Multilevel Monte Carlo with Surrogate Models for Resource Adequacy Assessment

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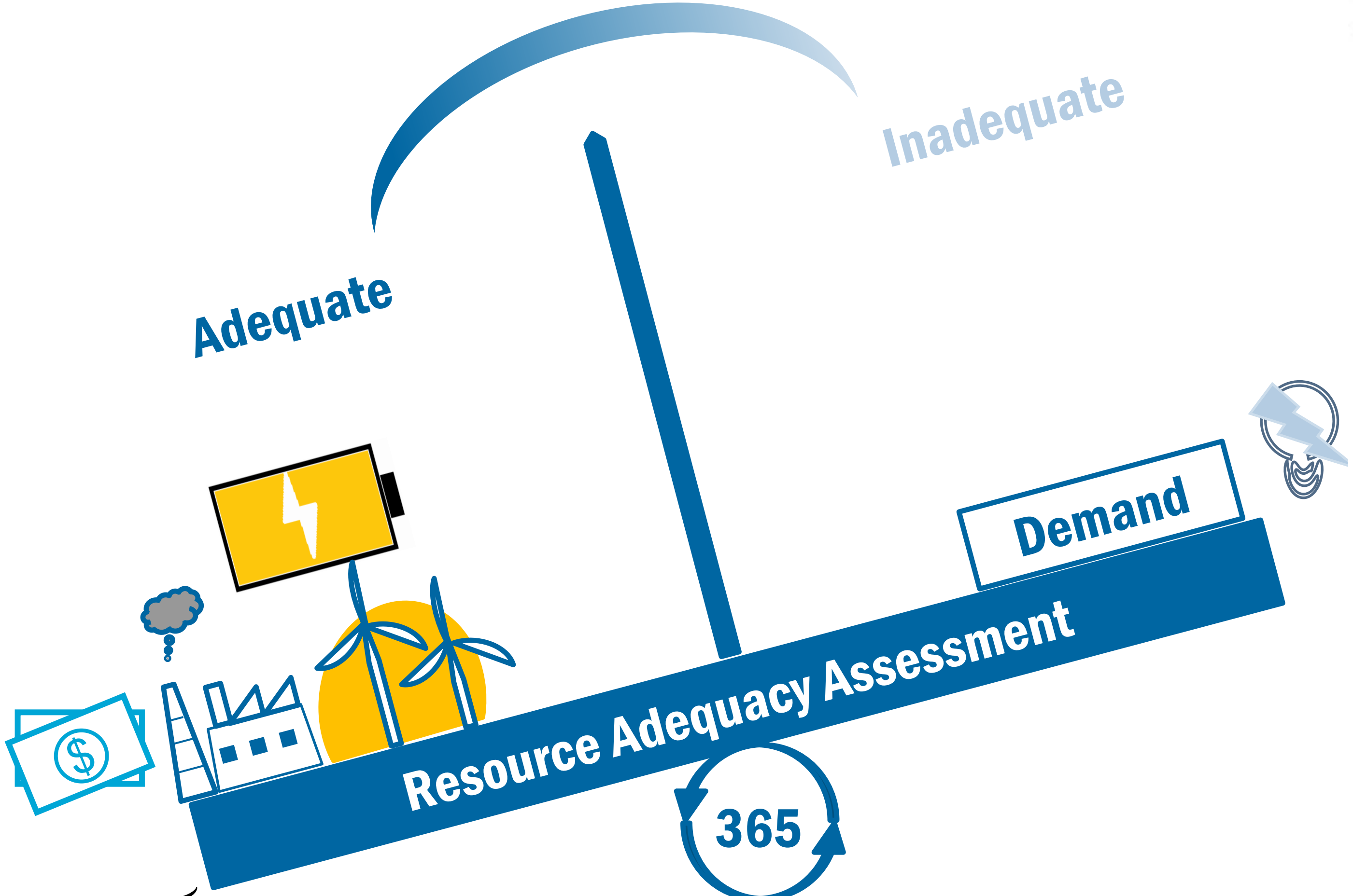
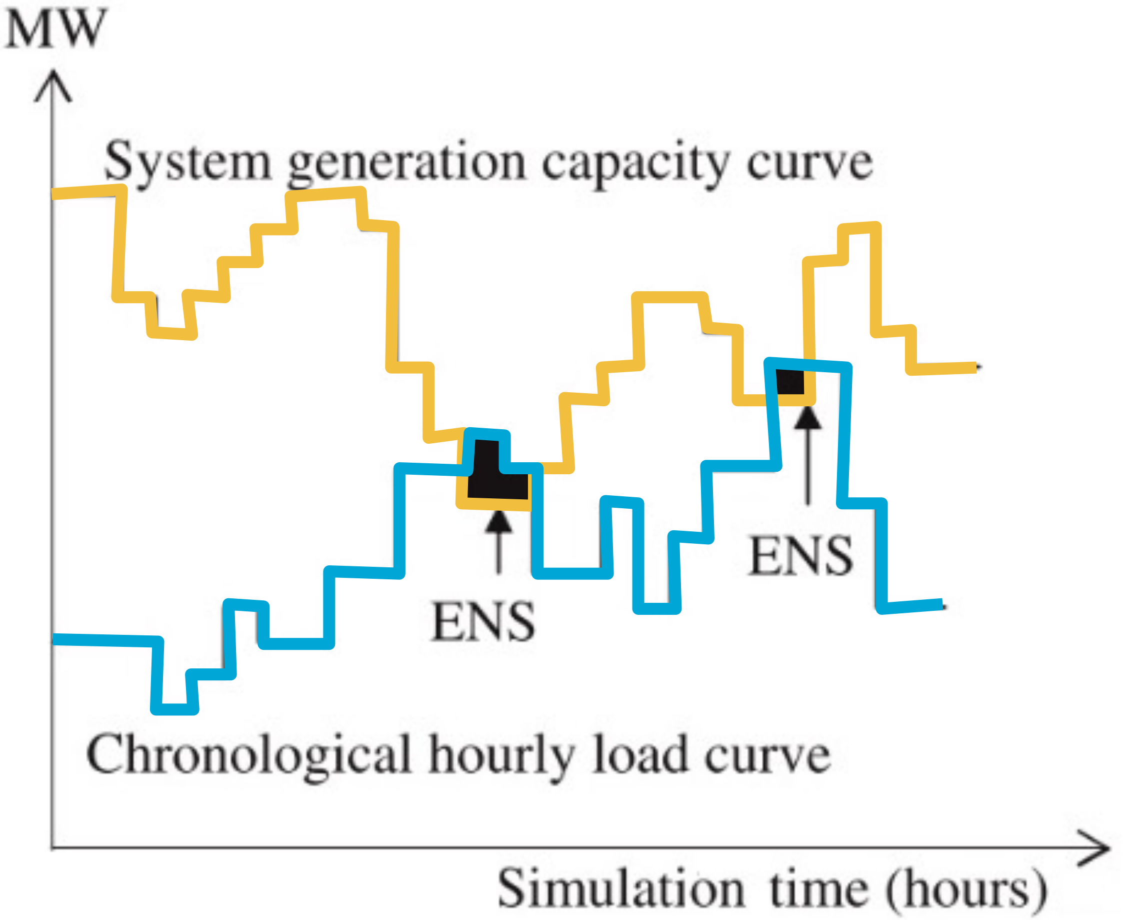
Resource Adequacy Assessment

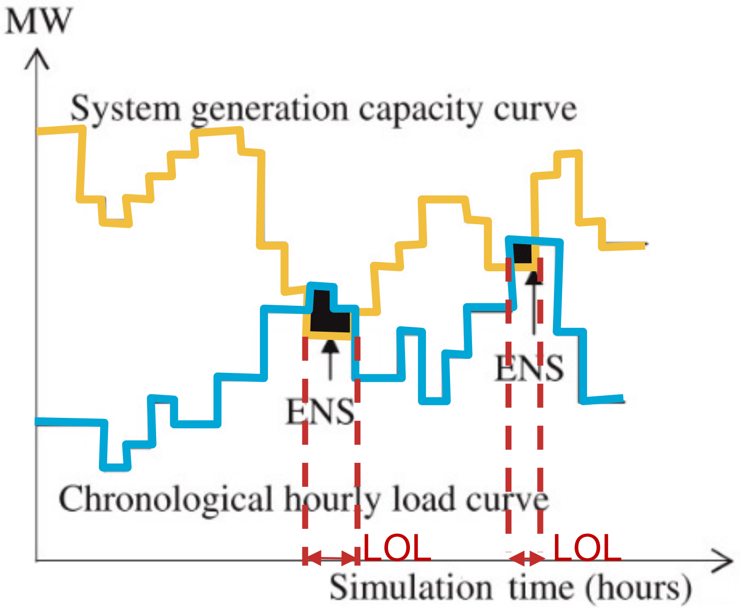




Measuring risk in system adequacy studies

Typically, risk measures for system adequacy are of the form expecta

Probabilistic bottom-up model → W random inputs → X = f(W) → $q = E[X]$

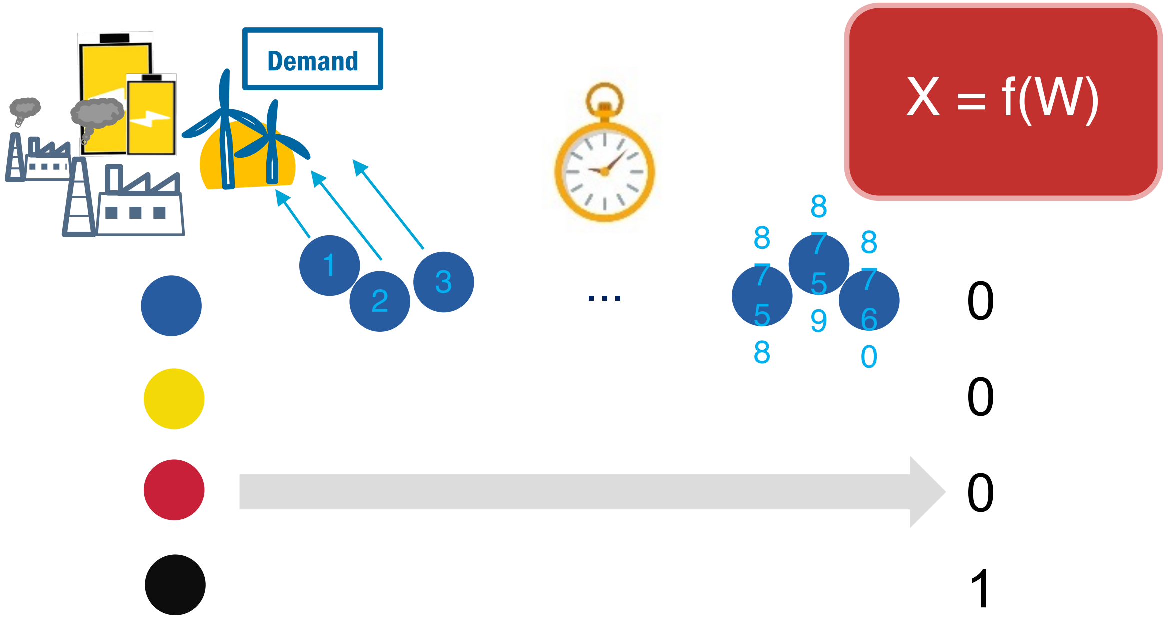


Examples

1. EENS/EUE : X = energy not served in a random year
2. LOLE (in hours) : X = number of hours of shortfall in a random year

Example: impact of storage in a model Great Britain system

- Probabilistic weather and power generation model
- Optimal use of batteries can mitigate shortfalls (needs sequential simulati
- multiple storage units with ENS-minimising policy (Evans et al., 2019)



M. P. Evans, S. H. Tindemans, and D. Angeli, “Minimizing Unserved Energy Using Heterogeneous Storage Units,” IEEE Transactions on Power Systems, vol. 34, no. 5, pp. 3647–3656, sep 2019.

Multi Level Monte Carlo (MLMC)

increasing accuracy = more work per sample

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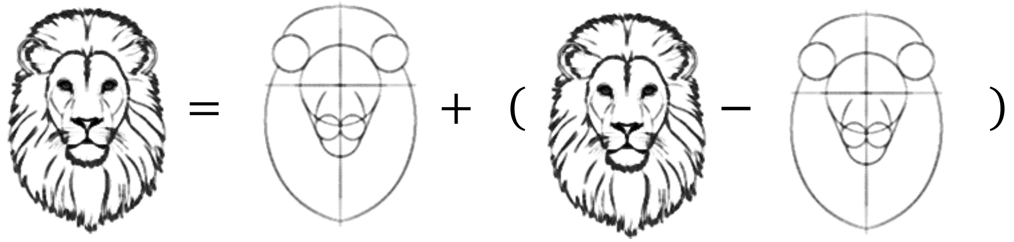
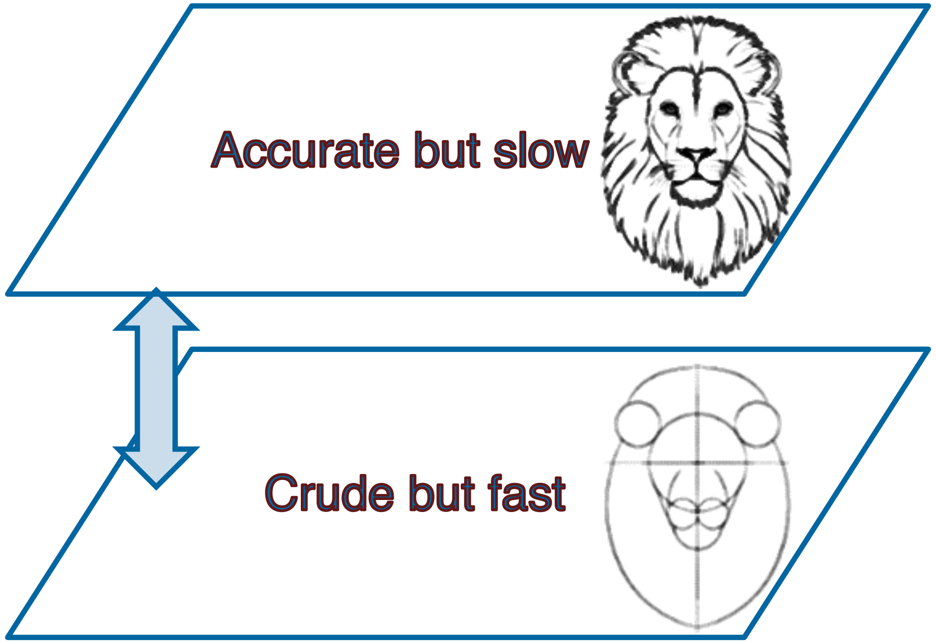
MLMC





Telescopic identity

$$
\begin{aligned}
q &= E[X_L] \\
&= E[X_0] + E[X_1 - X_0] + \cdots + E[X_L - X_{L-1}] \\
&= r_0 + r_1 + \cdots + r_L
\end{aligned}
$$

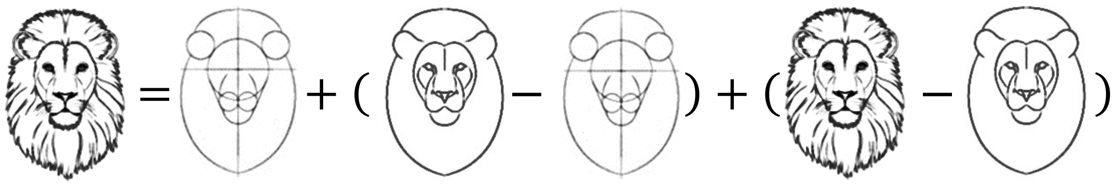
$$\approx \frac{1}{n}\sum_{i=1}^{n} x_L^{(i)} \quad \text{MC}$$

$$\approx \underbrace{\frac{1}{n_0}\sum_{i=1}^{n_0} x_0^{(i,0)}}_{\text{Rough estimation}} + \underbrace{\frac{1}{n_1}\sum_{i=1}^{n_1}\left(x_1^{(i,1)} - x_0^{(i,1)}\right) + \cdots}_{\text{Corrections}} \quad \text{MLMC}$$

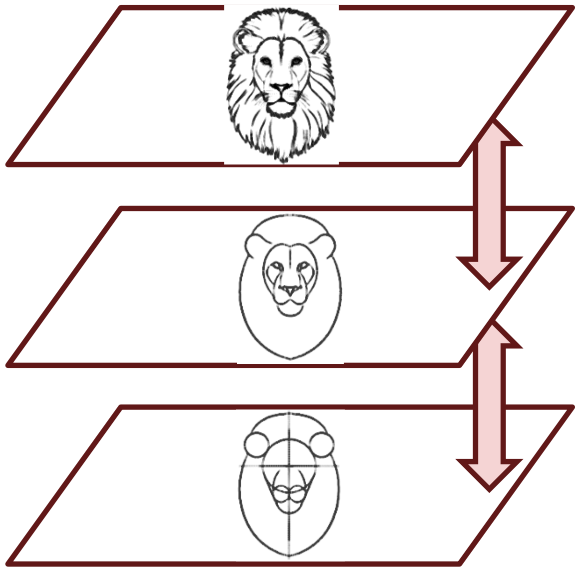
Rough estimation + Corrections ⇨ Can be faster

M. B. Giles, “Multilevel Monte Carlo methods,” Acta Numerica, vol. 24, pp. 259–328, may 2015.

https://www.easydrawingtips.com/how-to-draw-lion-face-head-step-by-step/



MLMC variance



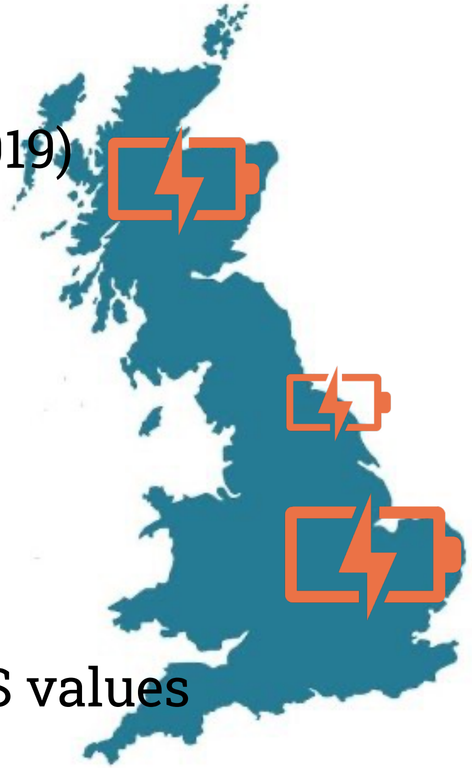
$$\mathrm{q} = \mathrm{E}[\mathrm{X}_1] + \mathrm{E}[\mathrm{X}_2 - \mathrm{X}_1] + \cdots + \mathrm{E}[\mathrm{X}_\mathrm{L} - \mathrm{X}_{\mathrm{L}-1}]$$

$$\boldsymbol{\sigma} = \sum_l \frac{\boldsymbol{\sigma}_l}{n_l}, \qquad \boldsymbol{\sigma}_\mathrm{L} = \boldsymbol{\sigma}_{\mathrm{X}_\mathrm{L}} + \boldsymbol{\sigma}_{\mathrm{X}_{\mathrm{L}-1}} - 2\,\mathrm{cov}(\mathrm{X}_\mathrm{L}, \mathrm{X}_{\mathrm{L}-1})$$

Example: storage and adequacy assessment

Range of models

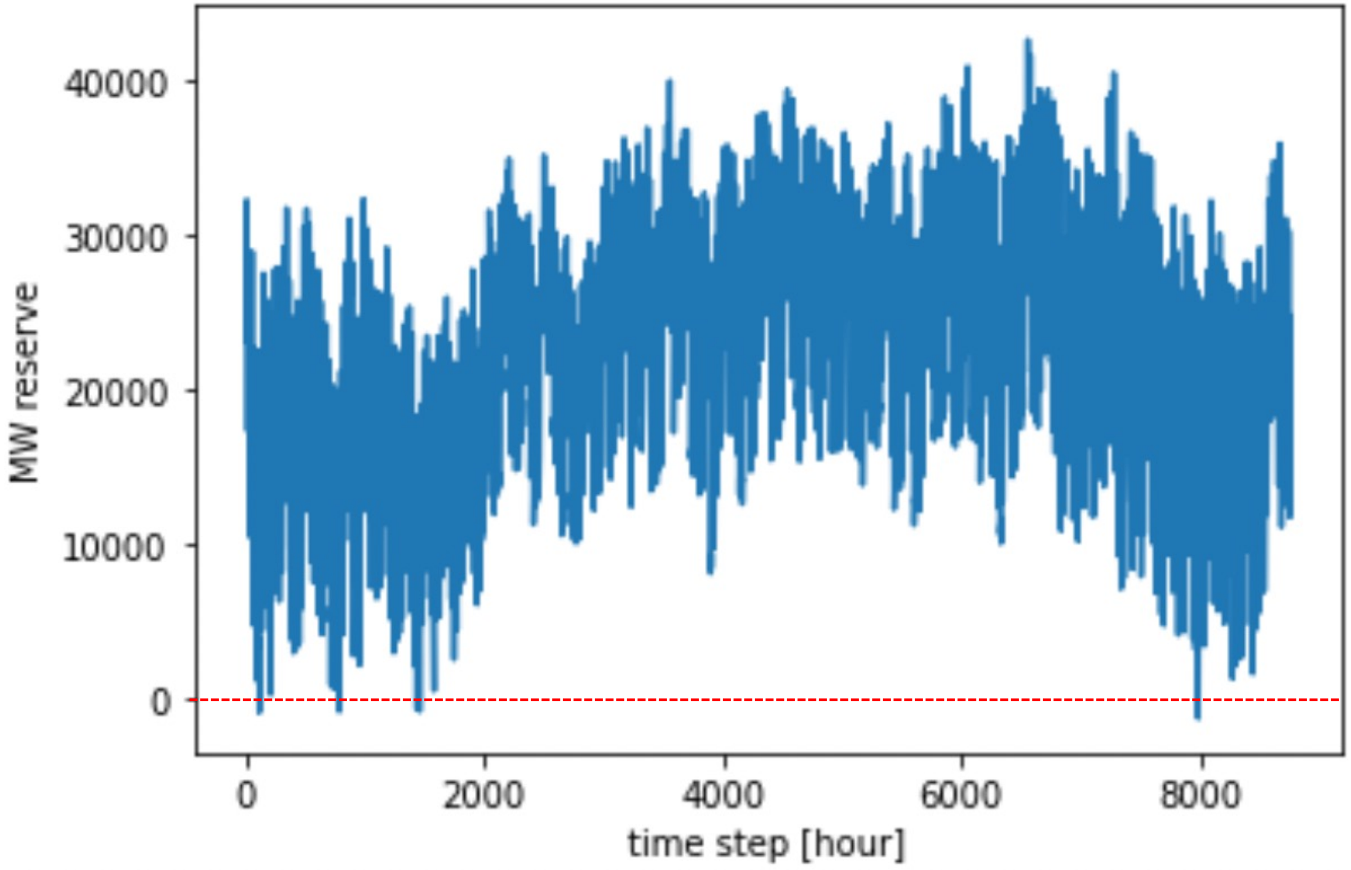
1. **Exact**: multiple storage units with ENS-minimising policy (Evans et al., 2019)
2. **Hand-tuned**
    1. **Average:** aggregate storage unit with fixed daily operation
    2. **Greedy:** multiple storage units with greedy operation (TS20)
3. **Surrogate models**
    1. **HGB+SVR**: black-box machine learning approach
    2. **HGB+Gre**: hybrid model that uses Greedy model to predict non-zero ENS values

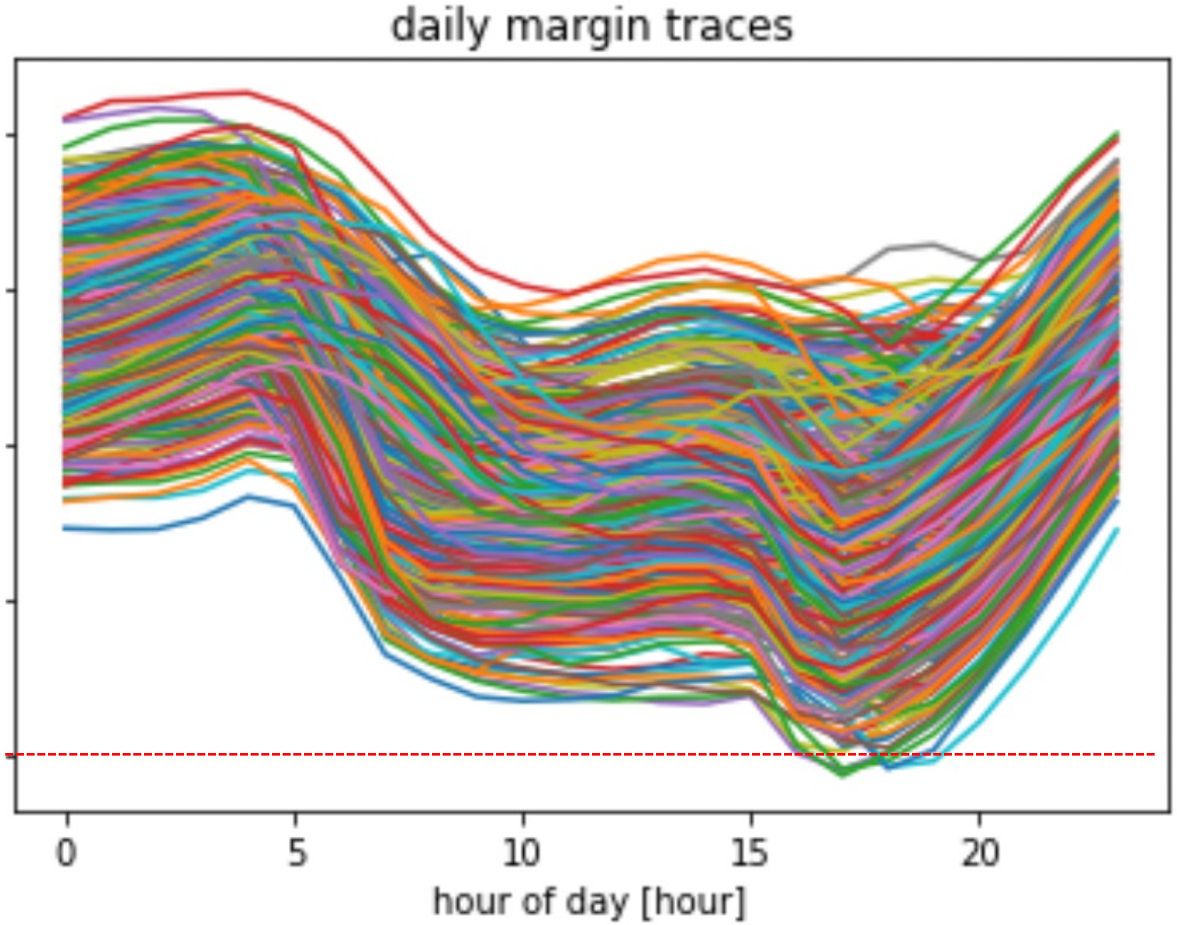


TS20: Tindemans, S., & Strbac, G. Accelerating system adequacy assessment using the multilevel Monte Carlo approach. *Electric Power Systems Research*, *189*, 106740, 2020.

Surrogate model

Daily Margin traces = Generation - demand





Different model stacks

regular MC	manual MLMC		MLMC with surrogate models			
reference	TS20 (base)	TS20 (full)	surrogate	surrogate + base	hybrid + base	full
Exact	Exact	Exact	Exact	Exact	Exact	Exact
	Average	Greedy	HGB+SVR	HGB+SVR	HGB+Gre	HGB+Gre
		Average		Average	Average	HGB+SVR
						Average

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Sharifnia E, Tindemans SH. Multilevel Monte Carlo with Surrogate Models for Resource Adequacy Assessment. 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS) 2022 (pp. 1-6). IEEE.

Results

comparable run time | measure two risk indices | speedup w.r.t. regular MC

Estimator	Architecture	Time (s)	LOLE (h/y)	EENS (MWh/y)	LOLE Speedup	EENS Speedup	
MC	Exact	26600	1.745 ± 0.039	2420.0 ± 72.0	n/a	n/a	
TS20 base	Exact | Avg	26200	1.743 ± 0.009	2406.0 ± 3.3	18	482	
Surr	Exact | HGB+SVR	25900	1.739 ± 0.005	2407.0 ± 10.0	47	49	2
TS20 full	Exact | Gre | Avg	26000	1.735 ± 0.003	2405.0 ± 1.2	125	3617	1
Surr+base	Exact | HGB+SVR | Avg	25900	1.738 ± 0.002	2408.0 ± 1.1	269	4775	
Hybrid+base	Exact | HGB+Gre | Avg	25800	1.738 ± 0.002	2405.0 ± 0.5	582	20946	
Full	Exact | HGB+Gre | HGB+SVR | Avg	25800	1.735 ± 0.001	2406.0 ± 0.4	840	30969	3

1. Hand-tuned models result in a large speedup (previously published, TS20)
2. With *only* a **machine-learned surrogate model**, speedups ~50x are within reach
3. Hand-tuned model stack can be further enhanced with ML models for **extreme speedups**

Summary and next steps

Summary

- Multilevel Monte Carlo can vastly speed up Monte Carlo adequacy assessment
- Hand-tuned models work well, but require expertise
- Machine-learned surrogate models can be used for a 'black box' approach
- Combining both approaches can be used for extreme speed-ups

Next steps

- Include the impact of training time
- Automatic selection of models

Sharifnia E, Tindemans SH. Multilevel Monte Carlo with Surrogate Models for Resource Adequacy Assessment. 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS) 2022 (pp. 1-6). IEEE.


Thank you
https://pixnio.com/nature-landscapes/spring/

Bonus slides

Training Surrogate models

- Suitable frame size
  - ✓ Minimum state dependency
  - ✓ Similar pattern
- One-off training

Simulation Speed

$$c_q = \frac{\sigma_Q}{q}$$

$$\frac{1}{{c_q}^2} = z_q \times t$$

$$z_q \coloneqq \frac{q^2}{t\sigma_Q^2}$$

Optimal n_l^*

$$t = \sum_l n_l \boldsymbol{\tau}_l \Rightarrow n_l^* = \frac{t}{\sum_{l'} \boldsymbol{\sigma}_{l'} \sqrt{\boldsymbol{\tau}_{l'}}} \times \frac{\boldsymbol{\sigma}_l}{\sqrt{\boldsymbol{\tau}_l}}$$

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M. B. Giles, “Multilevel Monte Carlo methods,” Acta Numerica, vol. 24, pp. 259–328, may 2015.

Better models with larger training sets

TABLE II
EFFECTS OF TRAINING SAMPLE SIZE ON SURROGATE ACCURACY

Surrogate model	Train size	Average RMSE	RMSE unit
SVR	500	175 ± 10	MWh/y
SVR	1000	142 ± 14	MWh/y
SVR	5000	97 ± 6	MWh/y

Impact of training size

TABLE III
EFFECT OF SURROGATE MODEL ACCURACY ON MLMC PERFORMANCE

Estimator	Train size	SVR RMSE (MWh/y)	HGBRT RMSE (h/y)	LOLE Speedup	EENS Speedup
TS20 full	-	-	-	125	3617
Hybrid+base	500	267	0.34	349	12553
Hybrid+base	1000	153	0.23	460	18723
Hybrid+base	5000	85	0.19	582	20946

more data → better match → higher speedup

Level pair correlations

Exact
LOLE correlation: 0.989
EENS correlation : 0.999
Avg

TS20 base

Exact
LOLE correlation: 0.999
EENS correlation : 0.999
Gre
LOLE correlation: 0.989
EENS correlation : 0.999
Avg

TS20 full

Exact
LOLE correlation: 0.998
EENS correlation : 0.999
HGB+SVR

Surr

Exact
LOLE correlation: 0.998
EENS correlation : 0.999
HGB+SVR
LOLE correlation: 0.988
EENS correlation : 0.999
Avg

Surr+base

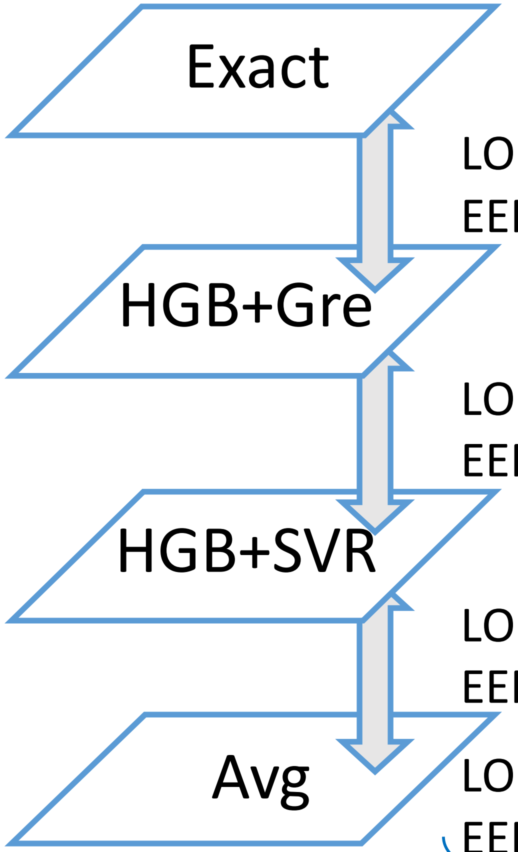
Exact
LOLE correlation: 0.999
EENS correlation : 0.999
HGB+Gre
LOLE correlation: 0.989
EENS correlation : 0.999
Avg

Hybrid+base

Exact
LOLE correlation: 0.999
EENS correlation : 0.999
HGB+Gre
LOLE correlation: 0.999
EENS correlation : 1
HGB+SVR
LOLE correlation: 0.989
EENS correlation : 0.999
Avg

Full

Level pairs contributions



Samples: %0.5 , Time: %99.2
LOLE contribution: 0.005158 h ± 0.00096 h
EENS contribution: -0.5761 MWh ± 0.16 MWh

Samples: %21.2 , Time: %0.5
LOLE contribution: -0.009317 h ± 0.00034 h
EENS contribution: 14.45 MWh ± 0.17 MWh

Samples: %78.3 , Time: %0.3
LOLE contribution: -0.4031 h ± 0.00092 h
EENS contribution: -155.9 MWh ± 0.34 MWh

LOLE contribution: 2.142 h ± 0.0 h
EENS contribution: 2548.0 MWh ± 0.0 MWh

MLMC LOLE : 1.735 h ± 0.0014 h
MLMC EENS : 2406.0 MWh ± 0.41 MWh