NREL
Transforming ENERGY

Dynamically Learning Incentives for Load Control

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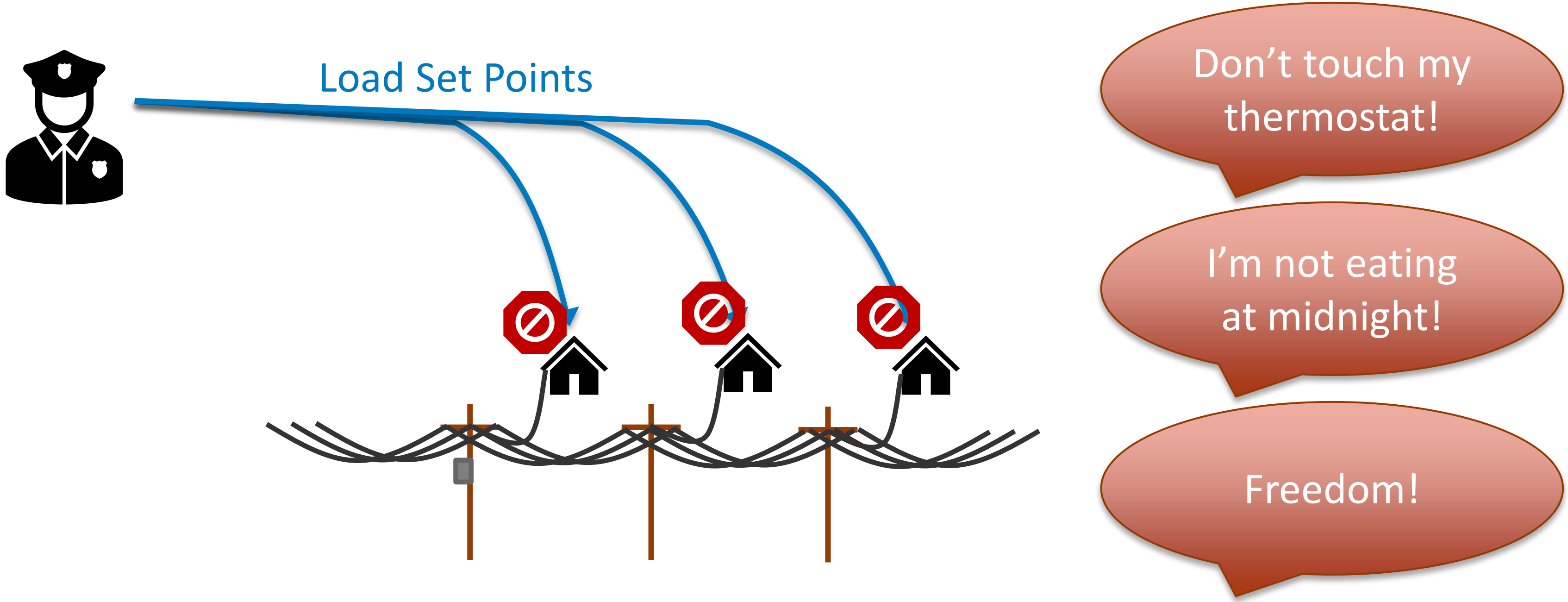
Data-Enabled Decision-Making in Energy Systems and Markets

2024 INFORMS Annual Meeting

October 22, 2024

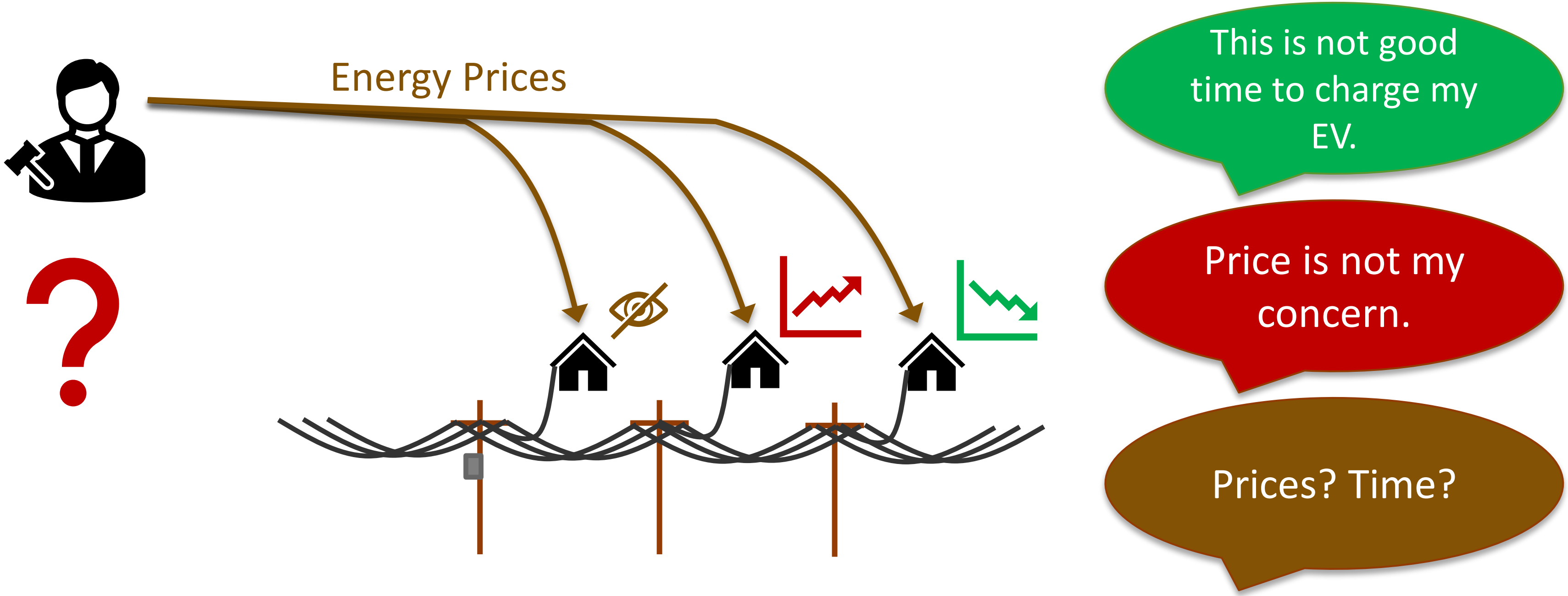
*UMass Amherst and NREL

Photo by Molly Rettig, NREL 68829



Direct Load Control

- System Operator directly controls loads to provide services to the grid
- Low Participation



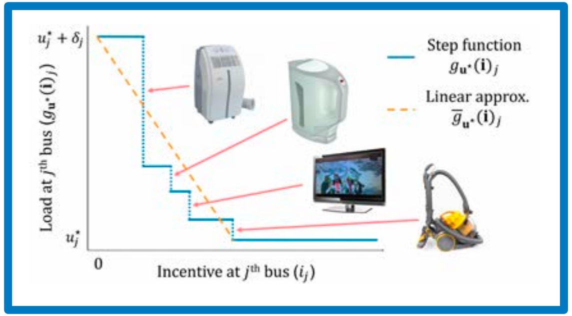
Indirect Load Control

- System Operator sends prices to influence the load amounts
- Unpredictable response

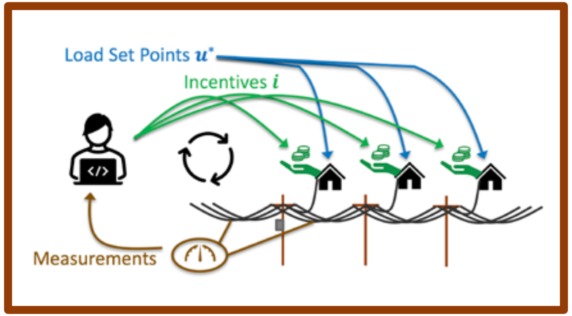
Problem: Grid operators lack control over end-user load behavior.

Approach: Dynamically optimize individualized incentives paired with load set points.

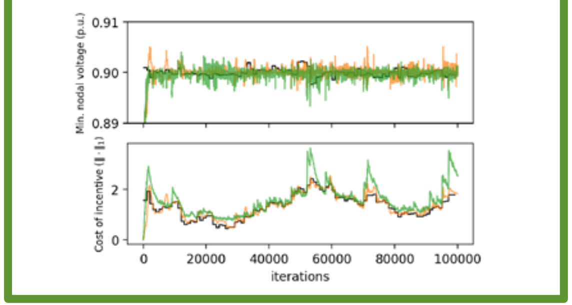
Human Behavior Model

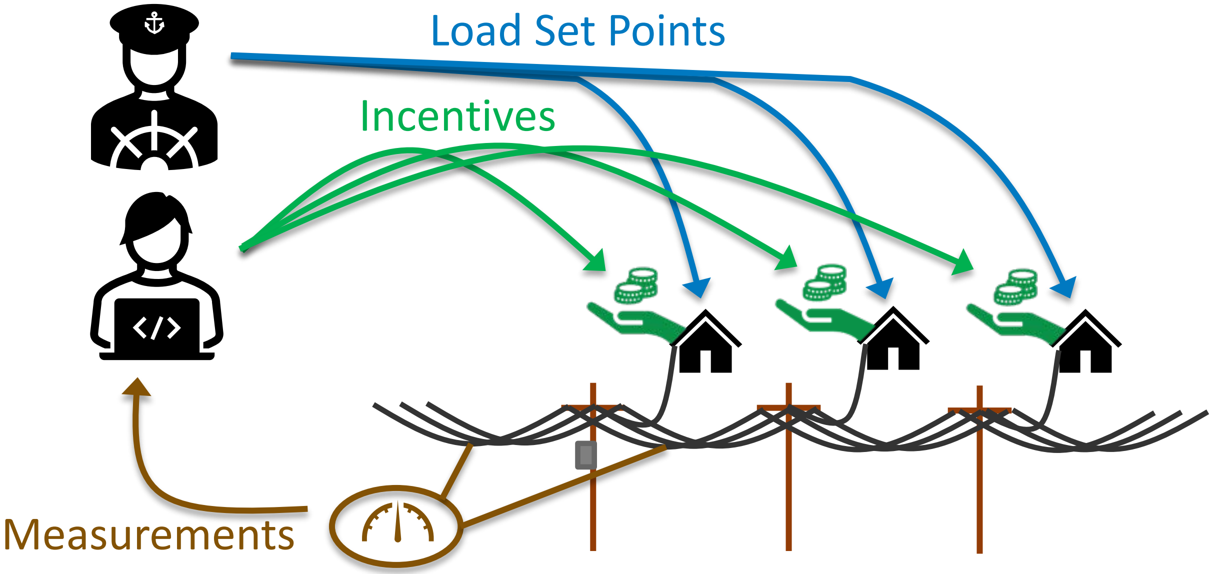


Incentive Optimization



Numerical Evaluation





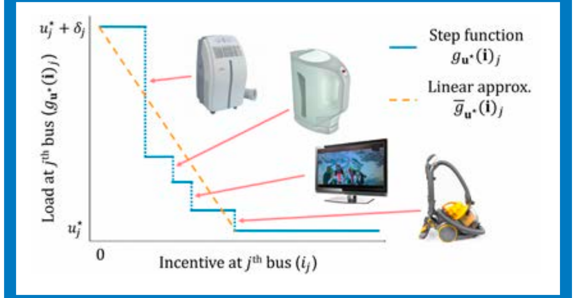
Incentivized Load Control

- Incentive amounts are based on **historical** performance with helping **grid objectives**.

Problem: Grid operators lack control over end-user load behavior.

Approach: Dynamically optimize individualized incentives paired with load set points.

Human Behavior Model



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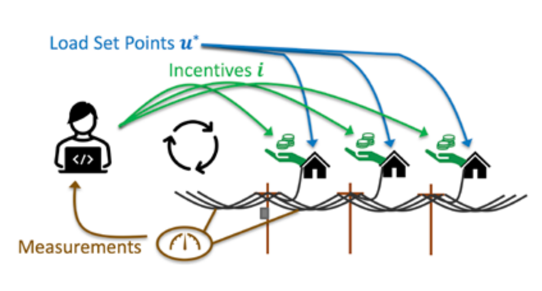

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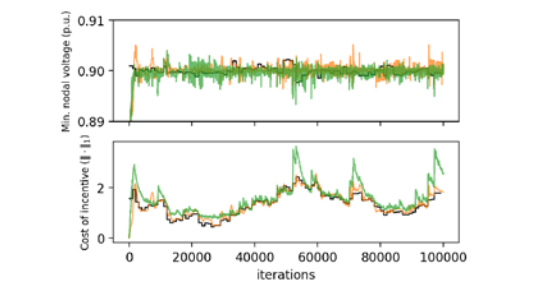


Human Response to Incentives

Load set points $\boldsymbol{u}^*$

Incentive amounts $\boldsymbol{i}$

$g_{\boldsymbol{u}^*}(\boldsymbol{i})$ Incentivized load values

<u>Assumptions</u>

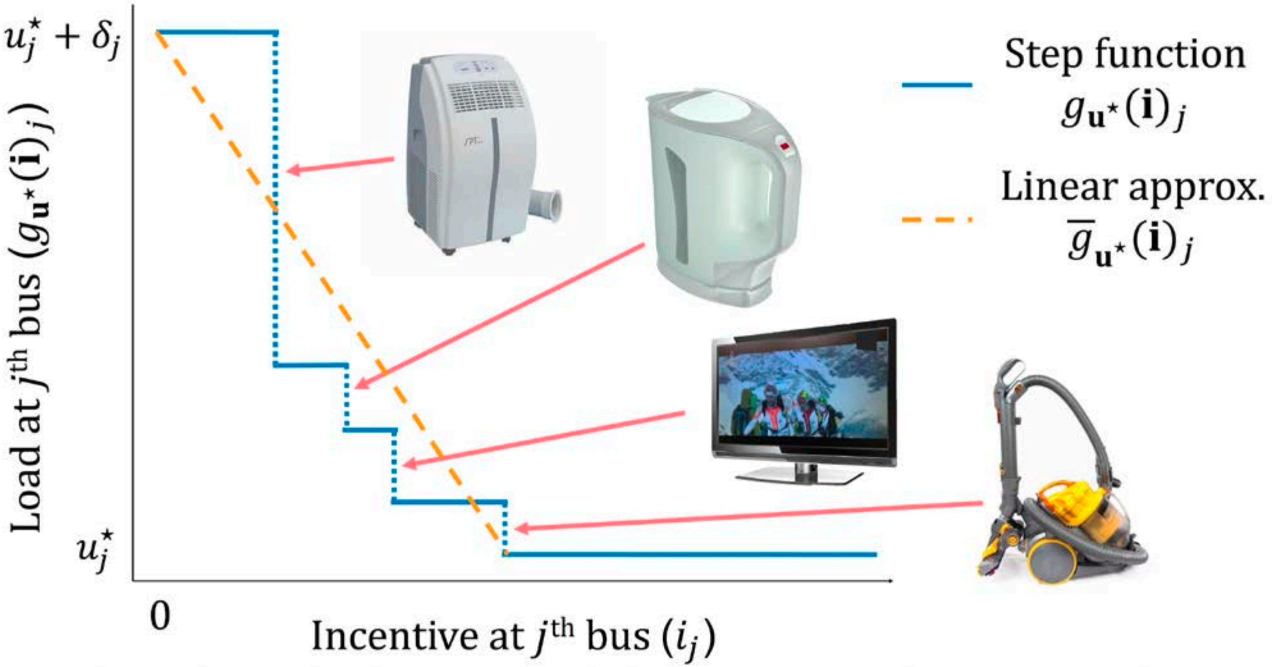
Monotonicity

$$\|g_{\boldsymbol{u}^*}(\boldsymbol{i}^{(1)}) - \boldsymbol{u}^*\| \leq \|g_{\boldsymbol{u}^*}(\boldsymbol{i}^{(2)}) - \boldsymbol{u}^*\|$$

$$\boldsymbol{i}^{(1)} \succcurlyeq \boldsymbol{i}^{(2)}$$

Ability to incentivize to get set point

$$\exists \boldsymbol{i}^* \text{ s.t. } g_{\boldsymbol{u}^*}(\boldsymbol{i}^*) = \boldsymbol{u}^*$$



Realistic Example

- Each device has an incentive threshold to turn off.
- Linear approximation is an estimated sensitivity to incentive amount.

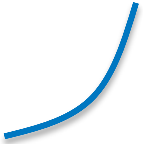
How well do grid operators know their customers?

More Information

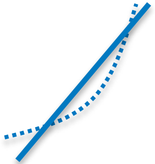
Less Information

$$g_{\boldsymbol{u}^*}(\boldsymbol{i})$$

1. Functional form: $g_{\boldsymbol{u}^*}(\boldsymbol{i})$



2. (Estimated) sensitivities: $\nabla g_{\boldsymbol{u}^*}(\boldsymbol{i})$

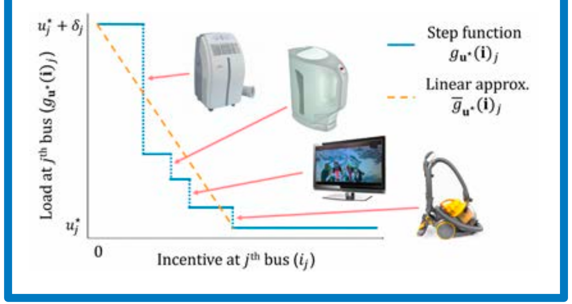


3. Grid measurements only (e.g., nodal voltage magnitudes)

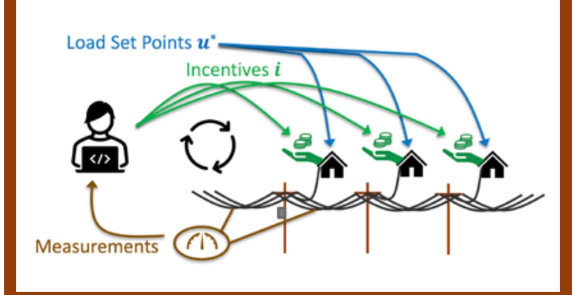
Problem: Grid operators lack control over end-user load behavior.

Approach: Dynamically optimize individualized incentives paired with load set points.

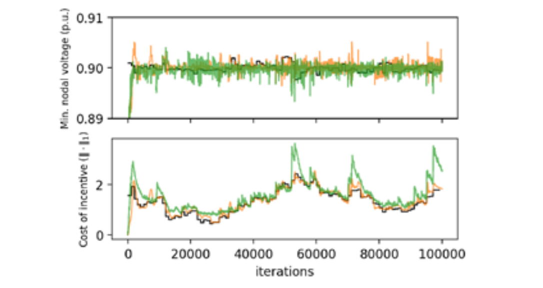
Human Behavior Model



Incentive Optimization



Numerical Evaluation



Incentives for Optimal Power Flow

Optimal Power Flow

(direct control of $\boldsymbol{u}$)

$$\min_{\boldsymbol{u}} \quad \mathrm{Cost}(\boldsymbol{u})$$

$$\text{s.t.} \quad \underline{\boldsymbol{V}} \leq \mathrm{Voltage}(\boldsymbol{u}) \leq \overline{\boldsymbol{V}}$$

$$\boldsymbol{u} \in \boldsymbol{\mathcal{U}}$$

Indirect

Incentivized Optimal Power Flow

(influence of $\boldsymbol{u}$ via $\boldsymbol{i}$)

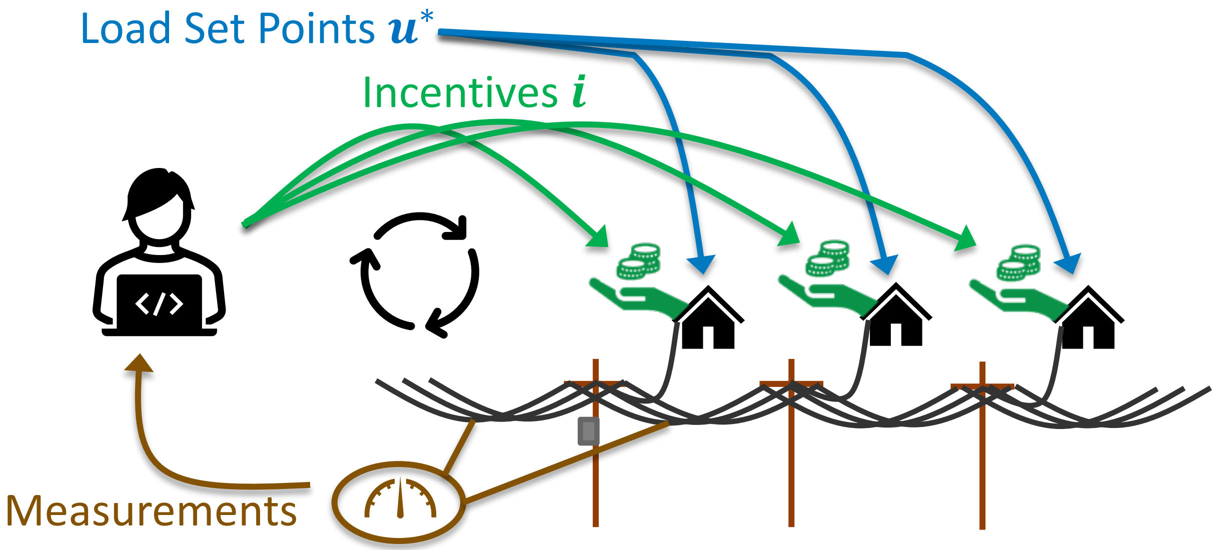
$$\min_{\boldsymbol{i}} \quad \mathrm{Cost}_{\boldsymbol{u}^*}(\boldsymbol{i})$$

$$\text{s.t.} \quad \underline{\boldsymbol{V}} \leq \mathrm{Voltage}\big(g_{\boldsymbol{u}^*}(\boldsymbol{i})\big) \leq \overline{\boldsymbol{V}}$$

$$\boldsymbol{i} \in \boldsymbol{\mathcal{I}}$$

Example:
$\mathrm{Cost}_{\boldsymbol{u}^*}(\boldsymbol{i}) = \|\boldsymbol{i}\|_1$

(Could be used to determine $\boldsymbol{u}^*$)



Feedback-based Control

- Grid Measurements are the feedback that updates the dual variables.
- Incentives are updated based on locational relation to the dual variables.

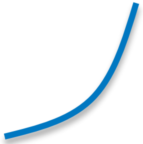
More Information

Less Information

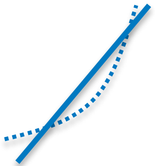
We prove convergence and tracking bounds.

Knowledge of Behavior

1. Functional form: $g_{\boldsymbol{u}^*}(\boldsymbol{i})$



2. (Estimated) Incentive Responsiveness: $\nabla g_{\boldsymbol{u}^*}(\boldsymbol{i})$



3. Grid measurements only (e.g., nodal voltage magnitudes)

Control Algorithm

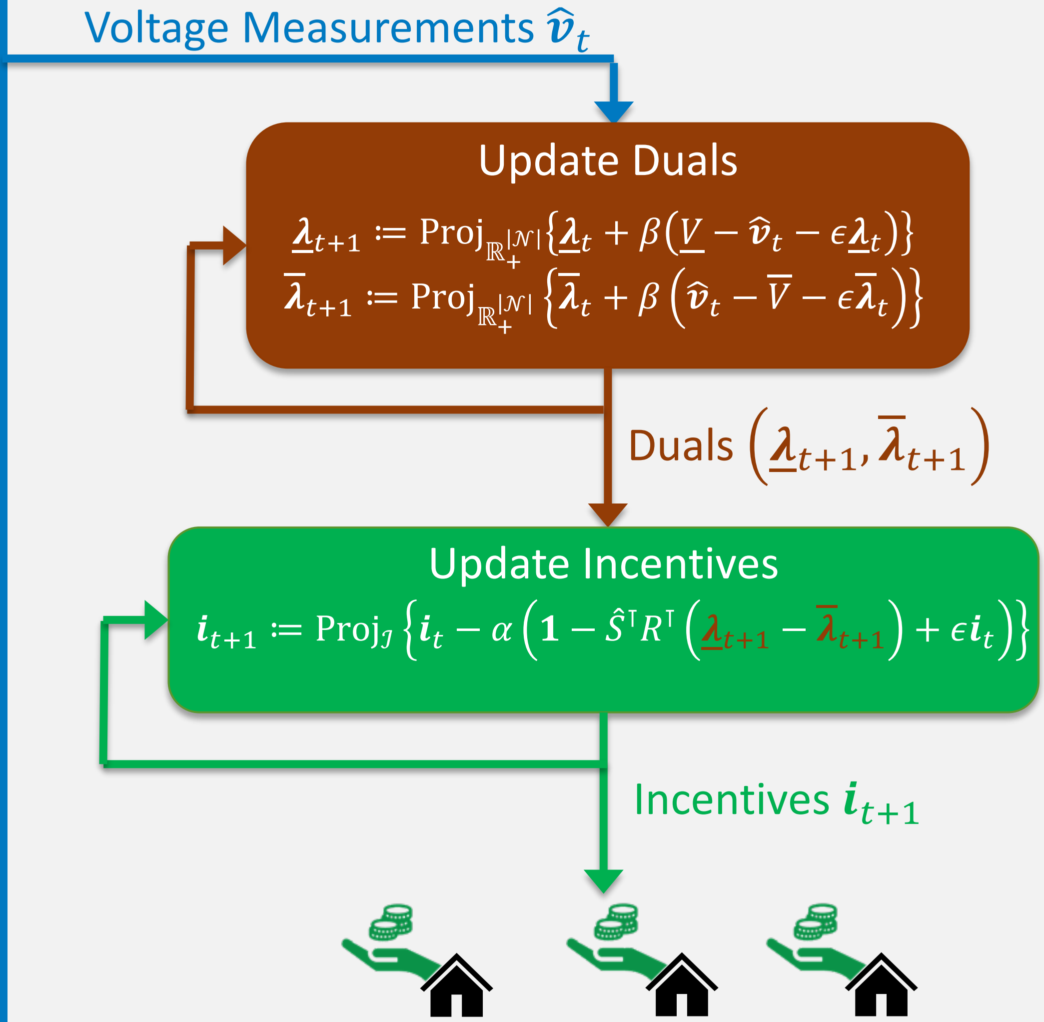
Dual Ascent

First-Order Primal-Dual

Zero-Order Primal-Dual

First-Order Primal-Dual Control Algorithm

- Requires:
  - Estimated Incentive Responsiveness $\hat{S}$
  - Linearized Power Flow R
- $\mathrm{Cost}_{\boldsymbol{u}^*}(\boldsymbol{i}) = \|\boldsymbol{i}\|_1$



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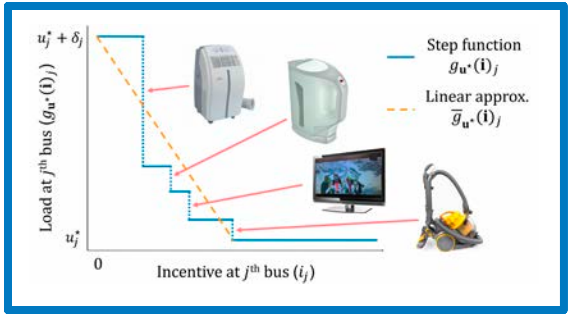
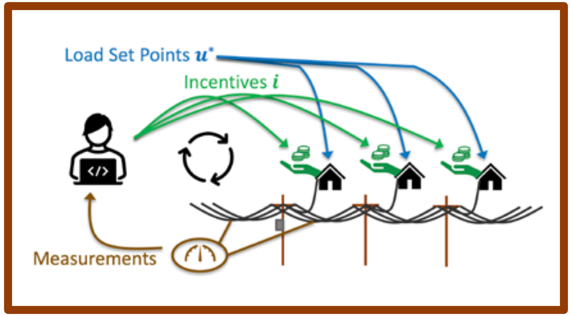
Approach: Dynamically optimize individualized incentives paired with load set points.

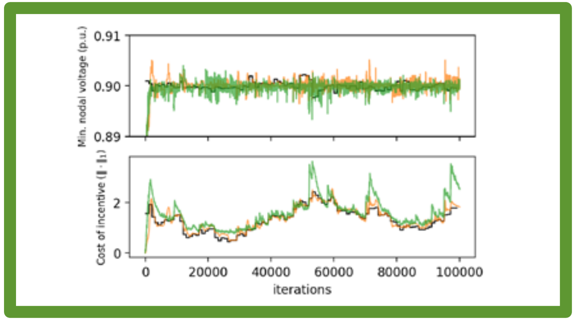
Human Behavior Model



Incentive Optimization



Numerical Evaluation

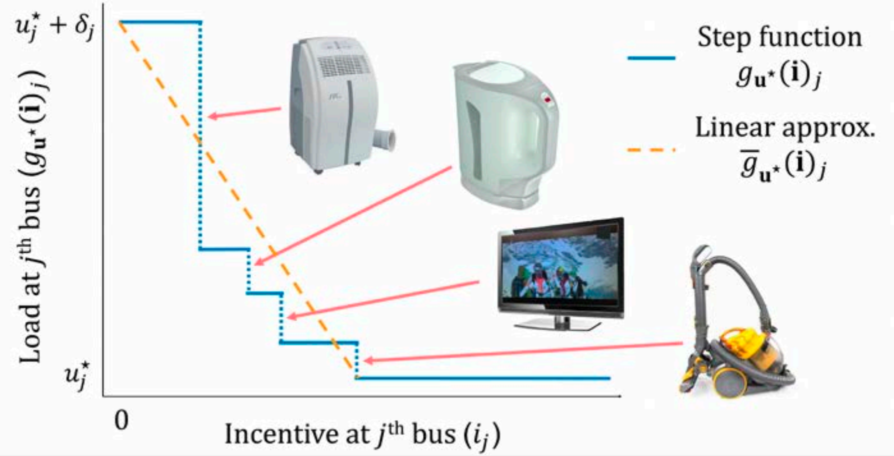


Setup: Time-varying human behavior

Objectives:

- Keep voltage above 0.9 p.u. with minimum total incentive.
- Compare First-Order and Zero-Order Primal Dual Algorithms.

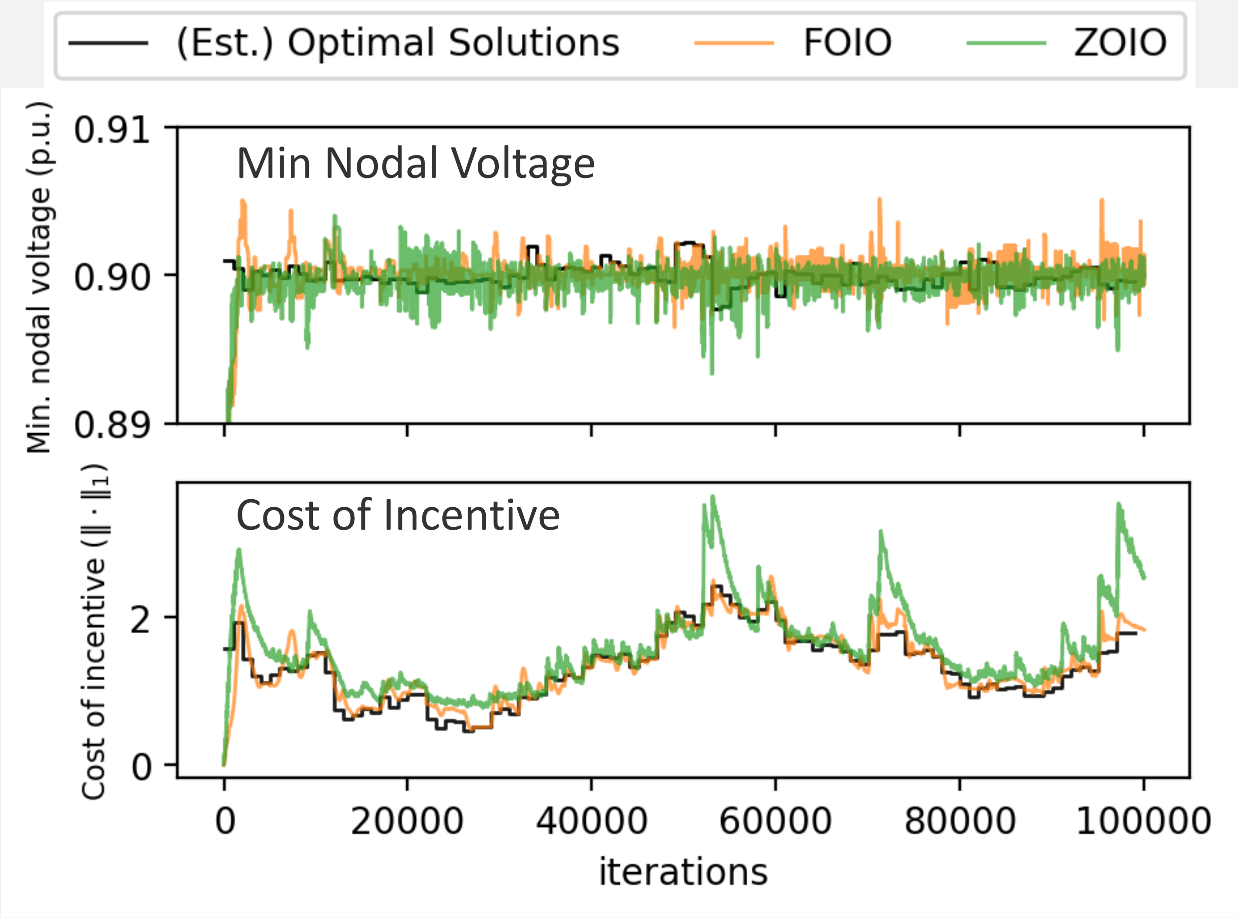
- Time-varying human behavior with 6 devices per customer randomly coming on- and off-line.
- First-Order Algorithm has access linear approximations.



- Time-varying base loads from UMass Amherst Smart Data Set (1-minute granularity).
- IEEE 33-bus distribution system.

Incentives are effective at providing voltage support.

- First-order with **rough estimated sensitivities** is more efficient than Zero-order.



Problem: Grid operators lack control over end-user load behavior.

Approach: Dynamically optimize individualized incentives paired with load set points.

Human Behavior Model

Realistic Flexible Model that integrates with Optimization Algorithms.

Incentive Optimization

Control algorithms that account for different behavior knowledge scenarios.

Numerical Evaluation

Dynamic incentives are effective at providing grid support in realistic scenarios.

Future direction: Expand human behavior model with state dependencies.

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Thank You!

https://arxiv.org/abs/2410.14936

NREL/PR-5D00-91673

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This work was authored in part by the National Renewable Energy Laboratory (NREL), operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. This work was supported by the Laboratory Directed Research and Development (LDRD) Program at NREL. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Advanced Scientific Computing Research, Department of Energy Computational Science Graduate Fellowship under Award Number DE-SC0024386.

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