# Improving Power Grid Resiliency with Bi-objective Stochastic Integer Optimization

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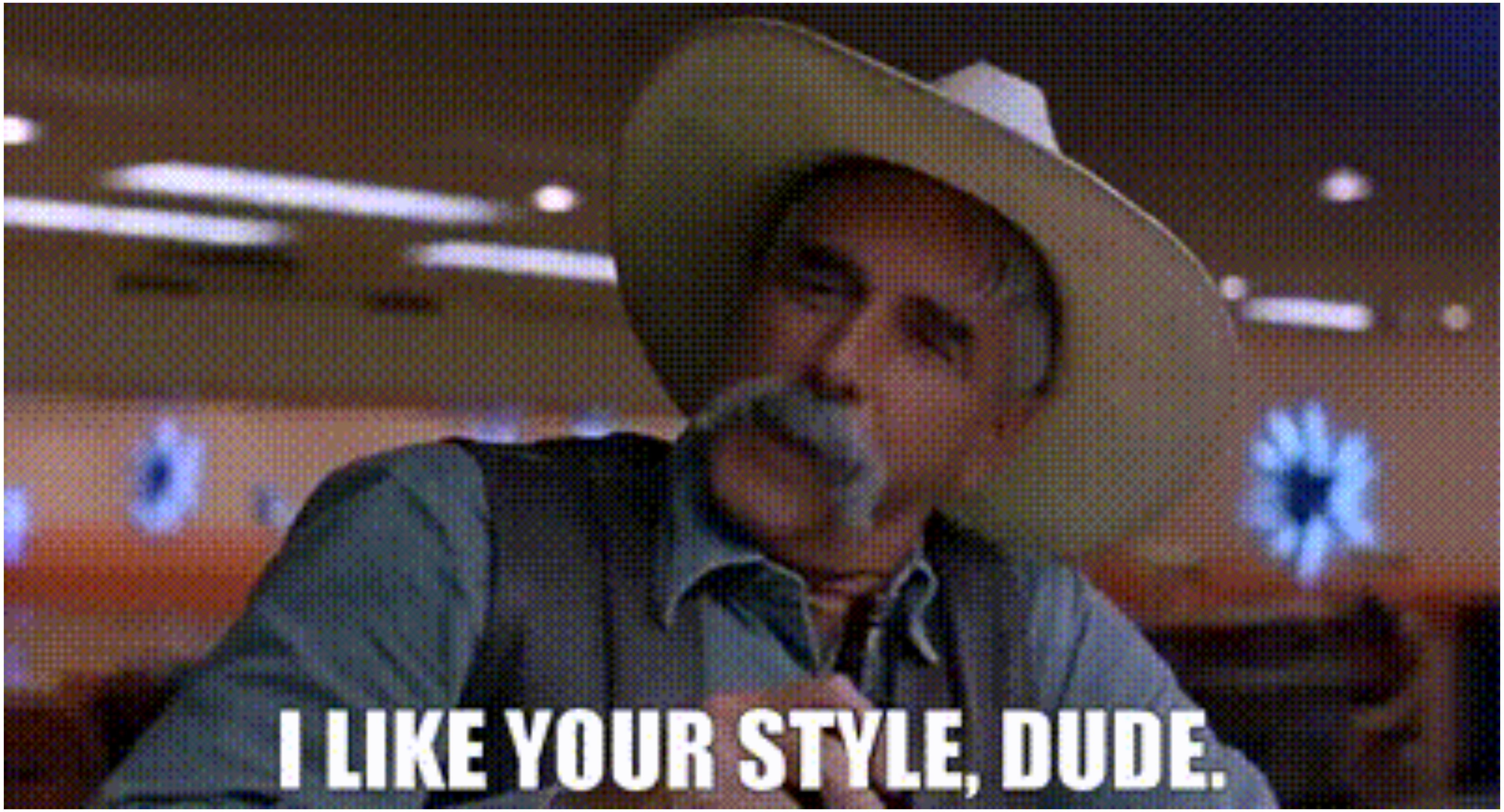
# Thank you Steve!



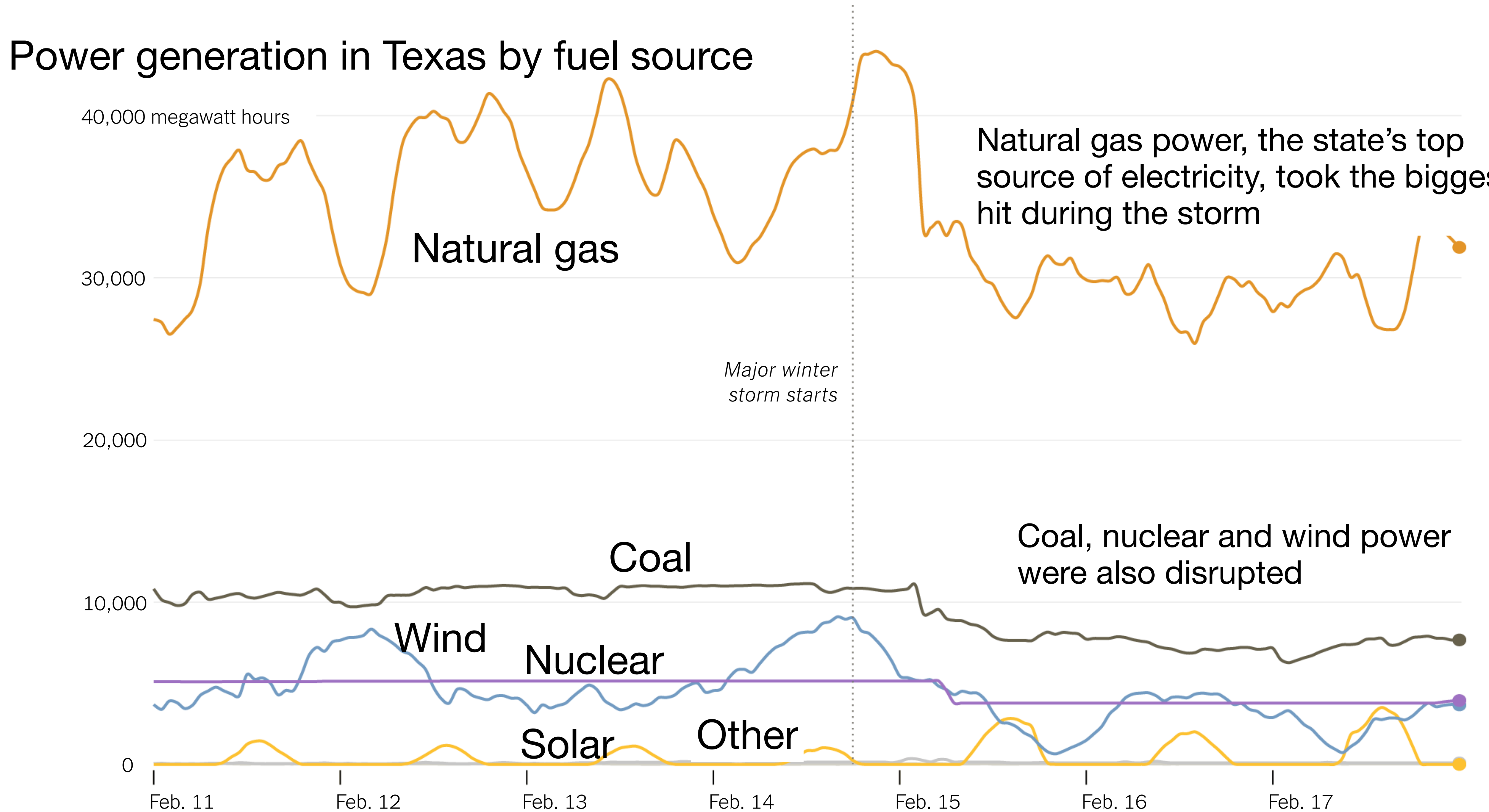
# Resource adequacy in the power grid

- Grid planners make long term decisions about which generators to build
- Problem: Balancing **low cost** of normal operation and **high resiliency** to extreme conditions
- Challenges:
  - **Weather dependence**
  - Demand variability
  - Wildfires
  - Energy storage
  - Generator operation requirements
  - Transmission line constraints

# Texas power crisis

## February 2021

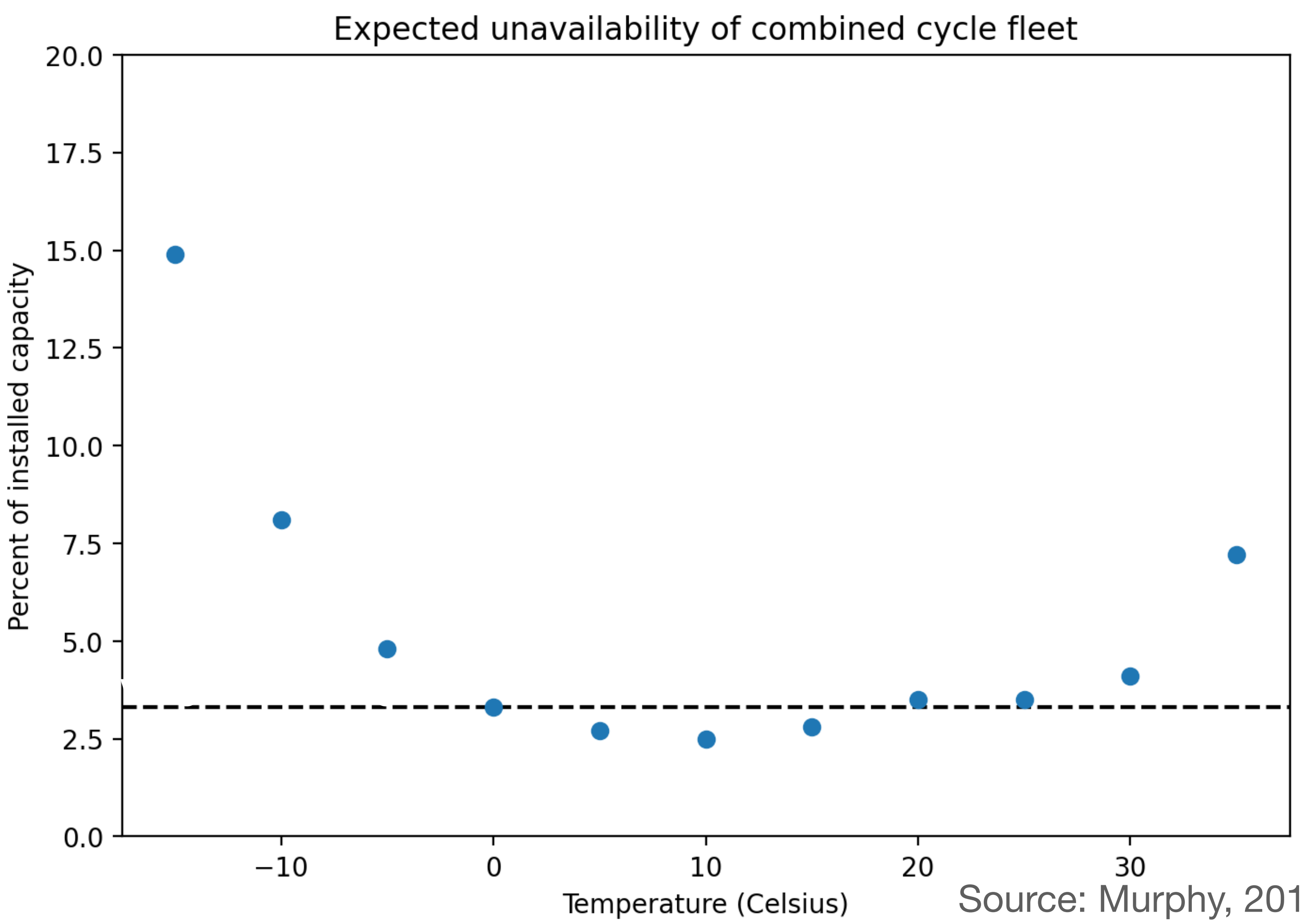
- Extreme cold
- High demand
- High generator outages across most technologies
- Widespread electricity outages




Source: New York Times

# Temperature dependence in the power grid

- Demand
- Natural gas supply
- Generator reliability
- Thermal plant capacity




Source: Murphy, 201

# Towards an optimization formulation

**Primary decision variables**

- For gas/coal/nuclear generators

$$x_i = \begin{cases} 1, & \text{if generator } i \text{ is built (base capacity is } \bar{p}_i\text{)} \\ 0, & \text{otherwise} \end{cases}$$

- For solar/wind locations: $x_i =$ base capacity to build (MW)

**Capital costs:** $c^\top x$ ($c_i$ is capital cost amortized to hourly basis)

**Operational impacts of generator mix (depends on random demand/capacity)**

- Cost to meet demands
- Amount of load shed (difficult to quantify as a cost)

# Modeling “random” quantities

- Random variables in our model: $(\mathbf{h}, \mathbf{T})$

  $\mathbf{h} =$ an hour (varies throughout time of day and year)
  $\mathbf{T}_i =$ temperature at location of generator $i$ in hour $\mathbf{h}$

- Separate spatially-dependent statistical model of $\mathbf{T}$ for each hour $h$

- **Total load:** temperature and hour dependent (estimated via regression): $D(\mathbf{h}, \mathbf{T})$

- **Capacities:** $\bar{\mathbf{p}}_i(\mathbf{h}, \mathbf{T})$
  - Deterministic dependence on hour (solar/wind capacity factors)
  - Random reduction from base capacity: mean reduction is function of $\mathbf{T}_i$

# Simple operational model

Model for fixed capital decisions $x$, hour $h$, and temperature vector $T$

$$
\begin{aligned}
Q_N^\lambda(x, h, T) = \min_{p,s} \sum_i c_{G,i} p_i + \lambda s \\
\text{s.t.} \sum_i p_i \geq D\left(h, T\right) - s \\
p_i \leq x_i \bar{p}_i \left(h, T_i\right) \\
s, p \geq 0
\end{aligned}
$$

- $p_i$ = Generation amount from generator $i$ (decision)
- $s$ = Amount of load shed (decision)
- $\lambda$ = "cost" of load shed (parameter set to attempt to limit load shed amount)

# Two-stage stochastic programming model

$$\min_x c^\top x + \mathbb{E}_{\mathbf{h},\mathbf{T}}\left[Q_N^\lambda(x,\mathbf{h},\mathbf{T})\right]$$

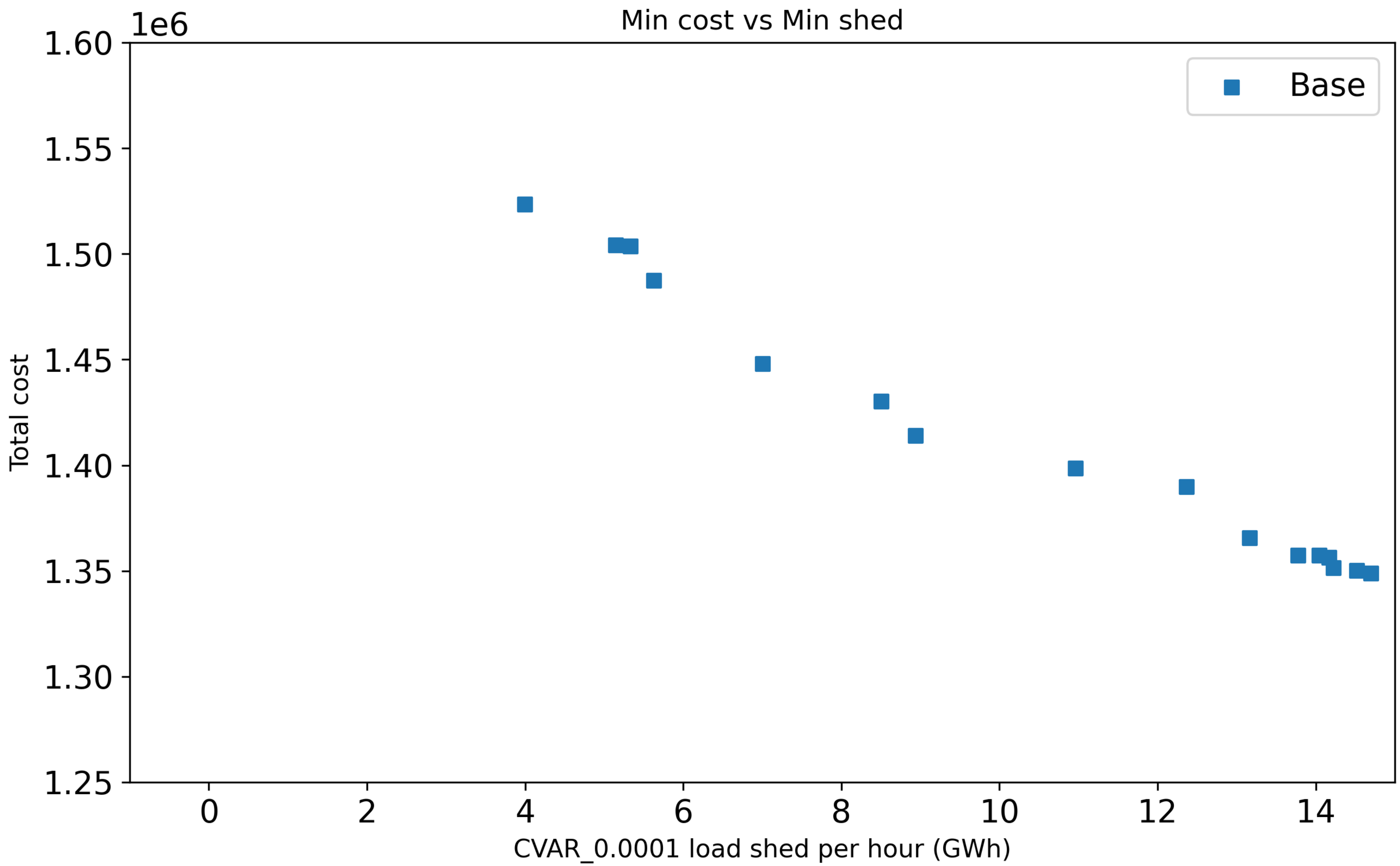
How to solve?

- Continuous opt methods (SGD, etc.) not applicable due to integer $x$
- Sample average approximation (SAA): replace expected value with finite sum
- Repeat with different random samples
- Solving SAA problem: *Extensive form* or decomposition algorithms

How to choose $\lambda$ ?

- Solve with varying values ⇒ Set of solutions that with varying trade-off between cost (capital + average generation cost) vs. risk of load shedding

# Trade-off between cost and risk of load shed

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# Potential drawbacks

$$\min_{x} c^\top x + \mathbb{E}_{\mathbf{h},\mathbf{T}}\left[Q_N^\lambda(x, \mathbf{h}, \mathbf{T})\right]$$

- Sampling error highly sensitive to high-impact (high load shed) low-probability events
- Expected value ignores risk aversion
- Objective changes in extreme situations
    - E.g., goal is to minimize load shed with little concern for cost

# Bi-objective perspective

- Objective 1: Min average cost = $c^\top x + \mathbb{E}_{\mathbf{h},\mathbf{T}}\left[Q_N^\lambda(x,\mathbf{h},\mathbf{T})\right]$
- Objective 2: Min risk of load shed = $\mathrm{CVaR}^\alpha_{\mathbf{h},\mathbf{T}}\left(Q_E(x,\mathbf{h},\mathbf{T})\right)$

$$Q_E(x,h,T) = \min_p s \qquad \text{s.t. } \sum_i p_i \geq D(h,T) - s$$

$$p_i \leq x_i \bar{p}_i\left(h, T_i\right)$$

$$s, p \geq 0$$

$\mathrm{CVaR}^\alpha_{\mathbf{h},\mathbf{T}}$: Average over $\alpha$ fraction of outcomes with worst load shed

- Also exploring $\mathbb{P}(Q_E(x,\mathbf{h},\mathbf{T}) > 0)$ as risk measure (“LOLP”) => chance constraint formulation

# How to solve bi-objective model

$$\min_x \; c^\top x + \mathbb{E}_{\mathbf{h},\mathbf{T}}\left[Q_N^\lambda(x,\mathbf{h},\mathbf{T})\right)$$
$$\text{s.t. } \mathrm{CVaR}^{\alpha}_{\mathbf{h},\mathbf{T}}\left(Q_E(x,\mathbf{h},\mathbf{T})\right) \le U$$

- Solve this model repeatedly with varying $U$. (Fix $\lambda$)
- Estimating normal operation costs: Sample average approximation
- CVaR of load shed: Sample average approximation
  - Sample from same distributions $\mathbf{h}$ and $\mathbf{T}$
  - With $\alpha = 0.0001$, this is very sensitive to sampling error

# Idea: Conditional sampling

$$\min_x \; c^\top x + \mathbb{E}_{\mathbf{h},\mathbf{T}}\left[Q_N^\lambda(x,\mathbf{h},\mathbf{T})\right)$$
$$\text{s.t. CVaR}^\alpha_{\mathbf{h},\mathbf{T}}\left(Q_E(x,\mathbf{h},\mathbf{T})\right) \le U$$

Motivation: extreme temperature is a proxy for extreme load shed

- Sample from $\mathbf{T}$ *conditionally* on being an extreme temperature (e.g. 1% hottest and coldest)
- Then use larger $\alpha$ in CVaR term over these extreme scenarios, e.g. $\alpha = 0.1$

Challenge

- “Tuning” $\alpha$ when using the conditional sampling

# An advantage of bi-objective formulation

**General bi-objective problem:**

- Find (approximation) of set of Pareto solutions to minimization of two objectives: $f(x)$ and $g(x)$

**Observation**

- If $h$ is any strictly increasing function, set of Pareto solutions is equivalent to set of Pareto solutions of two objectives: $f(x)$ and $h(g(x))$
- Implication: to obtain Pareto solutions, can use a highly incorrect estimate of $g$ as long as estimate is highly correlated with $g$

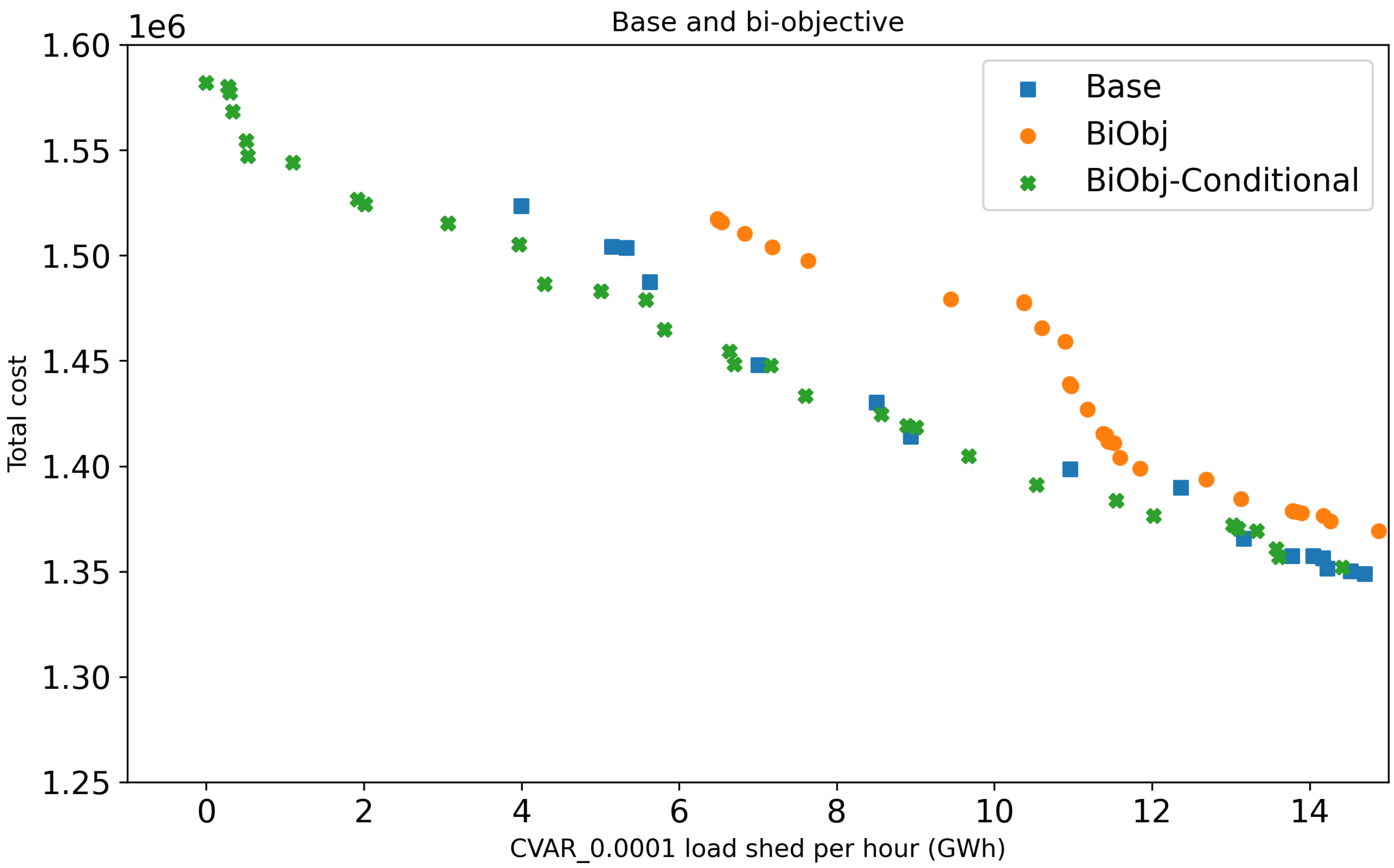
# Case study: Midwestern US

- Scope: 6 states (MN, IA, WI, MI, IN, IL)
- Existing generators and potential new wind and solar are available to build (~2000 $x_i$ vars)
- 15 samples to generate candidate solutions
- Unconditional and conditional temperature scenarios (county-by-county) from ANL collaborators
- Generator capacities sampled from model created from PJM outage data
- Target $\alpha = 0.0001$
- Conditional: $\alpha = 0.1$ with 1% extreme temperatures
- Evaluation of solutions done using true distribution with large sample size

Scenarios per sample

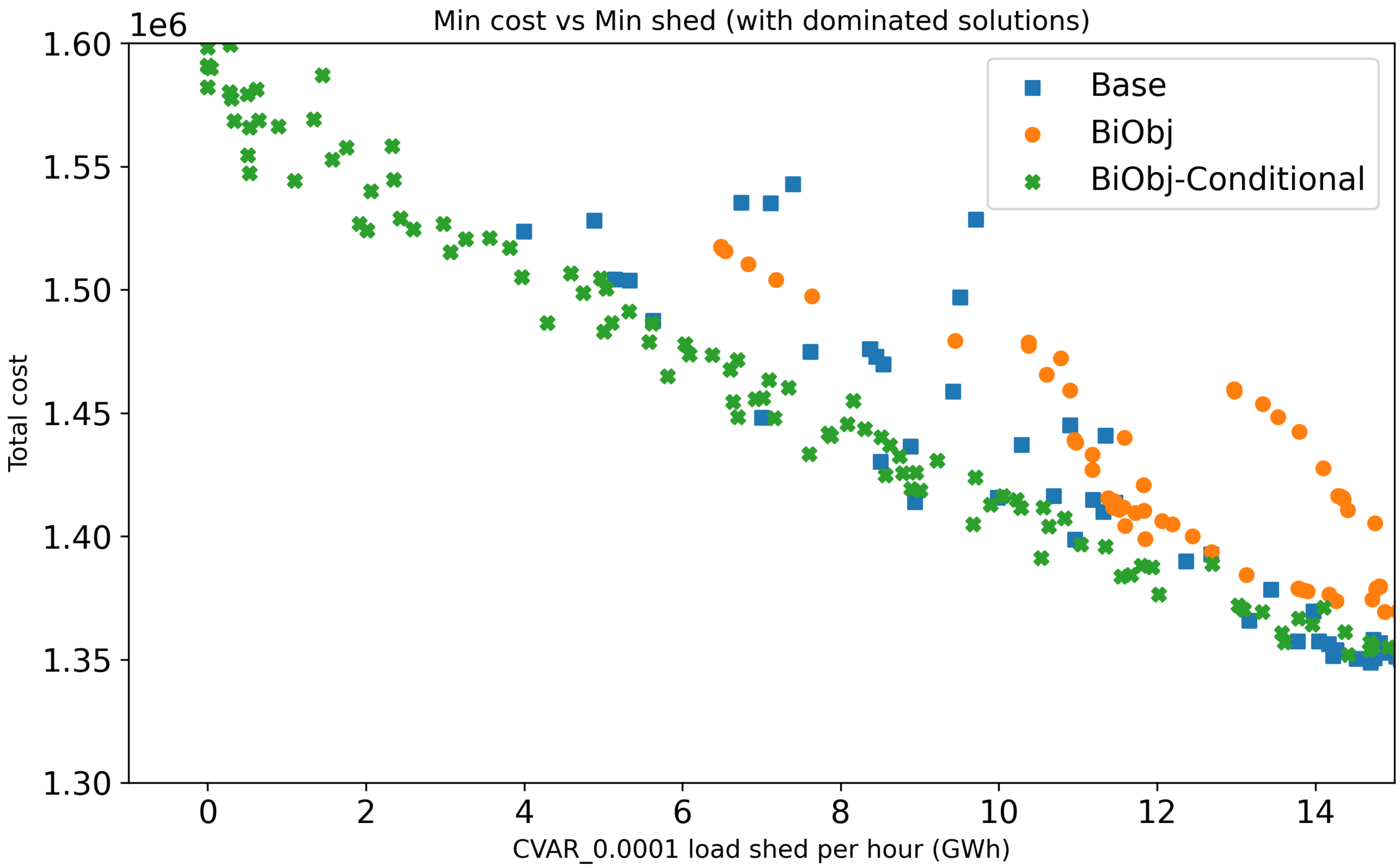
| | **Normal** | **Extreme** |
|---|---|---|
| **Bi-objective** | 1,008 | 1,008 |
| **Base** | 2,016 | 0 |
| **Test** | 5,040 | 25,008 |

# Conditional sampling yields lowest risk solutions




Solutions dominated by another solution obtained by same method are left out of this figure

# Conditional sampling yields more consistent solutions

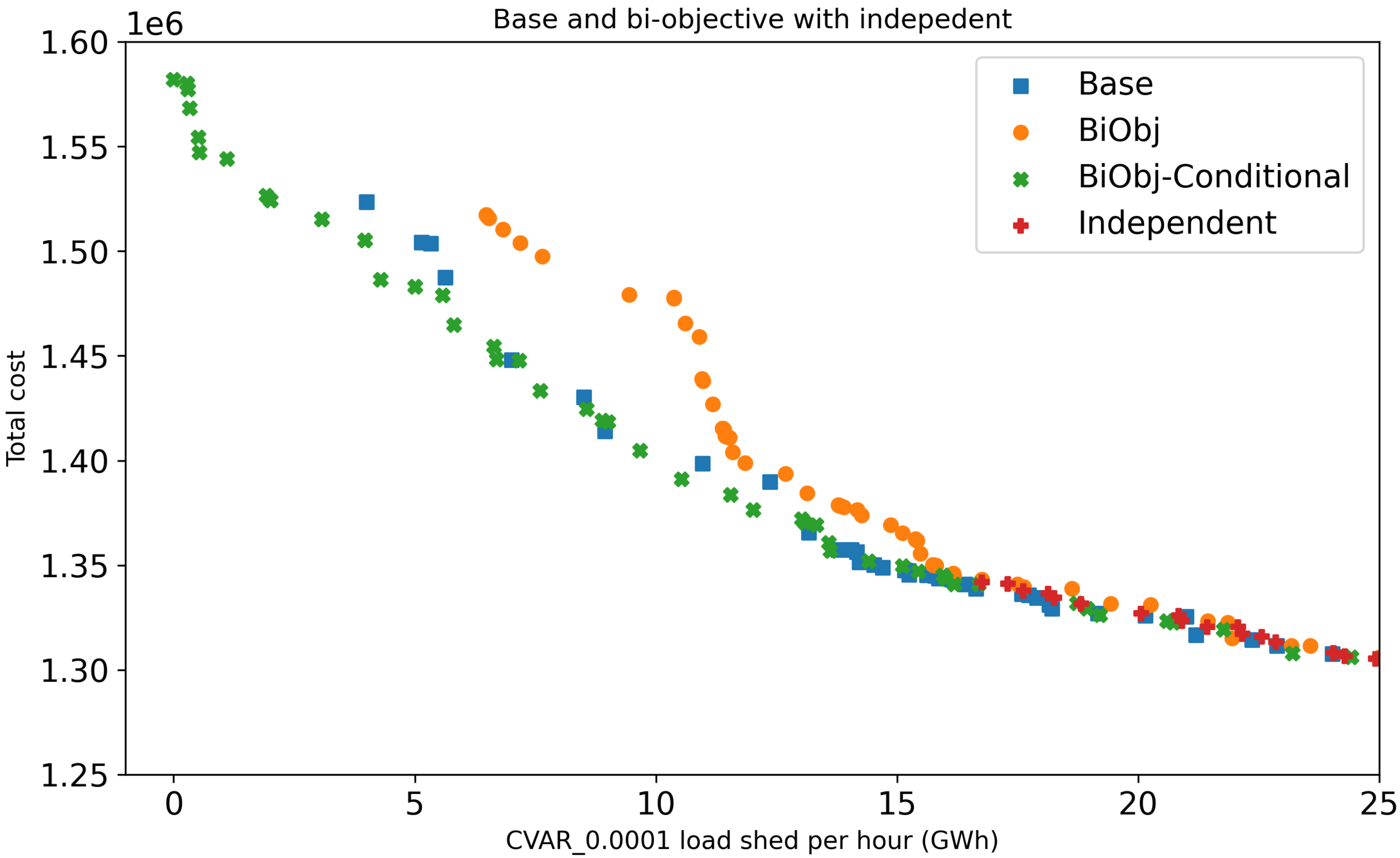



This figure includes solutions obtained from all 15 different samples at each trade-off parameter level

# Spatial distribution of temperatures

- $\mathbf{T}$ is spatially correlated: the temperature in one location is highly correlated with the temperature at nearby locations
- Spatially independent temperature distributions are sometimes used in practice (e.g. FEMA risk assessments)
- Experiment: solve the bi-objective model with conditional samples, but with all samples obtained from spatial independent distribution

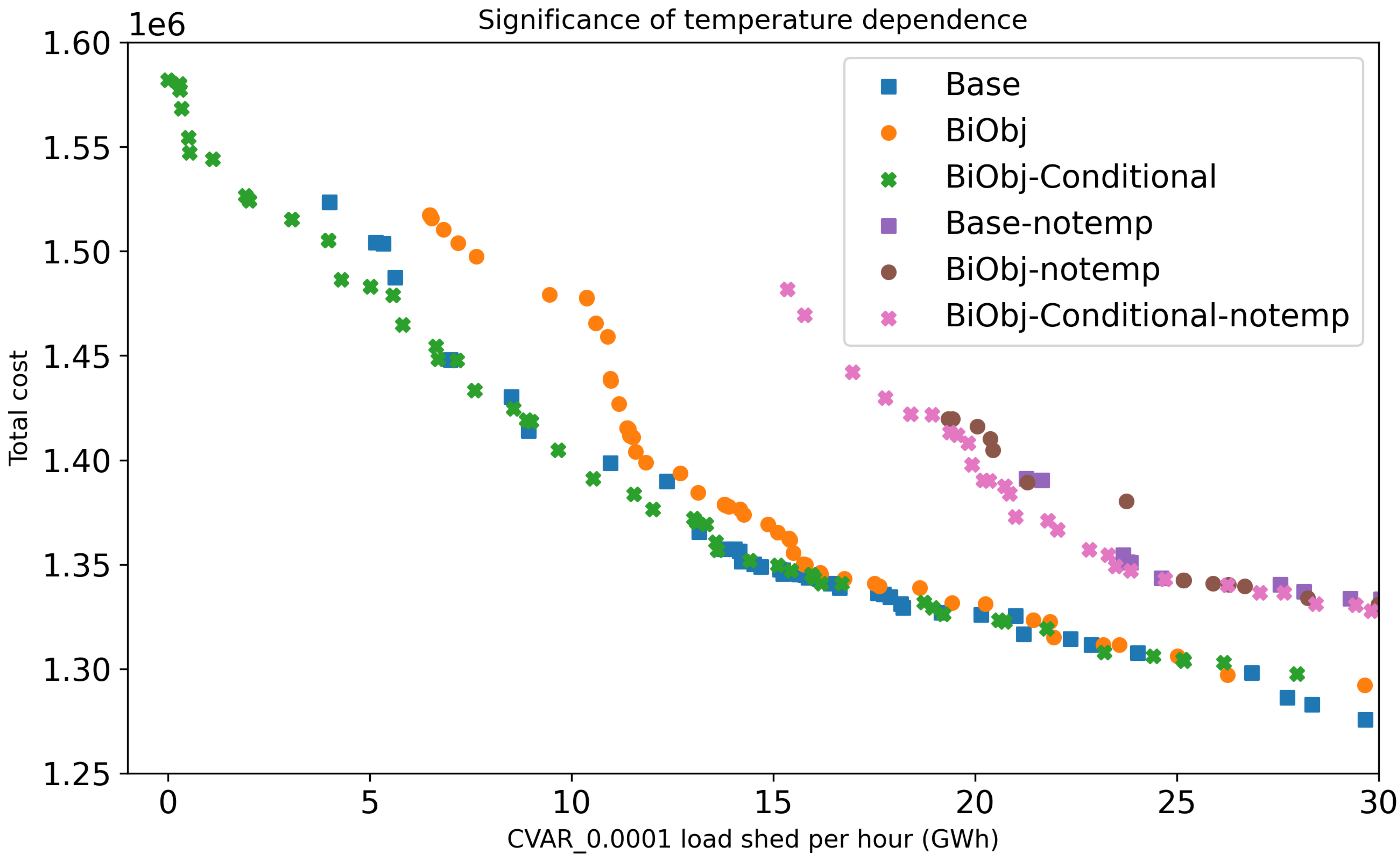
# Importance of spatial temperature distribution




Dominated solutions within a method are again excluded.

X-axis scale (CVaR) increased in this figure

# Importance of modeling temperature-dependent capacity



# Limitations/Future extensions

- No consideration of transmission constraints or capacity expansion
- Does not capture dynamic effects/constraints
    - Ramping and min up/down constraints
    - Effect of duration of extreme temperature events
    - Energy storage/ reservoir levels for hydro resources
- Additional weather-dependent factors

Most of these can be incorporated into same modeling framework, but new computational techniques will be required to solve it

Compare LOLP (chance constraint) to CVaR formulation



Insights about strategic location of generator capacity?

# References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# Normal and extreme temperatures