Physics Informed AI/ML for Power System Markets & Transients

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Two posters

Physics-Informed Machine Learning for Electricity Markets: A NYISO Case Study

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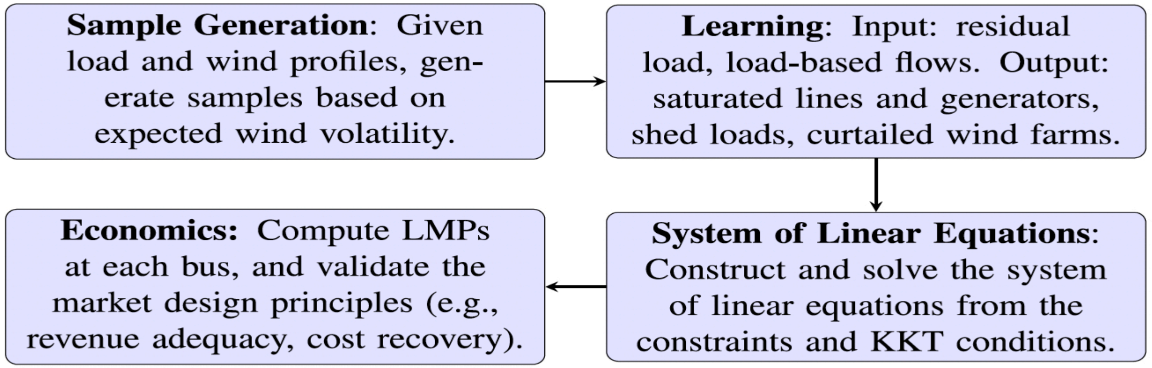
PIMA-AS-OPF Algorithm

We construct a physics-informed, market-aware active set OPF algorithm to recover both the primal and dual solutions of DC-OPF as formulated above.



Numerical Experiments

- Tests performed on New York Independent System Operator (NYIS0) 1814-bus system.
- Six sampling configurations corresponding to different unit commitments.
- Four different levels of noise: $\sigma = 1\%, 5\%, 10\%, 15\%$ of associated wind profiles.

Case	Time	Wind	On	$P_{\min}$	$P_{\max}$	P_{sched}
A7B	Aug.28, 7am	Base	273	87.49	289.41	231.10
A7H	Aug.28, 7am	High	273	87.49	289.41	231.10
A17B	Aug.28, 5pm	Base	313	102.53	336.59	312.79
A17H	Aug.28, 5pm	High	313	102.53	336.59	312.79
F0B	Feb.13, 12am	Base	187	55.78	184.71	142.67
F0H	Feb.13, 12am	High	141	50.81	158.43	123.89

Towards Model Reduction for Power System Transients with Physics-Informed PDE

Laurent Pagnier [1], Julian Fritzsch [2], Philippe Jacquod [2] and Michael Chertkov [1]

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$$m\ddot{\theta}_{\text{sys}} + d\,\dot{\theta}_{\text{sys}} = p_{\text{gen}} - p_{\text{cons}}$$

PDE (properly discretized) =>

$$m(\boldsymbol{r})\frac{\partial^2}{\partial t^2}\theta(t;\boldsymbol{r}) + d(\boldsymbol{r})\frac{\partial}{\partial t}\theta(t;\boldsymbol{r}) = p(t;\boldsymbol{r}) + \sum_{\alpha,\beta=1,2} \partial_{r_\alpha} b_{\alpha\beta}(\boldsymbol{r})\partial_{r_\beta}\theta(t;\boldsymbol{r}).$$

Can we make is simpler!?* *By that we mean: can we obtain a reduced model that gives similar results be is faster to simulate and easier to train?

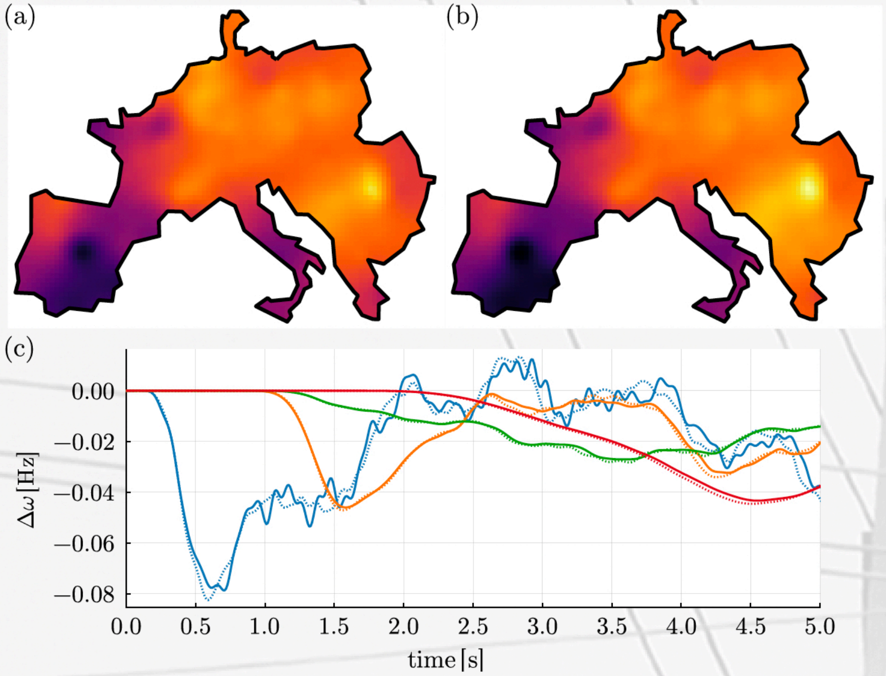

Fig. 5: *Model reduction. (a) Stable state of the full PDE model. (b) Stable state of the reduced PDE model. (c) Comparison of their dynamic responses.*

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