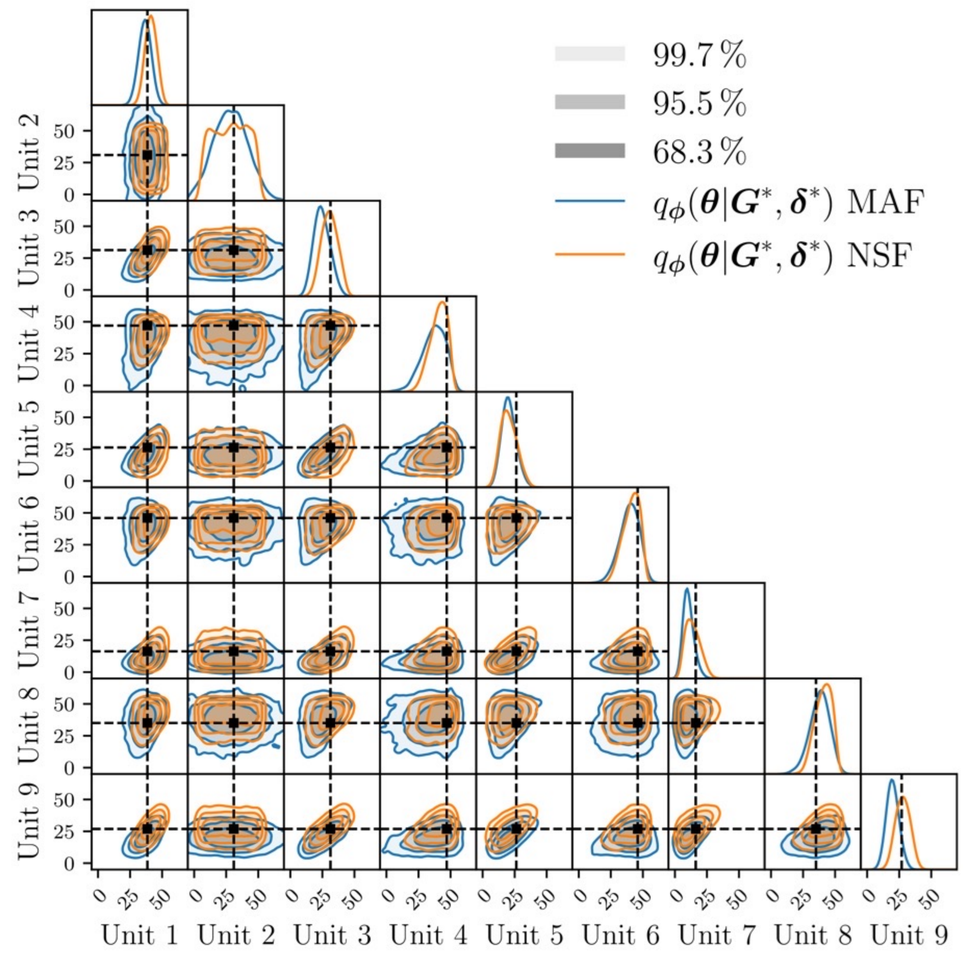
Experimental setup

- 10 generation units over a 24-hour horizon.
- Trained NPE models using Masked Autoregressive Flow (MAF) and Neural Spline Flow (NSF) involving 2^{16} simulations.

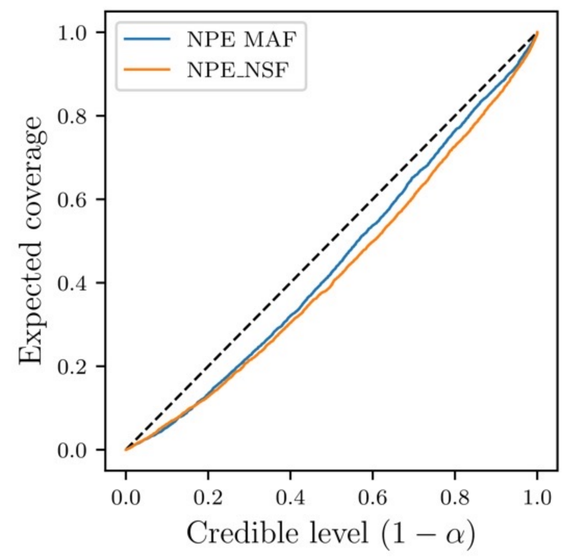
Results

1. Posterior Estimation

Learned posterior distribution $q_{\boldsymbol{\phi}}(\boldsymbol{\theta} \mid \boldsymbol{G}, \boldsymbol{\delta})$ capture true cost parameters.



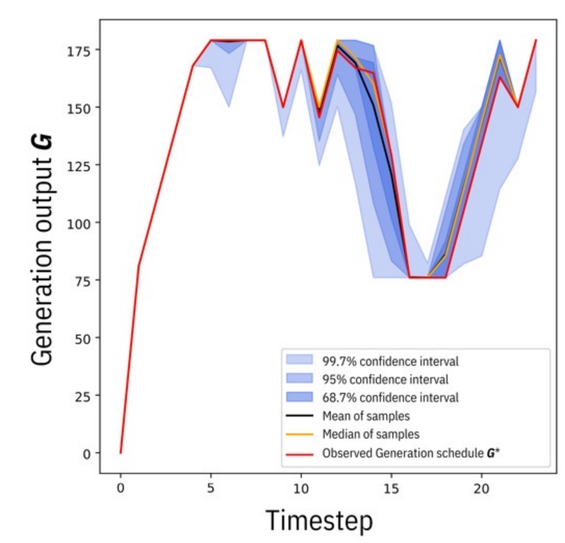
2. Coverage Analysis



$$\mathbb{E}_{p(\boldsymbol{\theta},\boldsymbol{G},\boldsymbol{\delta})} \left[\mathbb{1}\left\{ \boldsymbol{\theta}_i \in \boldsymbol{\Theta}_{q_\phi(\boldsymbol{\theta}|\boldsymbol{G}_i,\boldsymbol{\theta}_i)}(1-\alpha) \right\} \right]$$

OVERCONFIDENT

3. Posterior Predictive Checks



$$\boldsymbol{\theta}^* \sim q_\phi(\boldsymbol{\theta} \mid \boldsymbol{G}^*, \boldsymbol{\delta}^*)$$

$$\boldsymbol{G} = f(\boldsymbol{\psi}, \boldsymbol{\theta}^*, \boldsymbol{\delta})$$

$$p(\boldsymbol{G}|\boldsymbol{G}^*)$$

Future Work

- Address posterior overconfidence.
- Scale methods to handle high-dimensional UC problems and longer horizons.
- Model more complex UC problems with network considerations and renewable energy sources.