Assessing the Uncertainty of Emissions Reductions from Various Interventions

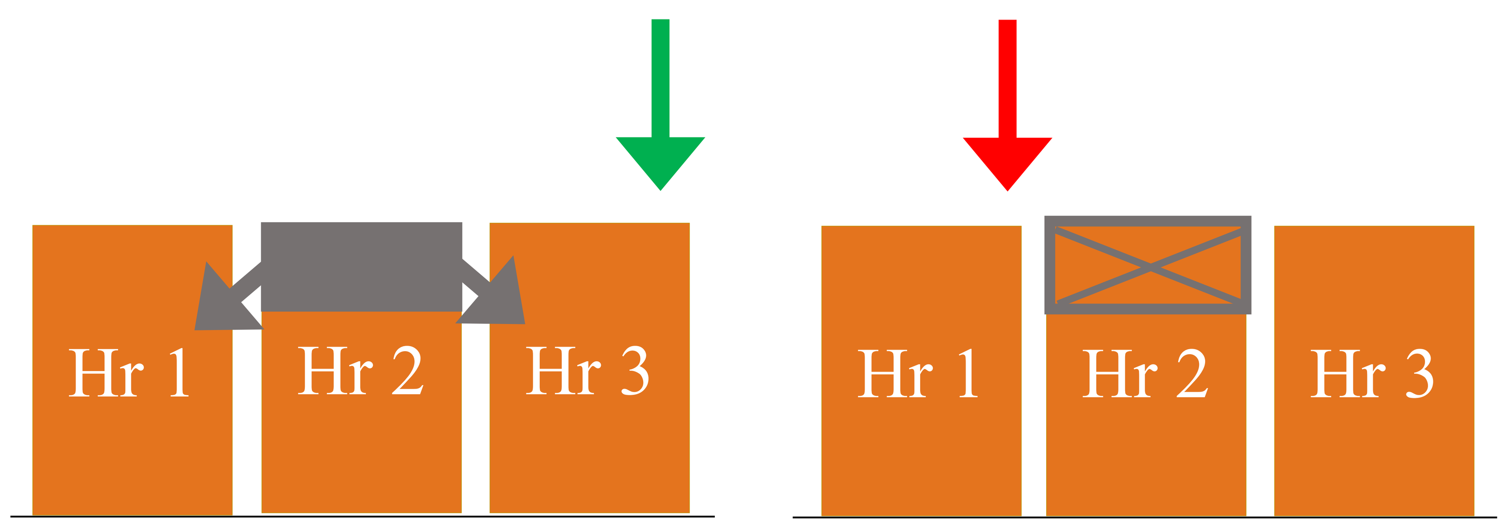
Priya L. Donti,*[,1,2] Inês Lima Azevedo,[1] and J. Zico Kolter[2]
[1] Engineering & Public Policy, Carnegie Mellon University; [2] Computer Science, Carnegie Mellon University
* pdonti@cmu.edu

Interventions vs. Emissions Accounting

Emissions profile assumptions may drive results when evaluating the effectiveness of power system interventions, e.g. by over-/under-stating effectiveness or suggesting different interventions altogether.

True MEFs: 5 100 5

Prediction 1: 5 195 5
Prediction 2: 5 5 5



Prediction 1 overstates effectiveness

Prediction 2 suggests wrong intervention

We seek to provide a systematic analysis of intervention effectiveness under various emissions assumptions.

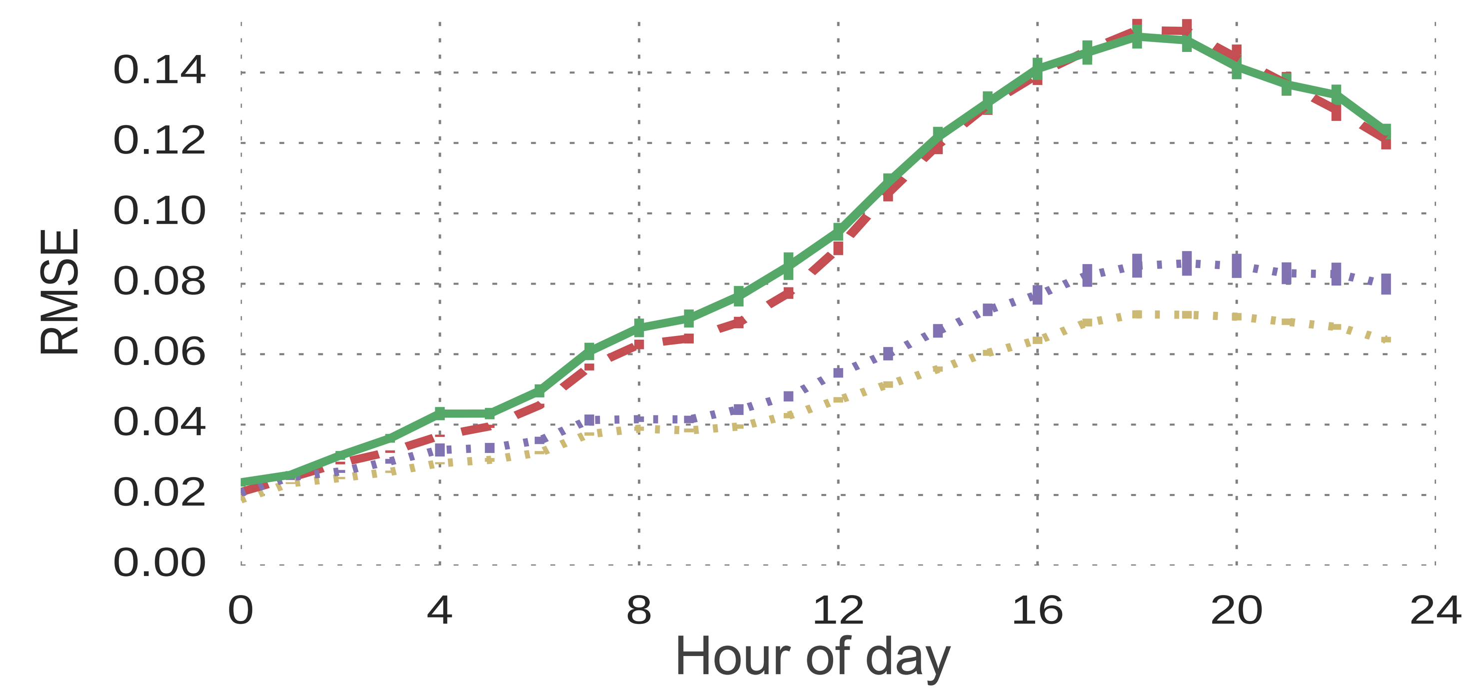
We will explore (some of) the following interventions.

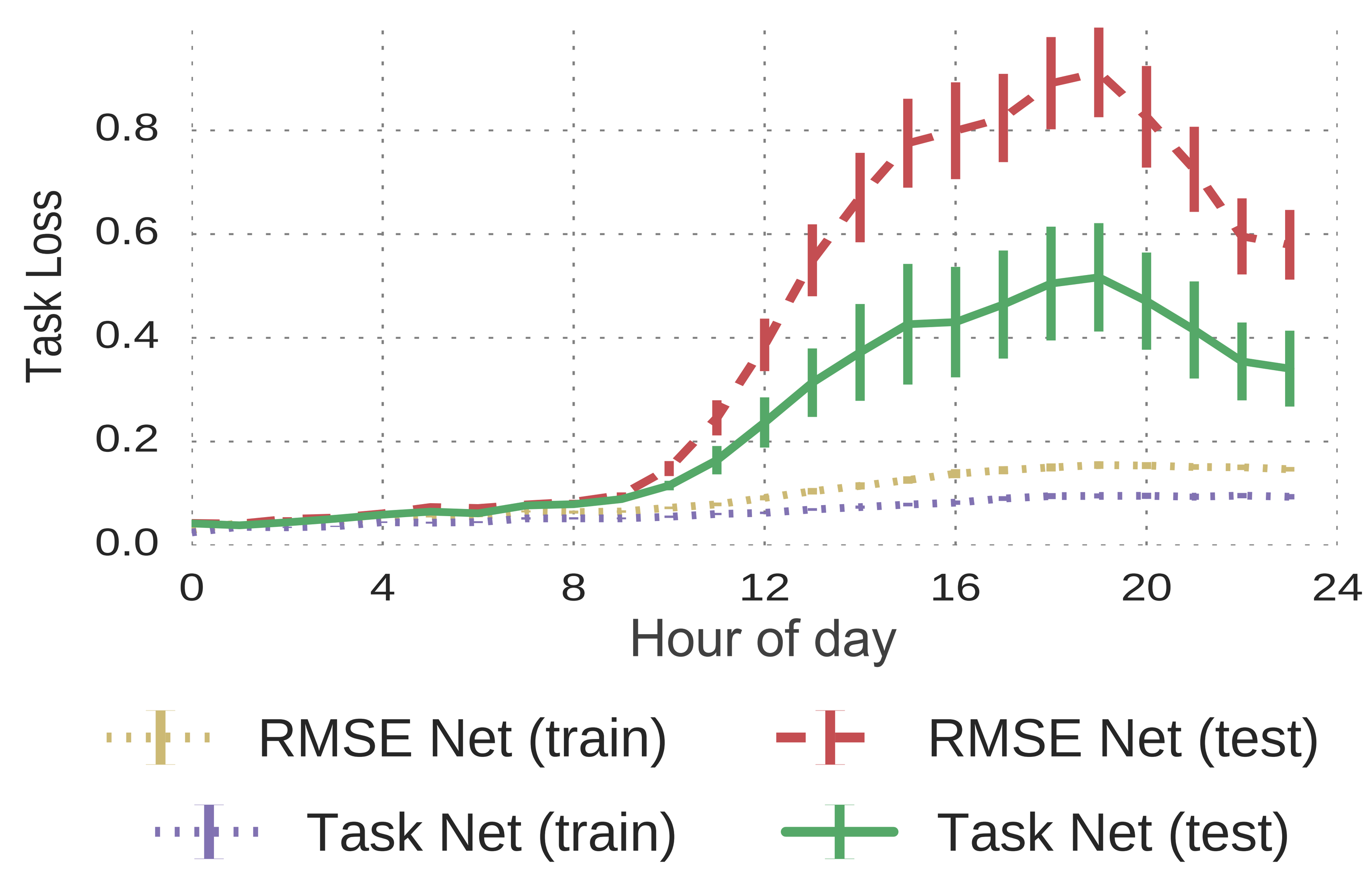
Interventions	Emissions Accounting
Installing wind/solar	EPA AVERT model
Load shifting (e.g. between data centers)	Linear regression on CEMS data [1]
Energy efficiency	Classical ML model on PJM data
Energy storage	Task-based model [2]

Task-based Emissions Accounting Model

Optimizing prediction algorithms for "generic" criteria can yield suboptimal outcomes. E.g., the two "predictions" in the previous load-shifting example have the same least-squares error but suggest very different interventions.

A task-based model optimizes for the expected goodness of decisions made based on the model's predictions.





The graphs above show performance on electricity demand prediction in the context of generator allocation [2]. While an RMSE-minimizing model yields generically "better" predictions (lower RMSE), a task-based model improves upon generator allocation costs (task loss) by 38.6%.

We will employ a task-based model as one of our emissions accounting schemes.

Toy Intervention Example

We will evaluate a toy intervention that shifts load between different hours in a day to minimize emissions.

Specifically, we can change the load in any given hour by at most +/- 5%. We make our load-shifting decisions based on the given emissions and load profiles.

$$\underset{x \in \mathbb{R}^{24}}{\text{minimize}} \; M^T x + \lambda \sum x_i^2$$
$$\text{subject to} \; -fL_i \le x_i \le fL_i$$
$$\sum x_i = 0$$

Emissions profile ($M \in \mathbb{R}_+^{24}$)
Load profile ($L \in \mathbb{R}_+^{24}$)
Shifting ($x \in \mathbb{R}^{24}$)
Allowable shift proportion ($f = 0.05$)
Regularization (λ)

This example will serve as a proof of concept, after which we will examine more "realistic" interventions.

Summary

- **We seek to assess the uncertainty of emissions reductions from various interventions, under different emissions accounting schemes.**
- Candidate interventions include renewables installation, various types of load-shifting, energy efficiency, and (bulk) energy storage.
- Candidate accounting methods include EPA AVERT, linear regression, classical machine learning, and task-based machine learning. Datasets include CEMS and PJM marginal generation.

Acknowledgments

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE1252522.

References

[1] K. Siler-Evans, I. L. Azevedo, and M. G. Morgan, "Marginal Emissions Factors for the U.S. Electricity System," Environmental Science and Technology, vol. 46, no. 9, pp. 4742–4748, 2012.
[2] P. L. Donti, B. Amos, and J. Z. Kolter. "Task-based End-to-end Model Learning." arXiv preprint arXiv:1703.04529 (2017).