

# Computing Counterfactual Explanations of Linear Problems

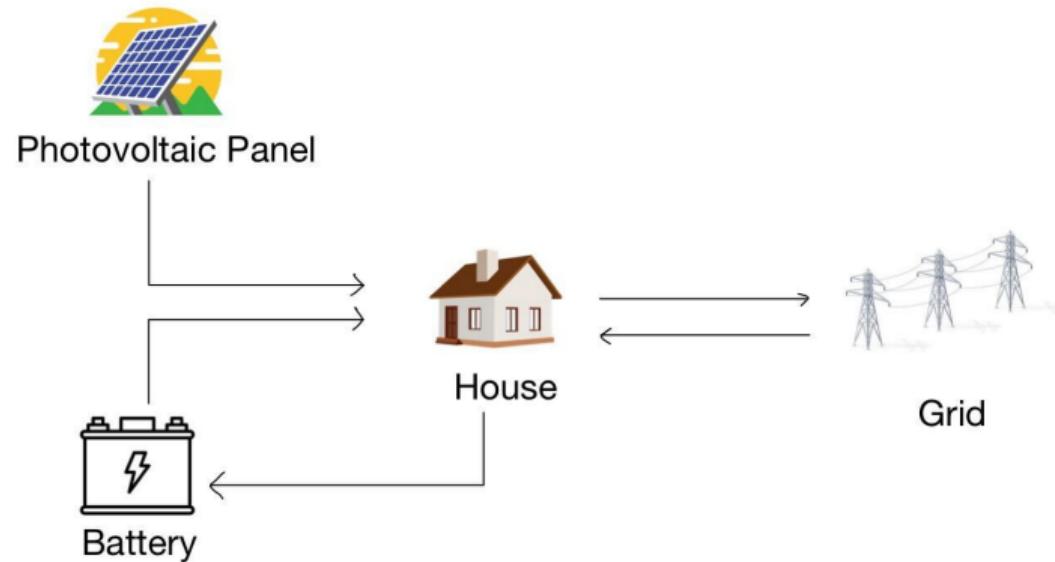
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**Henri Lefebvre, Martin Schmidt**

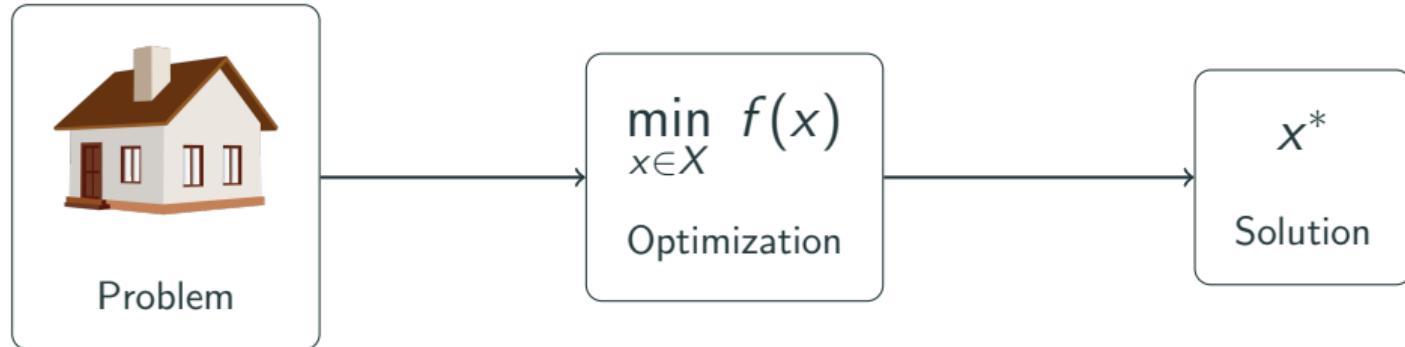
Trier University (Germany), Department of Mathematics

Darmstadt, 2024

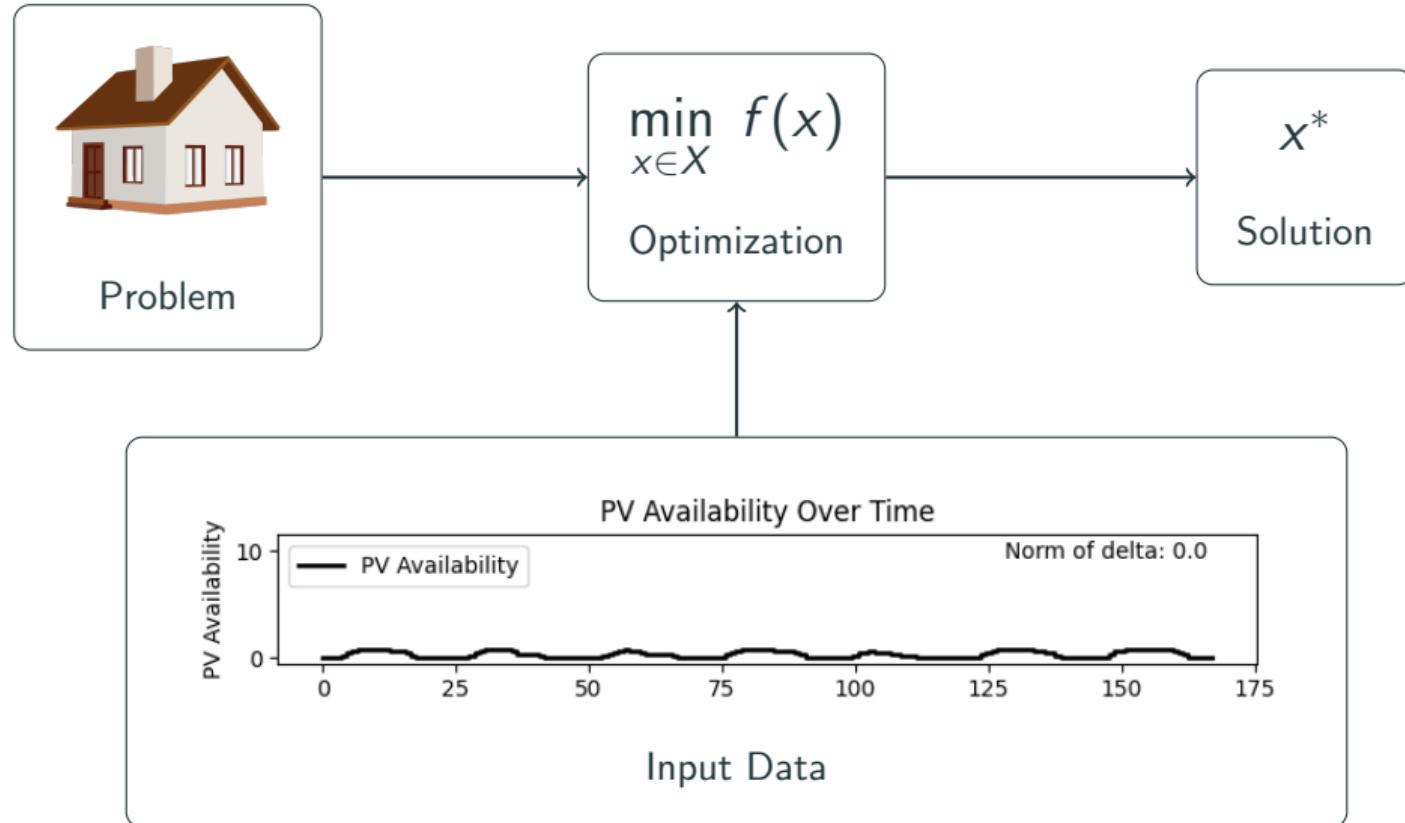
# Understanding Energy Model Decisions



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# Outline

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Motivation

Problem Formulation

Penalty Alternating Direction Method (PADM)

Applying the PADM to the Single-Level Reformulation

Numerical Results

Energy Model

NETLIB Instances

Conclusion

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# The Underlying Optimization Problem

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We consider the linear optimization problem

$$\min_{\mathbf{y}} \quad f^\top \mathbf{y} \quad \text{s.t.} \quad \bar{D}\mathbf{y} \geq b$$

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$$\min_{\mathbf{y}} \quad f^\top \mathbf{y} \quad \text{s.t.} \quad D(\mathbf{x})\mathbf{y} \geq b$$

with  $d_{ij}(\mathbf{x}) = \bar{d}_{ij} + \tilde{d}_{ij}^\top \mathbf{x}$  for some  $\mathbf{x} \in X$

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**Goal:** Find an  $\mathbf{x}$  so that an optimal point  $\mathbf{y}^*$  is in the desired space  $Y$

## Problem Formulation

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$$\inf_{\textcolor{red}{x}, \textcolor{blue}{y}} f(\textcolor{red}{x})$$

$$\text{s.t. } \textcolor{red}{x} \in X$$

$$\textcolor{blue}{y} \in Y$$

$$\textcolor{blue}{y} \in \arg \min_{\bar{y}} \left\{ f^\top \bar{y} : D(\textcolor{red}{x}) \bar{y} \geq b \right\}$$

## Bilevel Constraint

$$\textcolor{blue}{y} \in \arg \min_{\bar{y}} \{ f^\top \bar{y} : D(\textcolor{red}{x}) \bar{y} \geq b \}$$

# Strong-Duality Reformulation

## Bilevel Constraint

$$\textcolor{blue}{y} \in \arg \min_{\bar{y}} \{ f^\top \bar{y} : D(\textcolor{red}{x}) \bar{y} \geq b \}$$



## Single-Level Constraint

There exists  $\lambda$  s.t.

$$D(\textcolor{red}{x}) \textcolor{blue}{y} \geq b$$

$$D(\textcolor{red}{x})^\top \lambda = f, \quad \lambda \geq 0$$

$$f^\top \textcolor{blue}{y} \leq b^\top \lambda$$

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$$\inf_{\mathbf{x}, \mathbf{y}} f(\mathbf{x})$$

s.t.  $\mathbf{x} \in X, \mathbf{y} \in Y$

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## A General Optimization Problem

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$$\begin{aligned} \min_{\textcolor{red}{x}, \textcolor{blue}{y}} \quad & F(\textcolor{red}{x}, \textcolor{blue}{y}) \\ \text{s.t.} \quad & \textcolor{red}{x} \in \mathcal{X}, \quad \textcolor{blue}{y} \in \mathcal{Y}, \\ & g(\textcolor{red}{x}, \textcolor{blue}{y}) \leq 0. \end{aligned}$$

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**Assumption:** Solving over  $\textcolor{red}{x}$  for fixed  $\textcolor{blue}{y}$  is easy, and the other way around.

## Alternating Direction Method

**Given:** Initial values  $(\mathbf{x}^0, \mathbf{y}^0) \in \mathcal{X} \times \mathcal{Y}$ .

**for**  $i = 0, 1, \dots$  **do**

    Choose  $\mathbf{x}^{i+1} \in \arg \min_{\mathbf{x}} \{F(\mathbf{x}, \mathbf{y}^i) : g(\mathbf{x}, \mathbf{y}^i) \leq 0, \mathbf{x} \in \mathcal{X}\}$ .

    Choose  $\mathbf{y}^{i+1} \in \arg \min_{\mathbf{y}} \{F(\mathbf{x}^{i+1}, \mathbf{y}) : g(\mathbf{x}^{i+1}, \mathbf{y}) \leq 0, \mathbf{y} \in \mathcal{Y}\}$ .

**end for**

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**end for**

**Good (from a theoretical viewpoint):** Convergence is well understood

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**end for**

**Good (from a theoretical viewpoint):** Convergence is well understood

**Issues (from a practical viewpoint):**

1. Sub-problems may be infeasible because of the coupling constraints
2. Poor performance

## A Penalized Problem

For some penalty parameter  $\mu \in \mathbb{R}_{>0}^m$ ,

$$\begin{aligned} & \min_{\textcolor{red}{x}, \textcolor{blue}{y}} F(\textcolor{red}{x}, \textcolor{blue}{y}) \\ \text{s.t. } & \textcolor{red}{x} \in \mathcal{X}, \quad \textcolor{blue}{y} \in \mathcal{Y} \\ & g(\textcolor{red}{x}, \textcolor{blue}{y}) \leq 0 \end{aligned}$$



$$\begin{aligned} & \min_{\textcolor{red}{x}, \textcolor{blue}{y}} F(\textcolor{red}{x}, \textcolor{blue}{y}) + \sum_{i=1}^m \mu_i [g_i(\textcolor{red}{x}, \textcolor{blue}{y})]^+ \\ \text{s.t. } & \textcolor{red}{x} \in \mathcal{X}, \quad \textcolor{blue}{y} \in \mathcal{Y} \end{aligned}$$

$$[u]^+ = \max\{0, u\}$$

## Penalty Alternating Direction Method

**Given:** Initial values  $(\mathbf{x}^{0,0}, \mathbf{y}^{0,0}) \in \mathcal{X} \times \mathcal{Y}$  and  $\mu^0 \in \mathbb{R}_{\geq 0}^r$ .

**for**  $j = 0, 1, \dots$  **do**

    Set  $i \leftarrow 0$

**while**  $(\mathbf{x}^{i,j}, \mathbf{y}^{i,j})$  is not a partial minimizer of the penalized problem **do**

        Choose  $\mathbf{x}^{i+1} \in \arg \min_{\mathbf{x}} \{\phi(\mathbf{x}, \mathbf{y}^i; \mu) : \mathbf{x} \in \mathcal{X}\}$

        Choose  $\mathbf{y}^{i+1} \in \arg \min_{\mathbf{y}} \{\phi(\mathbf{x}^{i+1}, \mathbf{y}; \mu) : \mathbf{y} \in \mathcal{Y}\}$

        Set  $i \leftarrow i + 1$

**end while**

    Choose new penalty parameters  $\mu^{j+1} \geq \mu^j$ .

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**Good:** Convergence is well understood, e.g., Geißler et al. (2017).

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# Applying the PADM to the Single-Level Reformulation

## Single-Level Reformulation

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## Penalized Problem

$$\begin{aligned} & \min_{\textcolor{red}{x}, \textcolor{blue}{y}, \lambda} f(\textcolor{red}{x}) + \sum_{i=1}^m \rho_i [b_i - d_{i\cdot}(\textcolor{red}{x})\textcolor{blue}{y}]^+ + \sum_{j=1}^n \mu_j |c_j - d_{j\cdot}(\textcolor{red}{x})^\top \lambda| \\ \text{s.t. } & \textcolor{red}{x} \in X, \quad \textcolor{blue}{y} \in Y, \quad \lambda \geq 0, \quad f^\top \textcolor{blue}{y} \leq b^\top \lambda \end{aligned}$$

## The Sub-problems

1. Try to find feasible primal-dual point given  $\hat{\mathbf{x}}$  by solving

$$\begin{aligned} \min_{\mathbf{y}, \boldsymbol{\lambda}} \quad & \sum_{i=1}^m \rho_i [b_i - d_i \cdot (\hat{\mathbf{x}}) \mathbf{y}]^+ + \sum_{j=1}^n \mu_j |c_j - d_j \cdot (\hat{\mathbf{x}})^\top \boldsymbol{\lambda}| \\ \text{s.t.} \quad & \mathbf{y} \in Y, \quad \boldsymbol{\lambda} \geq 0, \quad f^\top \mathbf{y} \leq b^\top \boldsymbol{\lambda} \end{aligned}$$

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2. Try to repair infeasibilities of  $(\hat{\mathbf{y}}, \hat{\boldsymbol{\lambda}})$  by choosing a new  $\mathbf{x}$

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) + \sum_{i=1}^m \rho_i [b_i - d_i \cdot (\mathbf{x}) \hat{\mathbf{y}}]^+ + \sum_{j=1}^n \mu_j |c_j - d_j \cdot (\mathbf{x})^\top \hat{\boldsymbol{\lambda}}| \\ \text{s.t.} \quad & \mathbf{x} \in X \end{aligned}$$

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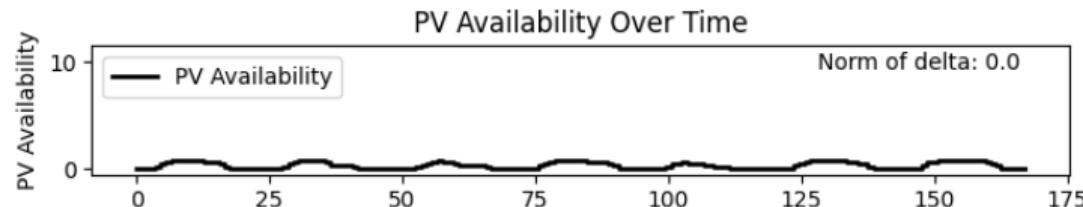
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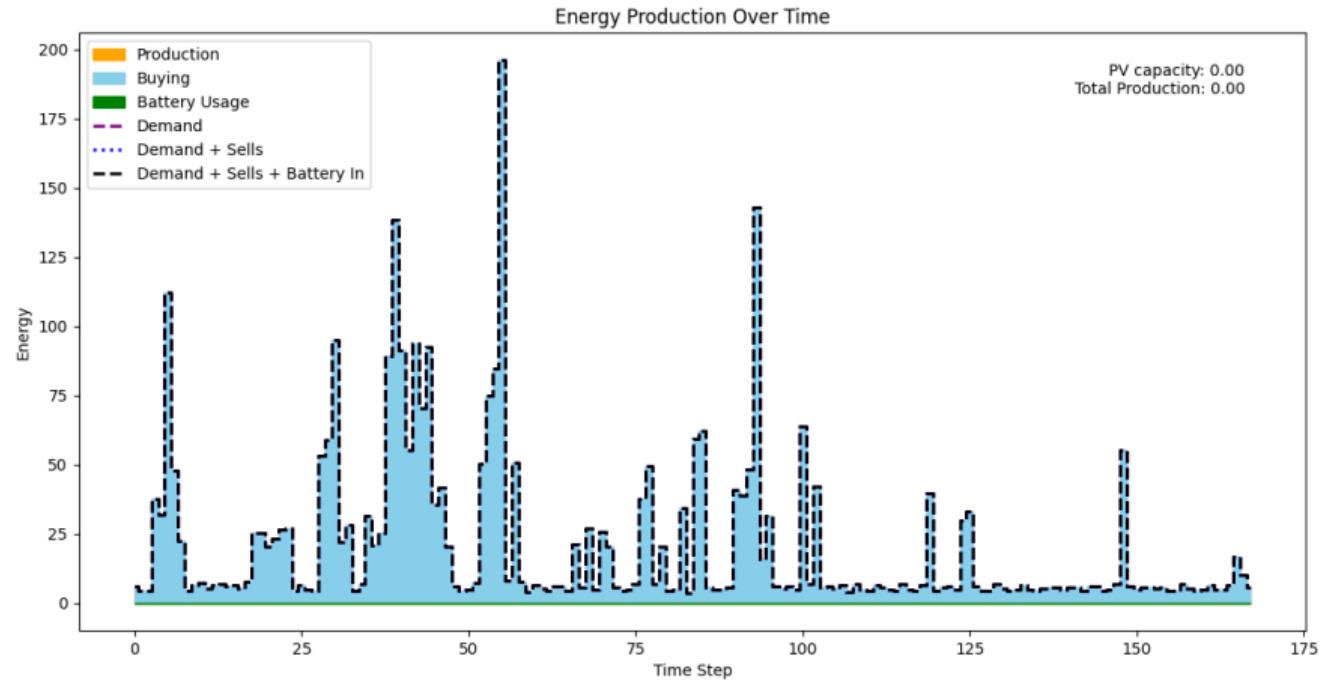
# One Example

We consider a given week with

1. costs for buying electricity
2. price for selling electricity surplus
3. house demands
4. cost for buying photovoltaic panels
5. historical data on PV availability:



# Status Quo: Only Buying From the Grid



## The Question

Keeping the current prices.

What should the PV availability be like so that one invests in PV panels?

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More explicitly: we ask for producing 1000 kWh during the week.

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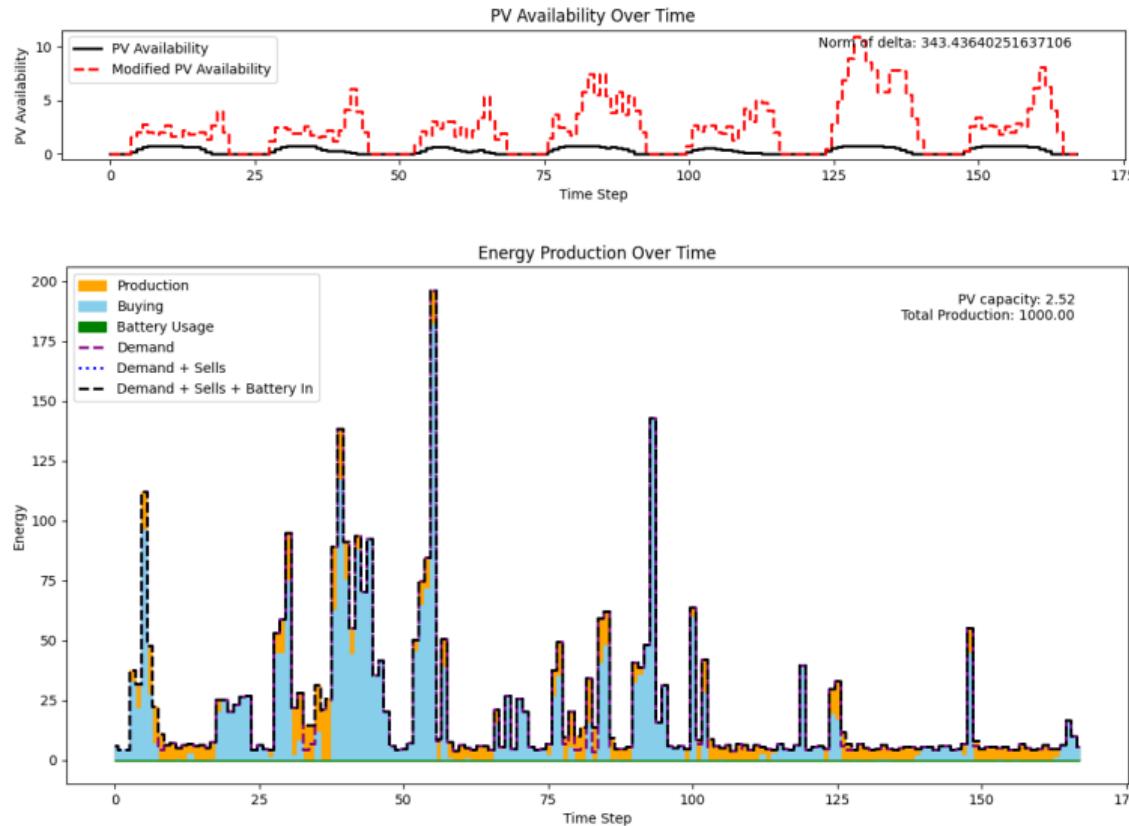
Keeping the current prices.

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Answer...

# Modified Solution



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## Setting

Instances based on the NETLIB library, adapted by Kurtz et al. (2024)

Type	Category	Intervals
# Variables	small	$0 \leq n \leq 534$
	medium	$534 \leq n \leq 2167$
	large	$2167 \leq n \leq 22275$
# Constraints	small	$0 \leq m \leq 351$
	medium	$351 \leq m \leq 906$
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- A total of 5 760 instances

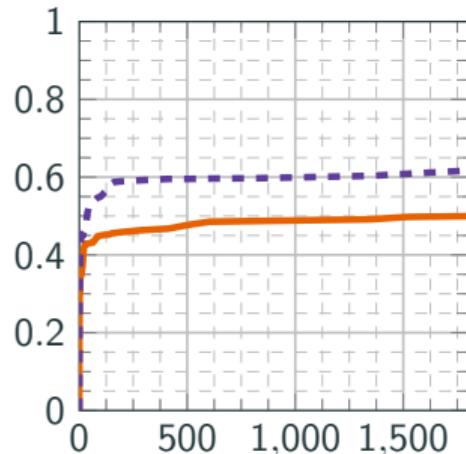
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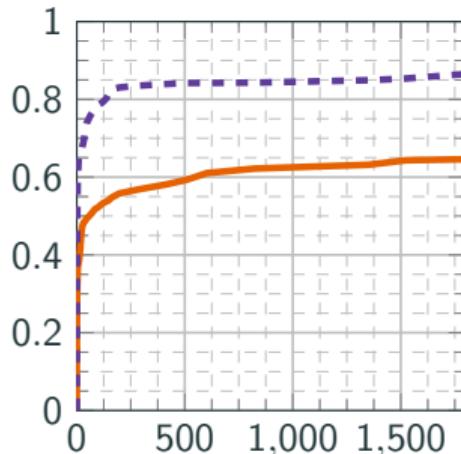
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- Randomly selects 1, 5, or 10 columns which are mutable
- A total of 5 760 instances
- Not all instances are feasible ( $\sim 55\%$ )

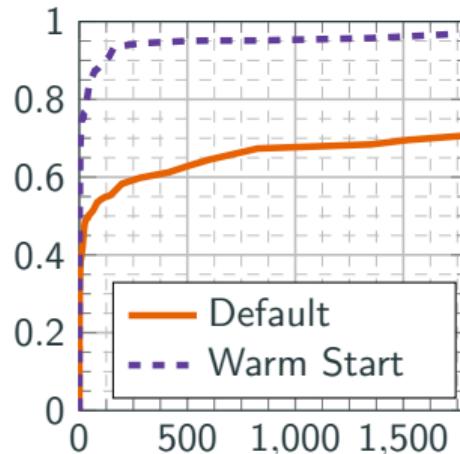
## ECDF of computation times for $f = \|\cdot\|_1$



(a) 1 mutable column

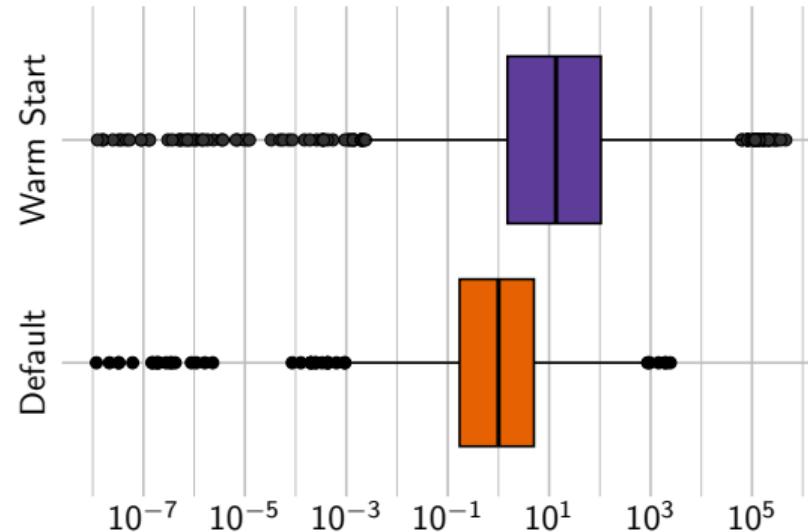


(b) 5 mutable columns



(c) 10 mutable columns

## Solution Quality



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## What We Have Done:

1. Computing counterfactual explanations of linear problems is challenging
2. We derive a single-level reformulation which we heuristically solve by the PADM
3. We can characterize the computed solutions (stationary points of the single-level reformulation)

## What to Do Then:

1. Polish the preprint and submit
2. Can we do the same for strong counterfactual explanations
3. Discuss next project steps