

Importance Sampling with Analog Scenarios for Stochastic Economic Dispatch

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Introduction

Increasing penetrations of renewable energy sources such as wind into power grids motivates the investigation of new approaches to computing 5-minute economic dispatch.

We investigate extending previous work on two-stage stochastic economic dispatch with importance sampling [1] to use historical data as a source of uncertainty scenarios.

Objective

To investigate the benefits of using importance sampling with analog scenarios in two-stage stochastic economic dispatch.

Methods

Six years of WIND Toolkit [2] data are used as synthetic historical wind data, and 1 year of WIND Toolkit data is used to simulate actuals on the RTS-GMLC network [3].

Network constraints on the RTS-GMLC are approximated by a transport network.

The investigation is conducted by comparing the standard Monte Carlo approach to the sample average approximation (SAA) of two-stage stochastic programs with our importance sampling approach.

Two-stage stochastic programming and SAA

Linear two-stage stochastic program:

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} + \mathbb{E}_{\xi} [L(\mathbf{x}, \xi)]$$

$$\text{where, } L(\mathbf{x}, \xi) = \min_{\mathbf{y}} \mathbf{c}_{\xi}^T \mathbf{y} \\ \text{s. t. } \mathbf{T}_{\xi} \mathbf{x} + \mathbf{W}_{\xi} \mathbf{y} = \mathbf{b}_{\xi} \\ \mathbf{y} \geq \mathbf{0}$$

\mathbf{x} – first stage variables (generator setpoints)

\mathbf{y} – second stage variables (e.g. wind dispatched, slack)

ξ – uncertain variable (wind deviation from persistence)

Second stage constraints include power flow constraints, power balance at nodes, constraints on 2nd stage variables.

Sample average approximation

$$\mathbb{E}_{\xi} [L(\mathbf{x}, \xi)] \approx \frac{1}{N} \sum_{i=1}^N L(\mathbf{x}, \xi_i)$$

Importance sampling

Continuous importance sampling

$$\mathbb{E}_p [L(\mathbf{x}, \xi)] = \int_{\Omega} L(\mathbf{x}, \xi) p(\xi) d\xi \\ = \int_{\Omega} \frac{L(\mathbf{x}, \xi) p(\xi)}{q(\xi)} q(\xi) d\xi = \mathbb{E}_q \left[\frac{L(\mathbf{x}, \xi) p(\xi)}{q(\xi)} \right]$$

Since we use a dataset to build our scenarios, we employ a discrete version of importance sampling over bins of analog scenarios.

Methods cont'd

Sampling with multiple wind sites:

1. Bin wind scenario deviations from persistence using percentiles defined by $\sum_i \xi_i$.
2. Compute average deterministic costs \bar{c}_j (sample with replacement) for each bin.
3. Set probability of selecting bin j by $\bar{c}_j / \sum_j \bar{c}_j$.
4. Select bin according to probability, draw scenario uniformly from bin, compute weight.

Experiments and Results

Experiment 1: two-stage stochastic economic dispatch over varying dates and times

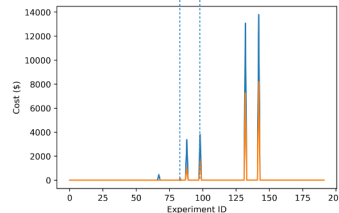
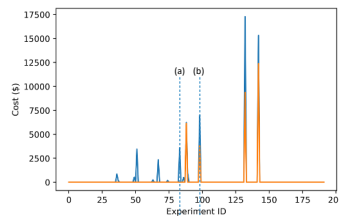


Figure 2: Importance sampling (orange) and standard Monte Carlo (blue) 2nd stage costs for datetimes in our test suite. (Top) 10 scenario, (bottom) 20 scenario experiments.

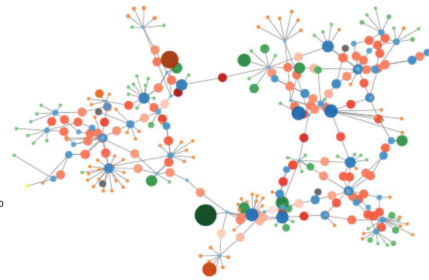


Figure 1: RTS-GMLC system with 120 lines, 73 buses, and 118 generators, 22 of which are wind plants.

Sampling method	# of scenarios	First stage costs (\$)	Second stage costs (\$)
MC	10	620418	58556
MC	20	620937	34512
IS	10	621374	31700
IS	20	622311	18317

Table 1: Comparing sums of first and second stage costs from stochastic economic dispatch experiments in Fig. 2. These experiments used standard and importance sampling for different sampling rates.

Experiment 2: repeated stochastic economic dispatch computations at timestamps (a) and (b)

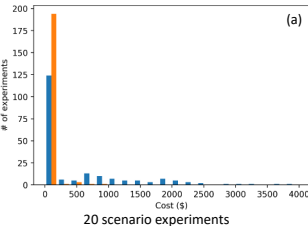
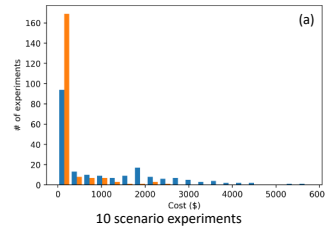
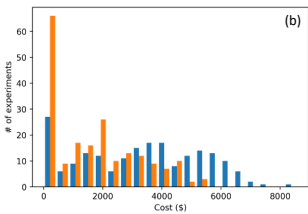
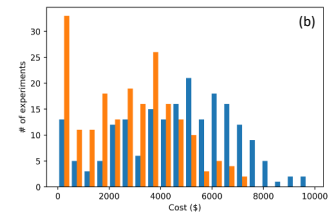


Figure 3: 2nd stage costs for std. MC sampling (blue) and IS (orange) on timestamps (a) and (b) defined in Figure 2.

Sampling method	Mean	Std.
10 MC	4639	2275
20 MC	3289	2072
10 IS	2746	1851
20 IS	1648	1519

Table 2: Statistics on 200 economic dispatch experiments, 2nd stage costs for (b).

Sampling method	Mean	Std.
10 MC	1033	1278
20 MC	512	813
10 IS	168	452
20 IS	17	97

Table 3: Statistics on 200 experiments, economic dispatch 2nd stage costs for (a).

Discussion

In our experiments, using importance sampling to select scenarios for the SAA leads to significant second-stage savings, corresponding to less loss-of-load.

First stage costs from the standard Monte Carlo sampling and importance sampling experiments are not significantly different.

In cases where there is a significant amount of wind-power decrease (see Fig. 4), as occurs at timestamp (b), importance sampling will not prevent loss-of-load.

However, the loss-of-load will be less severe than two-stage stochastic programming using standard MC sampling.

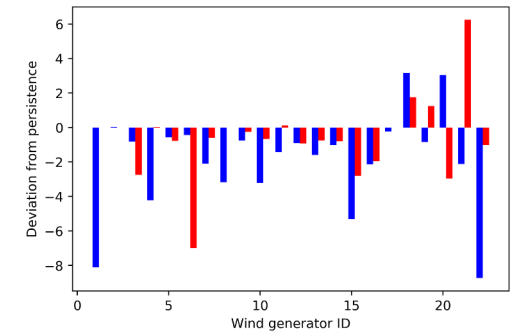


Figure 4: Deviation from persistence forecasts of wind power (in MW) for timestamps (a) red and (b) blue at 22 wind plants on RTS. Total deviations from persistence: (b) -41.5 MW (a) -13.9 MW.

Conclusions & Future Work

Importance sampling for stochastic economic dispatch using analog scenarios shows promise; our experiments demonstrate improved performance for 5-minute dispatch decisions in terms of cost over standard SAA approaches.

Future work will investigate higher-fidelity approaches to approximating average costs of bins.

Future work will also investigate different metrics for data binning. For example, binning by costs output from deterministic economic dispatch experiments would be ideal, but costly.

References

1. King, R., Reynolds, M., Sigler, D., Jones, W. "Advanced Scenario Creation Strategies for Stochastic Economic Dispatch with Renewables", <https://arxiv.org/abs/1806.10530> (submitted for publication).
2. C. Draxl, A. Clifton, B.-M. Hodge, and J. McGas, "The wind integration national dataset (WIND) toolkit," Applied Energy, vol. 151, 2015.
3. Grid Modernization Lab Consortium, "Reliability test system – Grid Modernization Lab Consortium," 2017, [Online; accessed 11-December-2017]. [Online]. Available: <https://github.com/GridMod/RTS-GMLC>

Acknowledgement:
Funding for this project provided by the Exascale Computing Project, ExASGD project.

