Task 1 Update: Realization of Advanced Energy Management Applications

Cybersecurity Technology for Critical Power Infrastructure AI-Based Centralized Defense and Edge Resilience

Yang Weng

Arizona State University

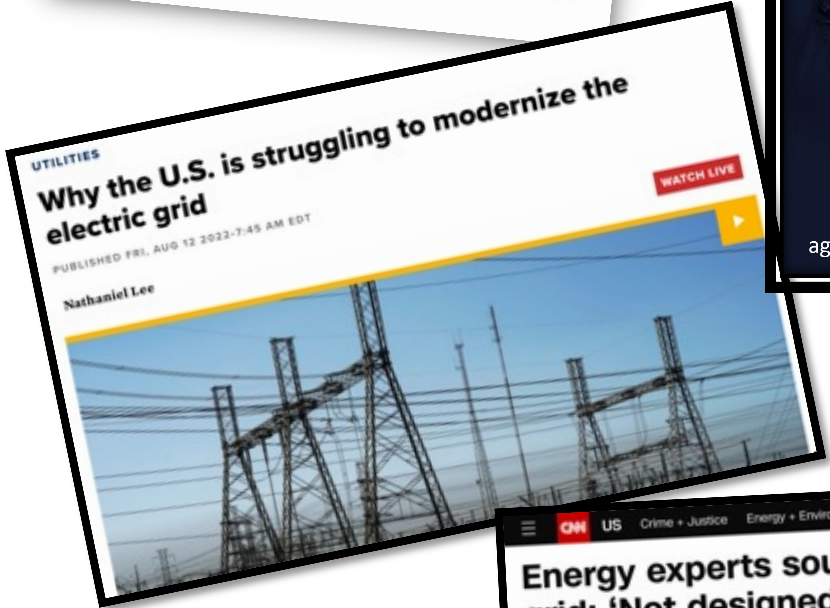
Mar. 2023

Challenges → Outcomes?

Businessweek | Technology

What Happens When Hackers Come for the Electrical Grid

Emergency training at a restricted facility off Long Island has aimed to minimize the potentially catastrophic effects of a cyberattack on U.S. power infrastructure.


UTILITIES

Why the U.S. is struggling to modernize the electric grid

WATCH LIVE

PUBLISHED FRI, AUG 12 2022-7:45 AM EDT

Nathaniel Lee


America's Power Grid Is Increasingly Unreliable

Behind a rising number of outages are new stresses on the system caused by aging power lines, a changing climate and a power-plant fleet rapidly going green


Winter storms put the US power grid to the test. It failed.

America's aging energy infrastructure and reliance on fossil fuels pushed local power grids to the brink.

By Rebecca Leber | @rebleber | rebecca.leber@vox.com | Dec 27, 2022, 2:30pm EST

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BUSINESS

A summer of blackouts? Wheezing power grid leaves states at risk.

Why the grid could buckle in large areas of the country

By Evan Halper

US | Crime + Justice | Energy + Environment | Extreme Weather | Space + Science

Energy experts sound alarm about US electric grid: 'Not designed to withstand the impacts of climate change'

By René Marsh, CNN

Updated 1:36 PM EDT, Thu June 2, 2022

Evening Standard

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TECH

People aren't using smart meters for one main reason

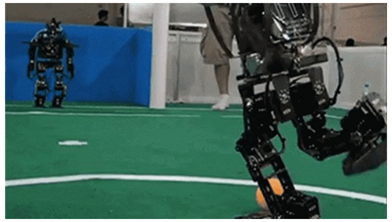
Despite the government's ongoing smart meter roll-out, nearly 50 per cent of people are concerned about the security risks of the devices

Power Engineers See: AI Not That Reliable and Secured

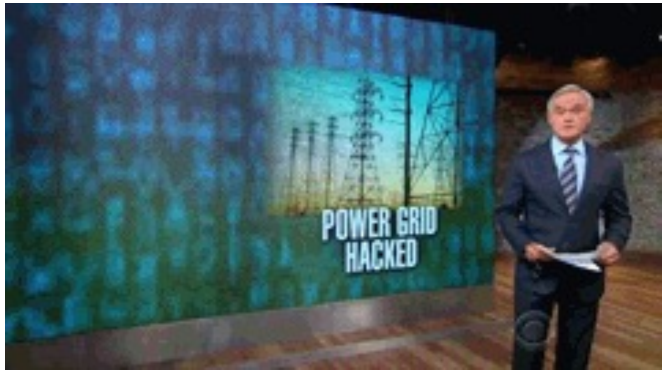
Critical Infrastructure?

Not That Safe

Not That Robust



Can Cause Security Issues

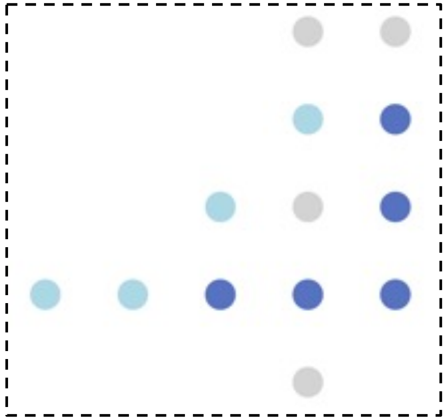


Problem Setup: Learn the Power Flow Equation in Distribution Grids

Why Today?

Pennsylvania Data

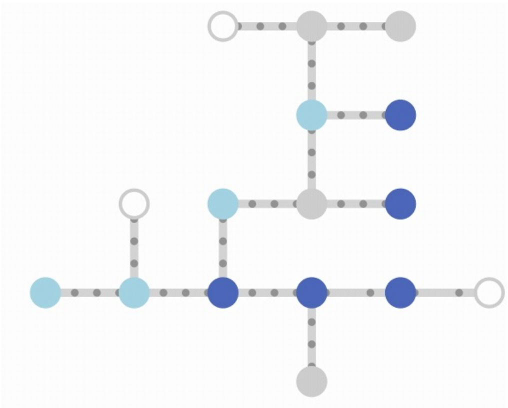
- Given: Sensor Data 



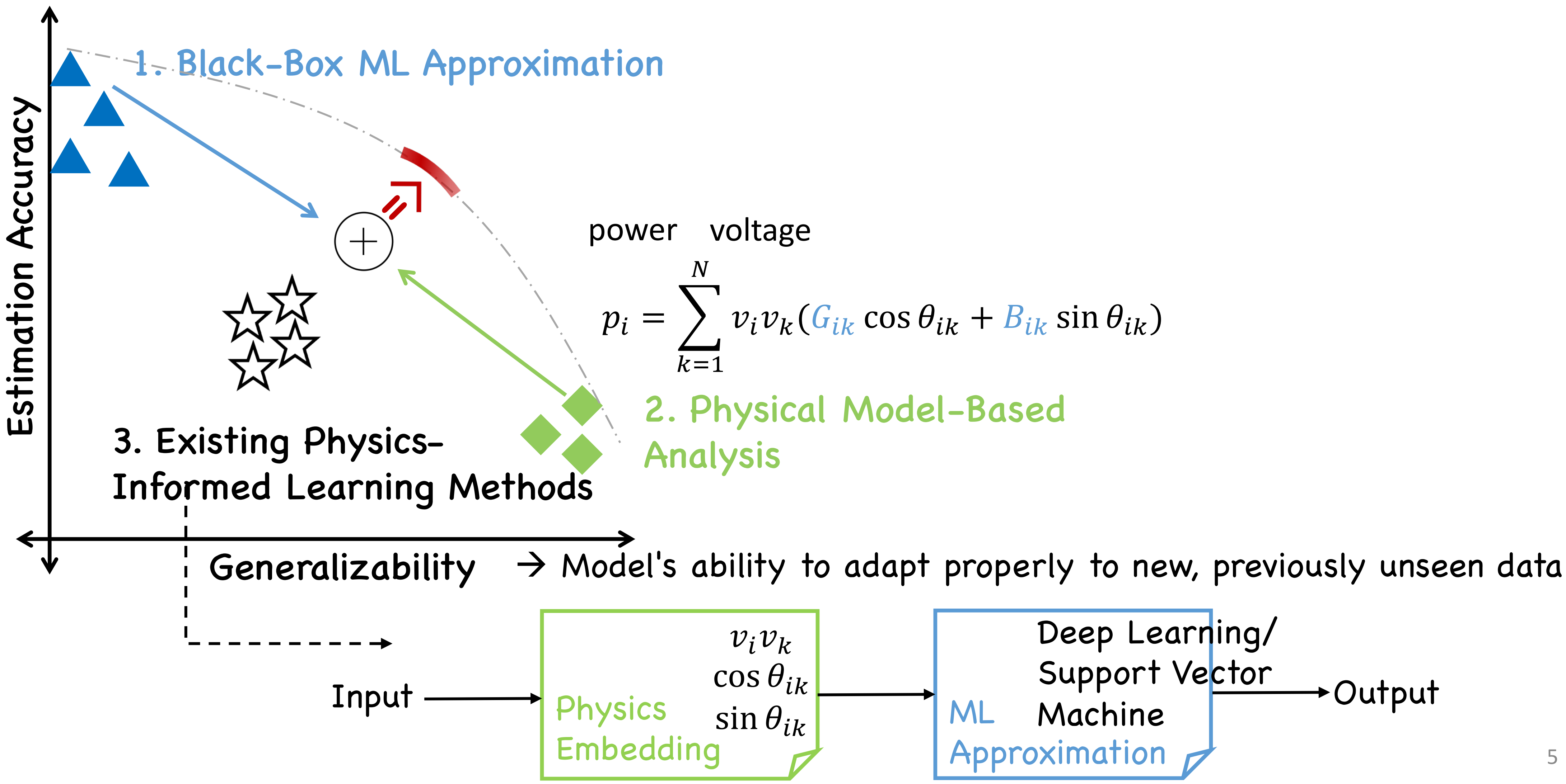
voltage power
(v, p)

✓, ✓
✓, X
X, ✓
X, X

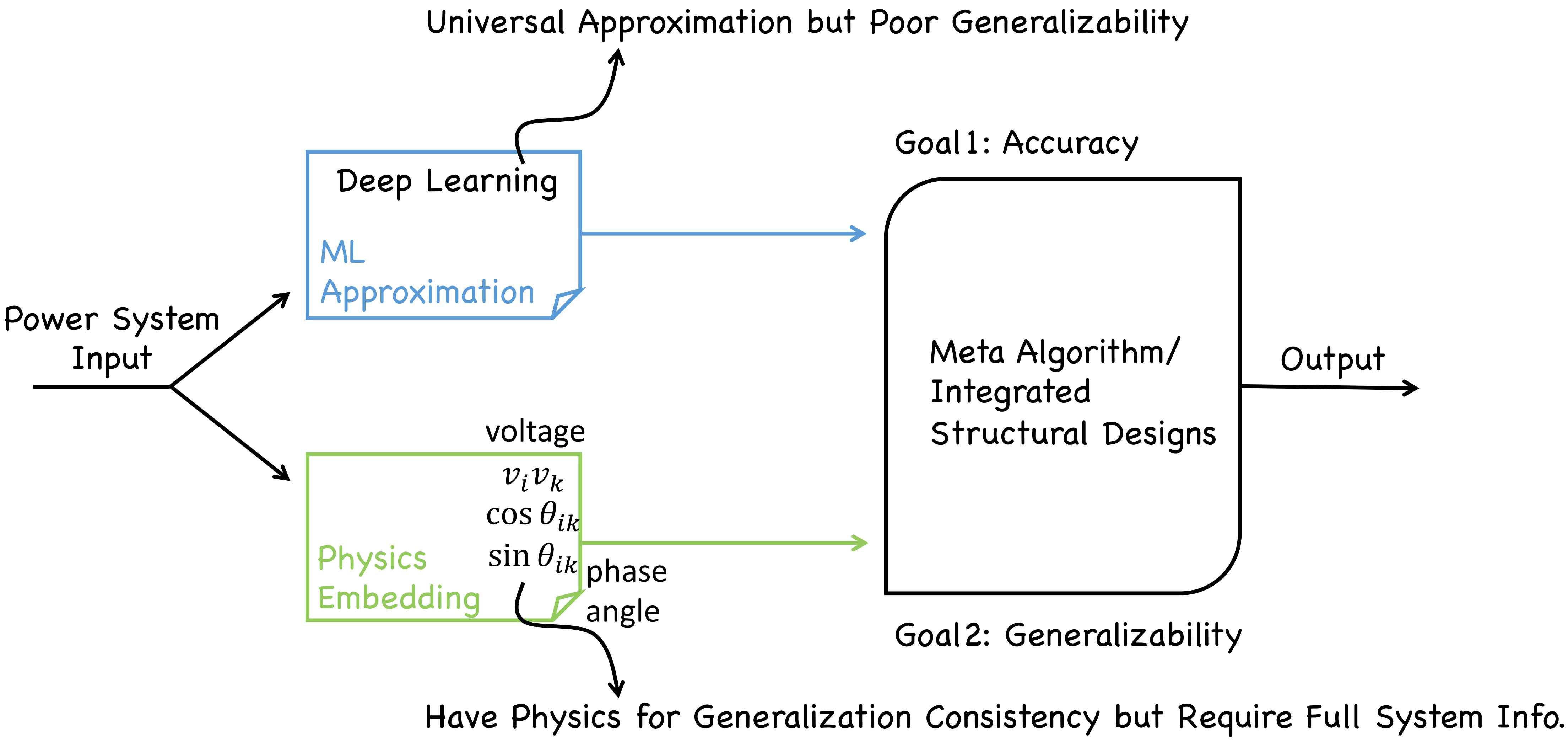
- Find: the Topology, Parameter, and Virtual Nodes for Power Flow Equation



Past Methods



New Idea: Series to Parallel → Enable Flexibility



Mathematical Modeling

Power Flow Equation

$$p_i = \sum_{k=1}^{N} v_i v_k (G_{ik} \cos\theta_{ik} + B_{ik} \sin\theta_{ik})$$

Physical Parameter

Data

Data

$$\boldsymbol{p} = \begin{pmatrix} p_i^{(1)} \\ \cdots \\ p_i^{(T)} \end{pmatrix} = \begin{bmatrix} v_i^{(1)} v_1^{(1)} \cos\theta_{i1}^{(1)} & \cdots & v_i^{(1)} v_N^{(1)} \cos\theta_{iN}^{(1)} & v_i^{(1)} v_1^{(1)} \sin\theta_{i1}^{(1)} & \cdots & v_i^{(1)} v_N^{(1)} \sin\theta_{iN}^{(1)} \\ & & \cdots & \cdots & & \\ v_i^{(T)} v_1^{(T)} \cos\theta_{i1}^{(T)} & \cdots & v_i^{(T)} v_N^{(T)} \cos\theta_{iN}^{(T)} & v_i^{(T)} v_1^{(T)} \sin\theta_{i1}^{(T)} & \cdots & v_i^{(T)} v_N^{(T)} \sin\theta_{iN}^{(T)} \end{bmatrix} \begin{pmatrix} G_{i1} \\ \cdots \\ G_{iN} \\ B_{i1} \\ \cdots \\ B_{iN} \end{pmatrix}$$

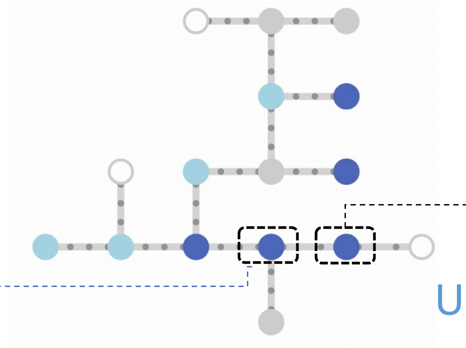
$\phi(\mathrm{V}, \Theta) \in \mathbb{R}^{T \times 2N}$

$\boldsymbol{\beta}^* \in \mathbb{R}^{2N}$

$$\boldsymbol{p} = \phi\, \boldsymbol{\beta}^*$$

$\boldsymbol{p} \in \mathbb{R}^T$: power injection at bus i up to time T, $\mathrm{V} = (v_k^{(t)}) \in \mathbb{R}^{T \times N}$: voltage magnitude at N buses up to time T,
$\Theta = (\theta_{ik}^{(t)}) \in \mathbb{R}^{T \times N}$: voltage angle difference between bus i and other buses up to time T, and $T \in \mathbb{N}$: No. of historical samples.

Separate the Physically Recoverable Part and the Virtual Parts



Observable
bus set $\mathcal{O}$

Unknown
set $\mathcal{U}$

Boundary
set B

$$\boldsymbol{p} = \phi(\mathrm{V},\Theta)\boldsymbol{\beta}^* = \big(\underbrace{\phi(\mathrm{V}_{\mathcal{O}},\Theta_{\mathcal{O}}) \quad \phi(\mathrm{V}_{\mathcal{O}B},\Theta_{\mathcal{O}B})}_{(\mathrm{V},\Theta)} \quad \underbrace{\phi(\mathrm{V}_{B\mathcal{U}},\Theta_{B\mathcal{U}}) \quad \phi(\mathrm{V}_{\mathcal{U}},\Theta_{\mathcal{U}})}_{\text{Unknown}}\big)\begin{pmatrix}\boldsymbol{\beta}_{\mathcal{O}\mathcal{O}}\\ \boldsymbol{\beta}_{\mathcal{O}B}\\ \boldsymbol{\beta}_{B\mathcal{U}}\\ \boldsymbol{\beta}_{\mathcal{U}\mathcal{U}}\end{pmatrix}$$

If Physically
Learnable:

Physical
Contribution

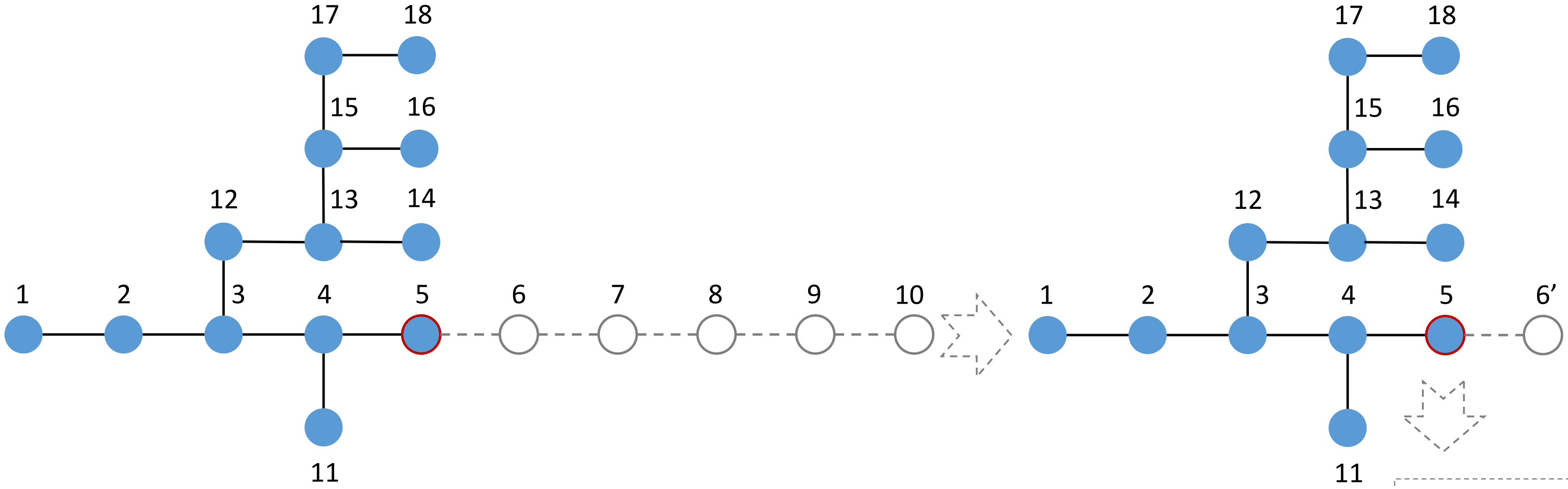
Borrow

$$\boldsymbol{p} = \boldsymbol{h}_p\big(\phi(\mathrm{V},\Theta)\big) \quad + \quad \boldsymbol{h}_v(\mathrm{V},\Theta)$$

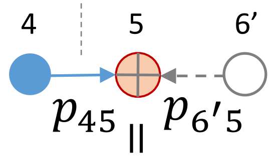
Use Blackbox Learning Methods

An Example: How Physics and Approximation Work Together?

Target: Representation Learning for p_5



Large Flow → More Physical Representation



Physics → Calibration

$$p_5 = p_{45} + p_{6'5}$$

$$= h_p(\phi(\mathrm{V},\Theta)) + h_v(\mathrm{V},\Theta)$$

$$p_5 = \begin{pmatrix} v_5 v_4 \cos\theta_{54} \\ v_5 v_4 \sin\theta_{54} \\ v_5^2 \\ v_5 v_6 \cos\theta_{56} \\ v_5 v_6 \sin\theta_{56} \end{pmatrix}^{\top} \begin{pmatrix} G_{54} \\ B_{54} \\ G_{55} \\ G_{56} \\ B_{56} \end{pmatrix} = \underbrace{\begin{pmatrix} v_5 v_4 \cos\theta_{54} \\ v_5 v_4 \sin\theta_{54} \\ v_5^2 \end{pmatrix}^{\top} \begin{pmatrix} G_{54} \\ B_{54} \\ G_{55} \end{pmatrix}}_{h_p(\phi(\mathrm{V},\Theta))} + \boxed{p_{56}}$$

$$h_v(\mathrm{V},\Theta)$$

J. Yuan and Y. Weng, "Physics Interpretable Shallow-Deep Neural Networks for Physical System Identification with Unobservability", IEEE International Conference on Data Mining (ICDM), Auckland, New Zealand, Dec 2021.

Learning Targets

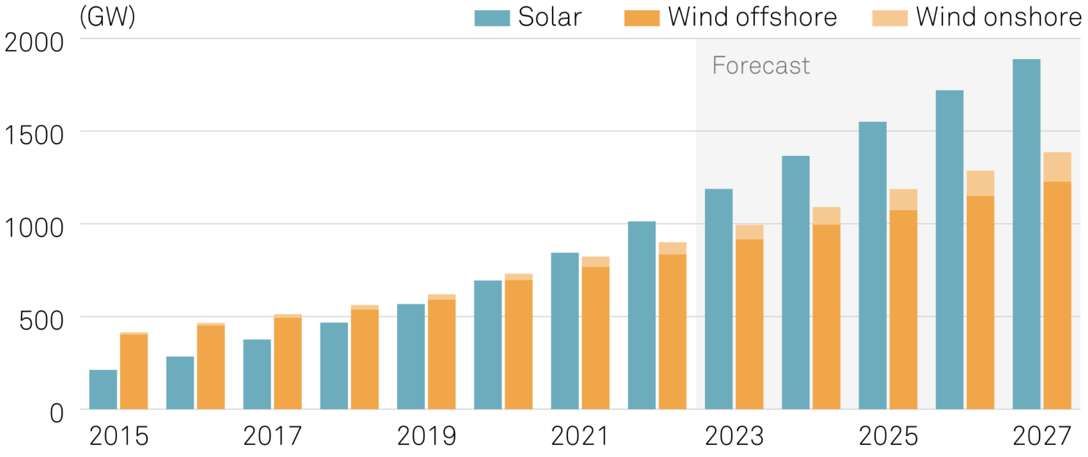
Minimize Error + Maximize Generalizability

Definition 1. [Error of estimating powers] In a system with N buses and T time slots, we have voltage data V, Θ and power data $\boldsymbol{p}$. An approximator of power $f(\cdot)$ has an error as $\varepsilon_p = \frac{1}{T}||\boldsymbol{p} - f(\mathrm{V}, \Theta)||_2$.

Definition 2. [Error of physical parameters] In a system with voltage data V, Θ and power data $\boldsymbol{p} = \phi(\mathrm{V}, \Theta)\, \boldsymbol{\beta}^* \in \mathbb{R}^T$, an estimated physical parameter $\widehat{\boldsymbol{\beta}}$ has an error $\varepsilon_\beta = ||\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}^*||_2$.

Generalizability, e.g.,
New Operating Point

Global installed solar, wind capacity (cumulative)



Twin Neural Network Model and the Objective

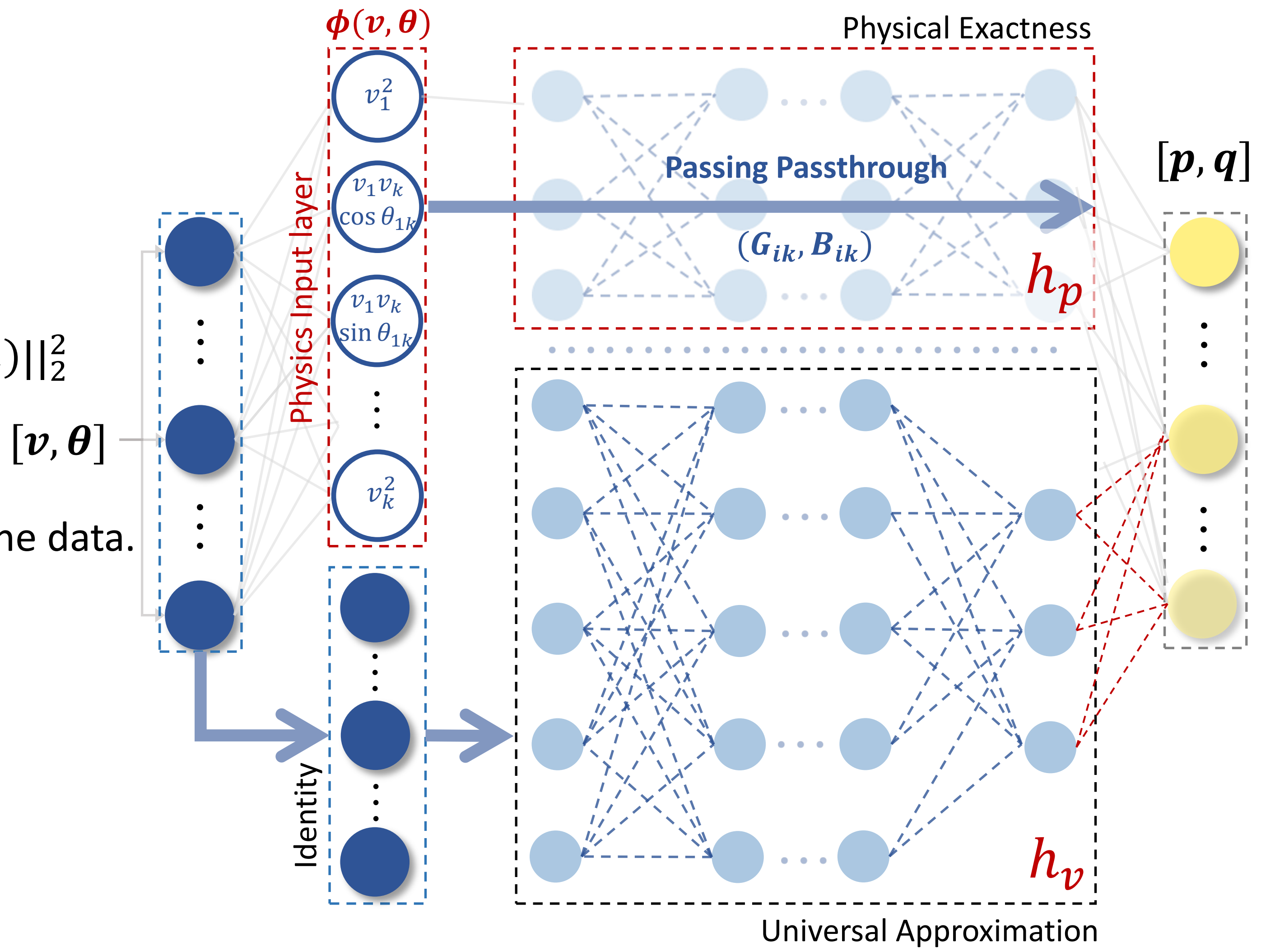
Optimization

$$\min \varepsilon_p^2$$

$$= \min \frac{1}{T} ||\boldsymbol{p} - f(\mathrm{V}, \Theta)||_2^2$$

$$= \min_{\boldsymbol{\beta}, W_v} \frac{1}{T} \sum_{t=1}^{T} ||\boldsymbol{p}_t - h_p(\phi(\boldsymbol{v}_t, \boldsymbol{\theta}_t)) - h_v(\boldsymbol{v}_t, \boldsymbol{\theta}_t)||_2^2$$

Condition for the universal approximation:
there exists a function $f(.,.)$ to perfectly fit the data.

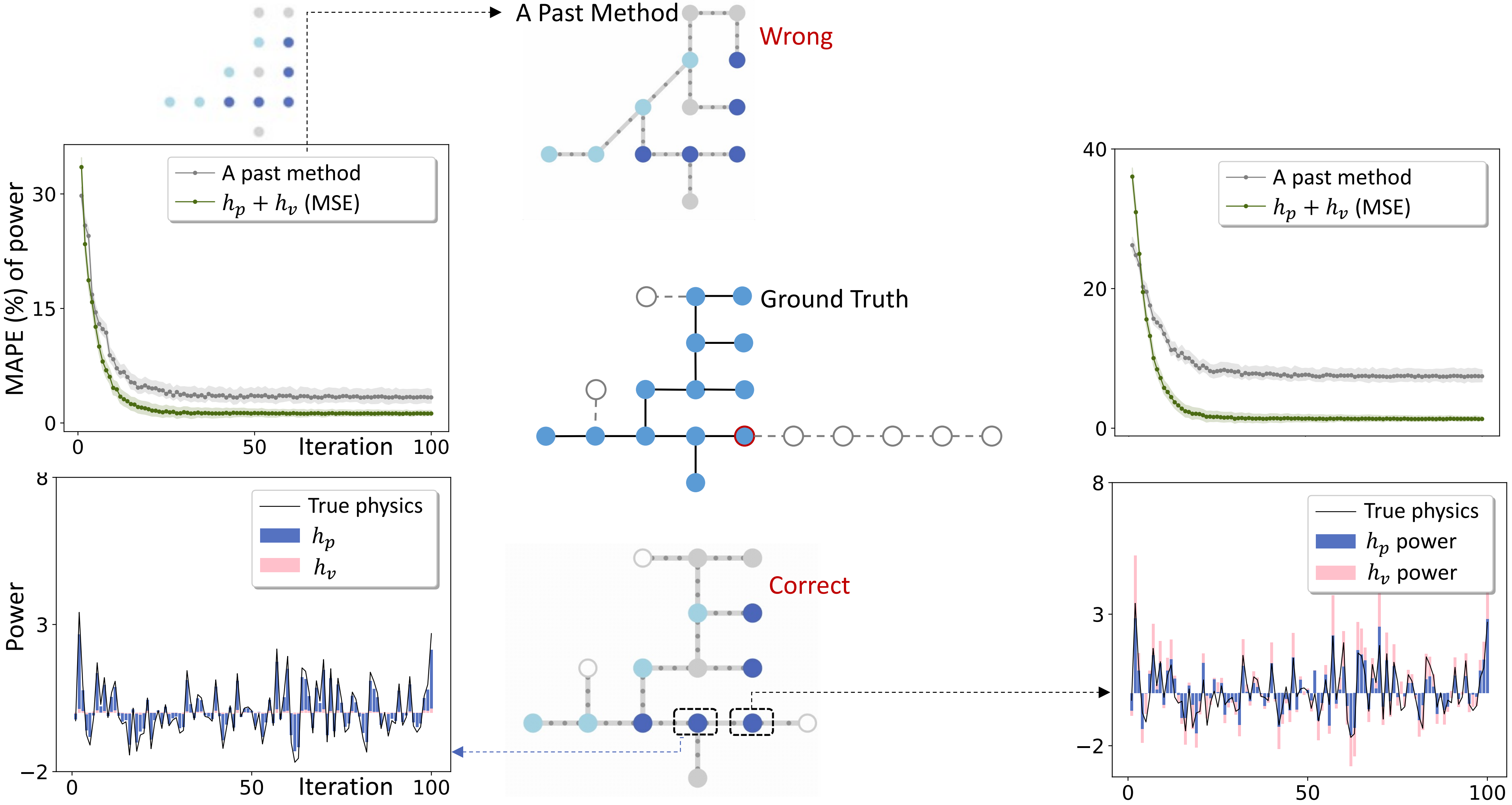


In the Rest of the Slides

$[\boldsymbol{v}, \boldsymbol{\theta}] \rightarrow \boldsymbol{v}$ $\quad$ $[\boldsymbol{p}, \boldsymbol{q}] \rightarrow \boldsymbol{p}$

$\boldsymbol{\beta}$: parameters of $h_p(\cdot)$, a linear layer. W_v: parameters of $h_v(\cdot)$, a deep neural network.

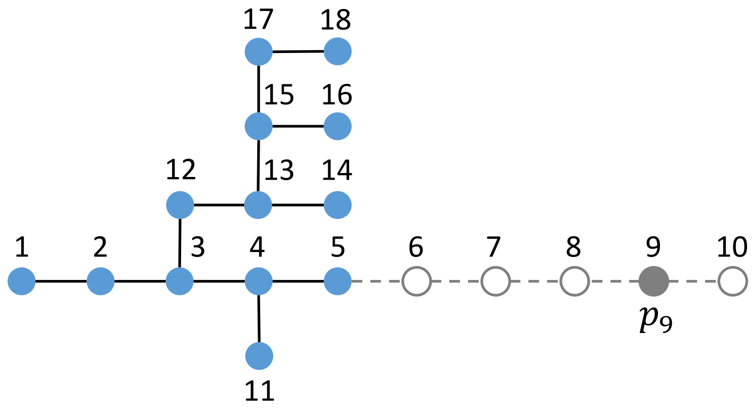
Numerical Result: Proposed Collaboration is Better

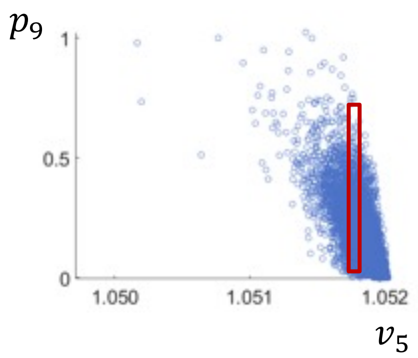


When Will the Method Have Bigger Errors?

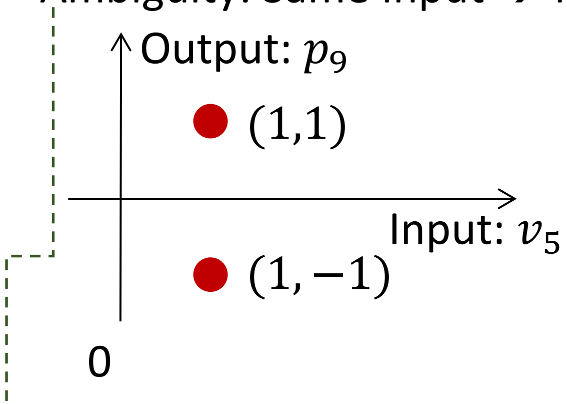
Assumption on universal approximation for h_v:

Prerequisite: existence of an underlying function $f\colon \mathcal{X} \to \mathcal{Y}$ with an arbitrarily small error.





Ambiguity: Same Input → Multiple Outputs

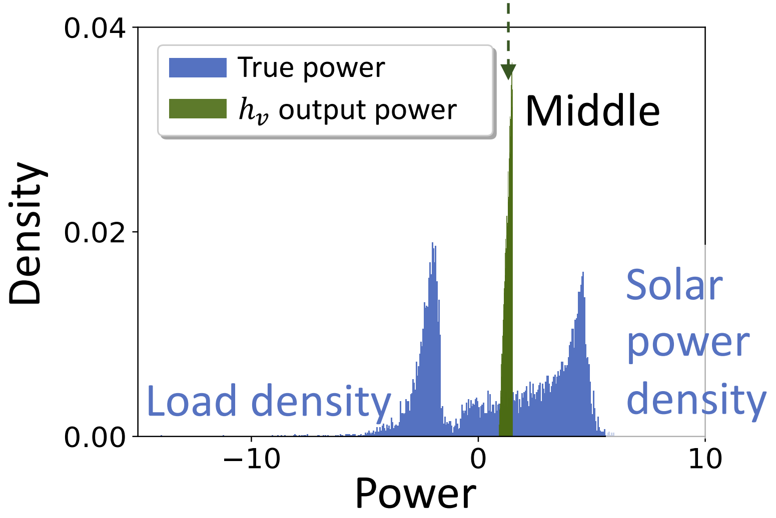


Correct Output: $1, -1$

Learning:

$$\min \frac{1}{T} ||\boldsymbol{p} - f(\mathrm{V})||_2$$

Incorrect Output: 0

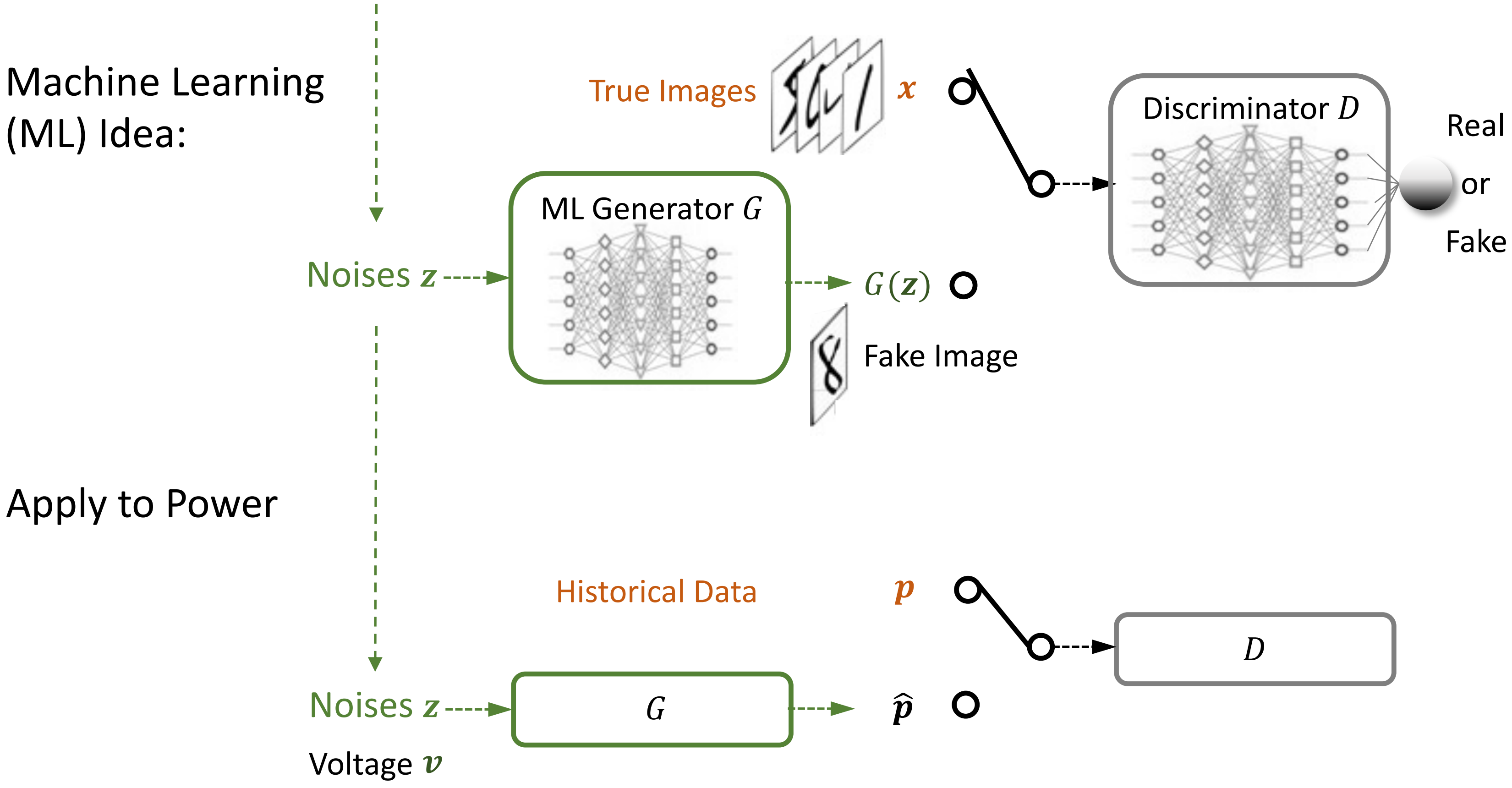


Ideas:

1. Keep the Uncertainty
2. Make a Choice Later

Model Design: Generative Adversarial Network with MSE Regularization

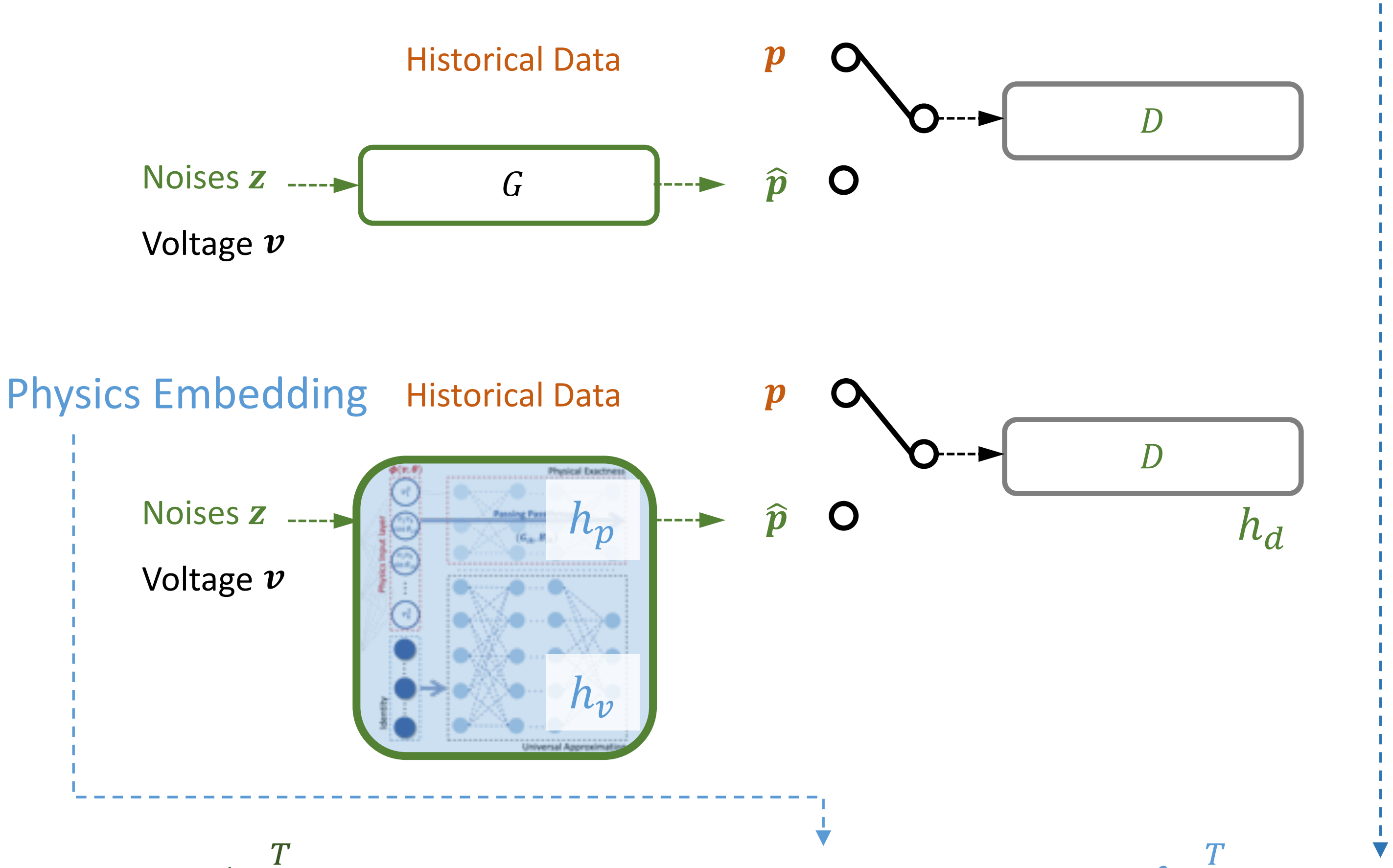
Goal: keep the uncertainty according to the distribution and make a choice later.



[Goodfellow, et al. 14] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, Generative adversarial networks, NeurIPS, 2014. [Arjovsky, et al. 17] Martin Arjovsky, Soumith Chintala, Léon Bottou, Wasserstein GAN, ICML 2017.

Robustness: Generative Adversarial Network with MSE Regularization

Goal: keep the uncertainty according to the distribution and make a choice later.

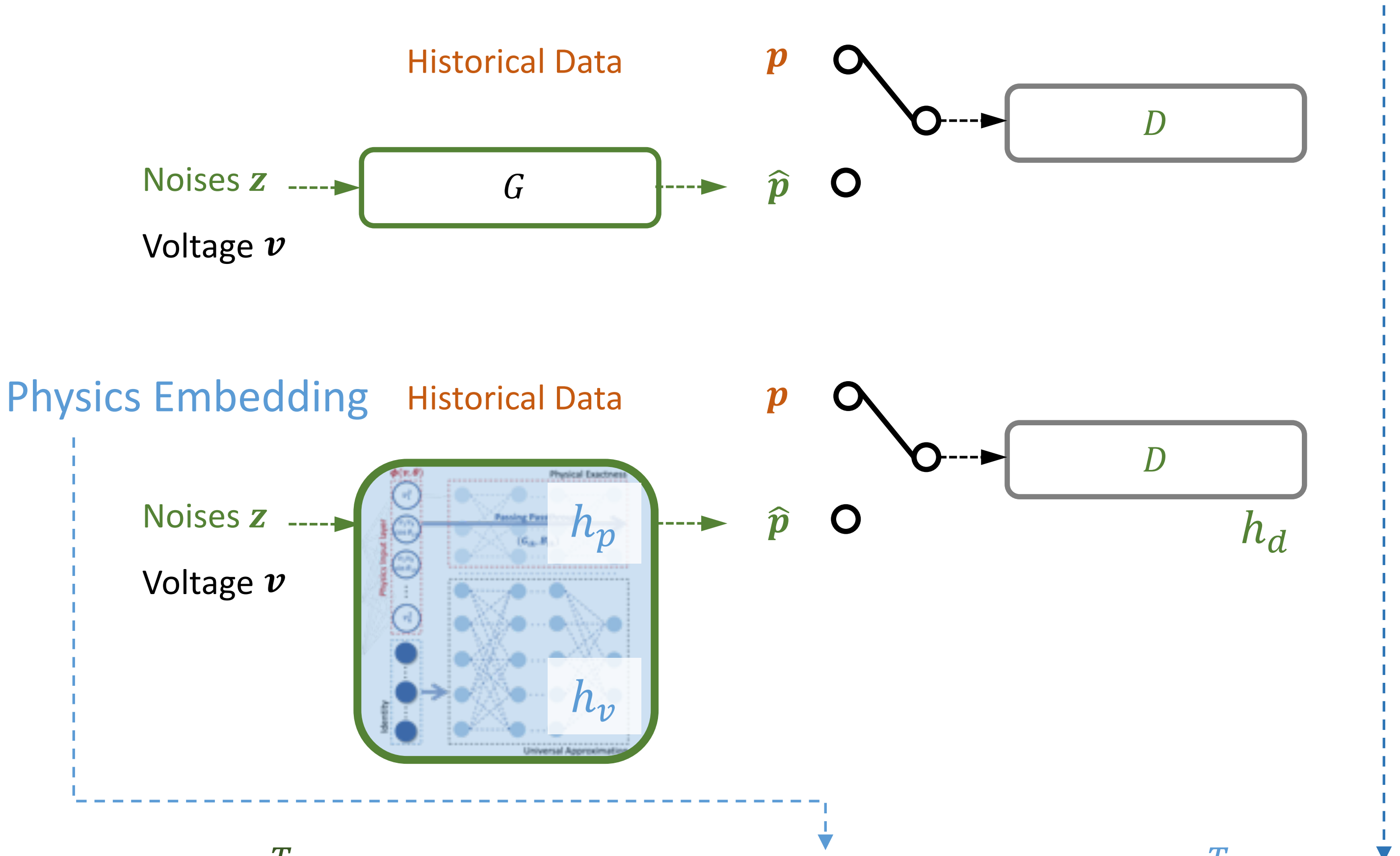


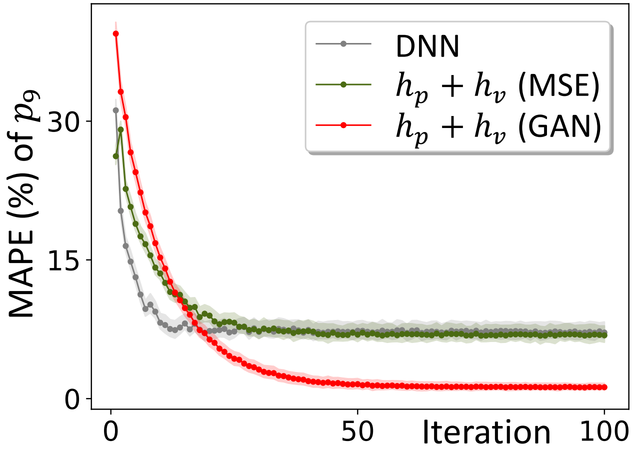
W_d: parameters of $h_d(\cdot)$, a deep neural network.

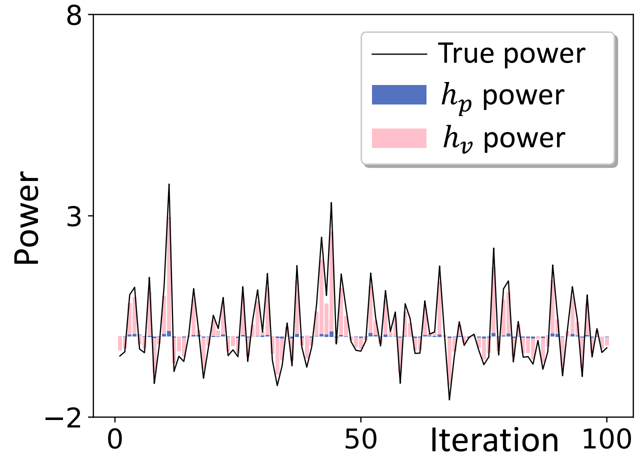
$$\min_{\boldsymbol{\beta}, W_v} \max_{W_d} \frac{1}{T}\sum_{t}^{T} h_d(\boldsymbol{p}_t) - h_d\big(h_p(\phi(\boldsymbol{v}_t)) + h_v(\boldsymbol{v}_t, \boldsymbol{z}_t)\big) + \frac{\lambda}{T}\sum_{t}^{T}\big(\boldsymbol{p}_t - h_p(\phi(\boldsymbol{v}_t)) - h_v(\boldsymbol{v}_t, \boldsymbol{z}_t)\big)^2$$

Robustness: Generative Adversarial Network with MSE Regularization

Goal: keep the uncertainty according to the distribution and make a choice later.

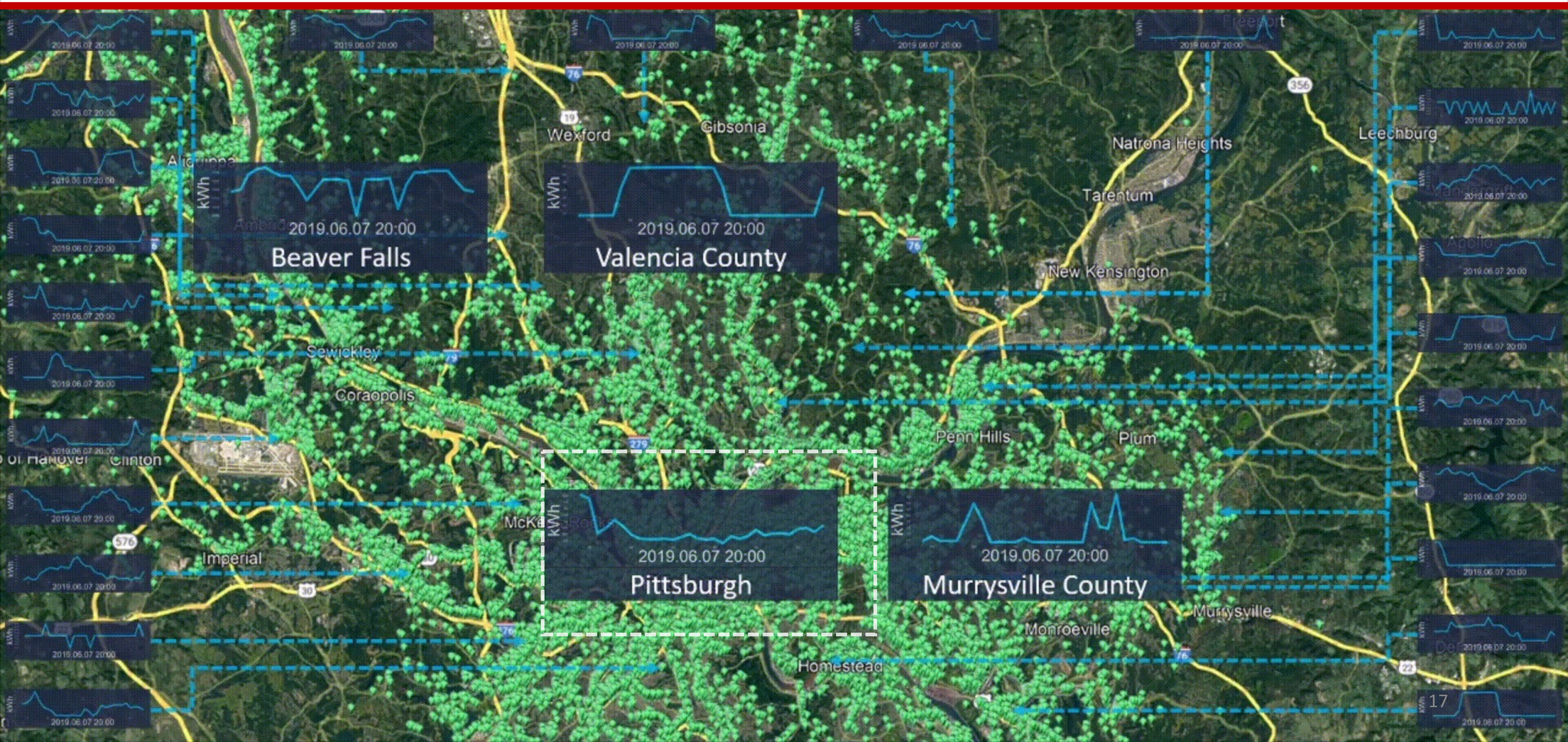




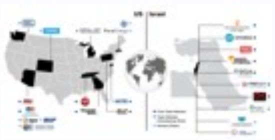


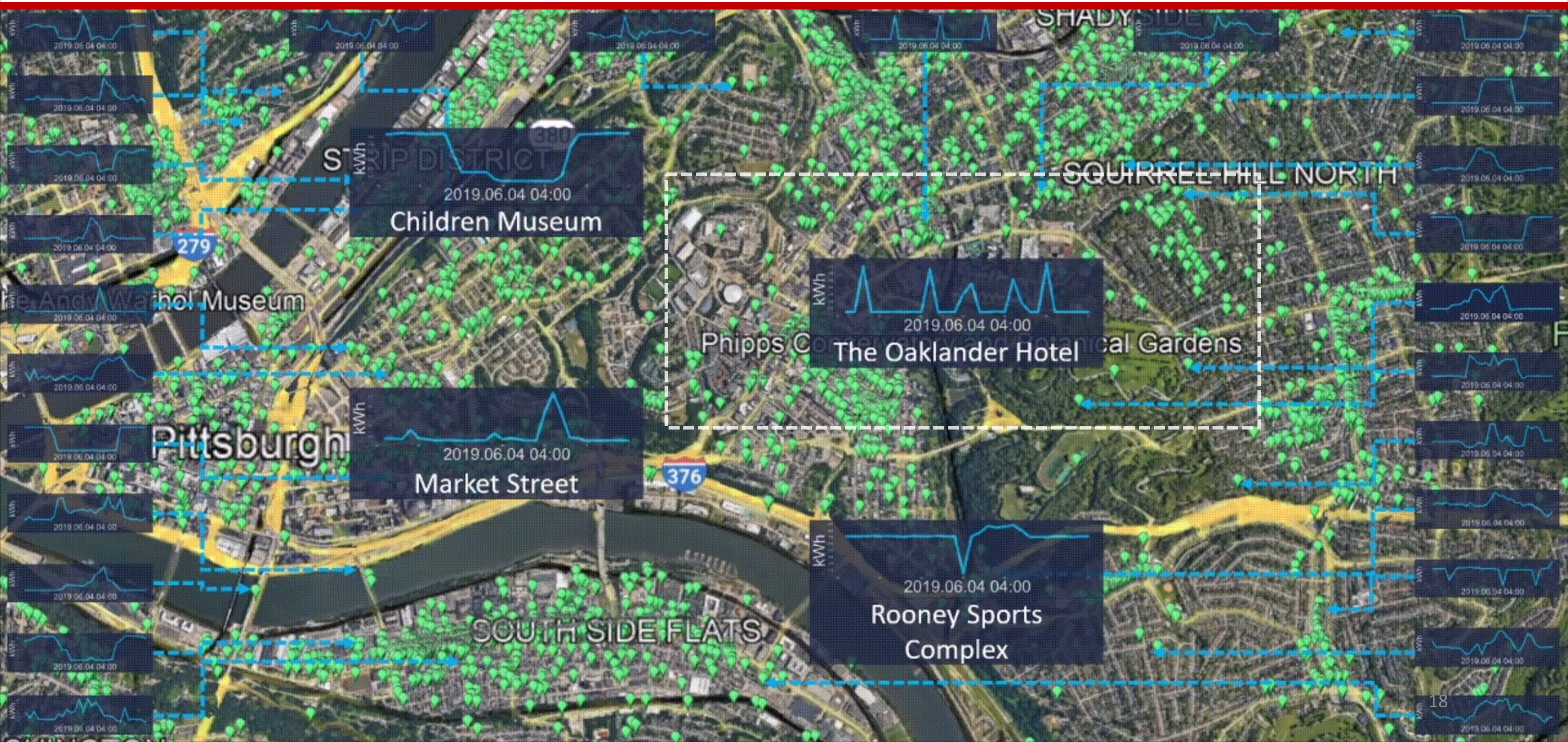
$$\min_{\boldsymbol{\beta}, W_v} \max_{W_d} \frac{1}{T} \sum_{t}^{T} h_d(\boldsymbol{p}_t) - h_d\big(h_p(\phi(\boldsymbol{v}_t)) + h_v(\boldsymbol{v}_t, \boldsymbol{z}_t)\big) + \frac{\lambda}{T} \sum_{t}^{T} \big(\boldsymbol{p}_t - h_p(\phi(\boldsymbol{v}_t)) - h_v(\boldsymbol{v}_t, \boldsymbol{z}_t)\big)^2$$

Testing at West Pennsylvania

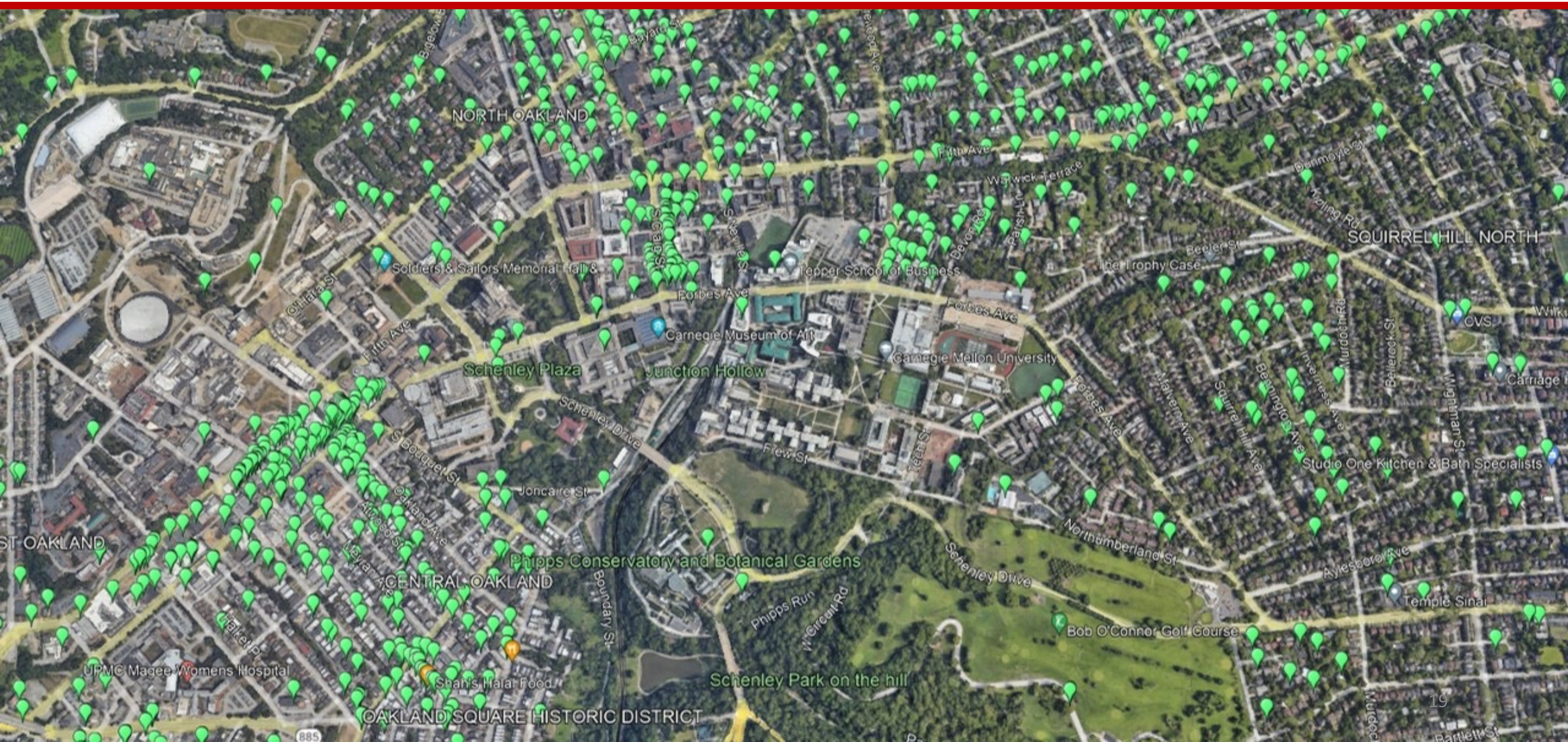


Testing at West Pennsylvania

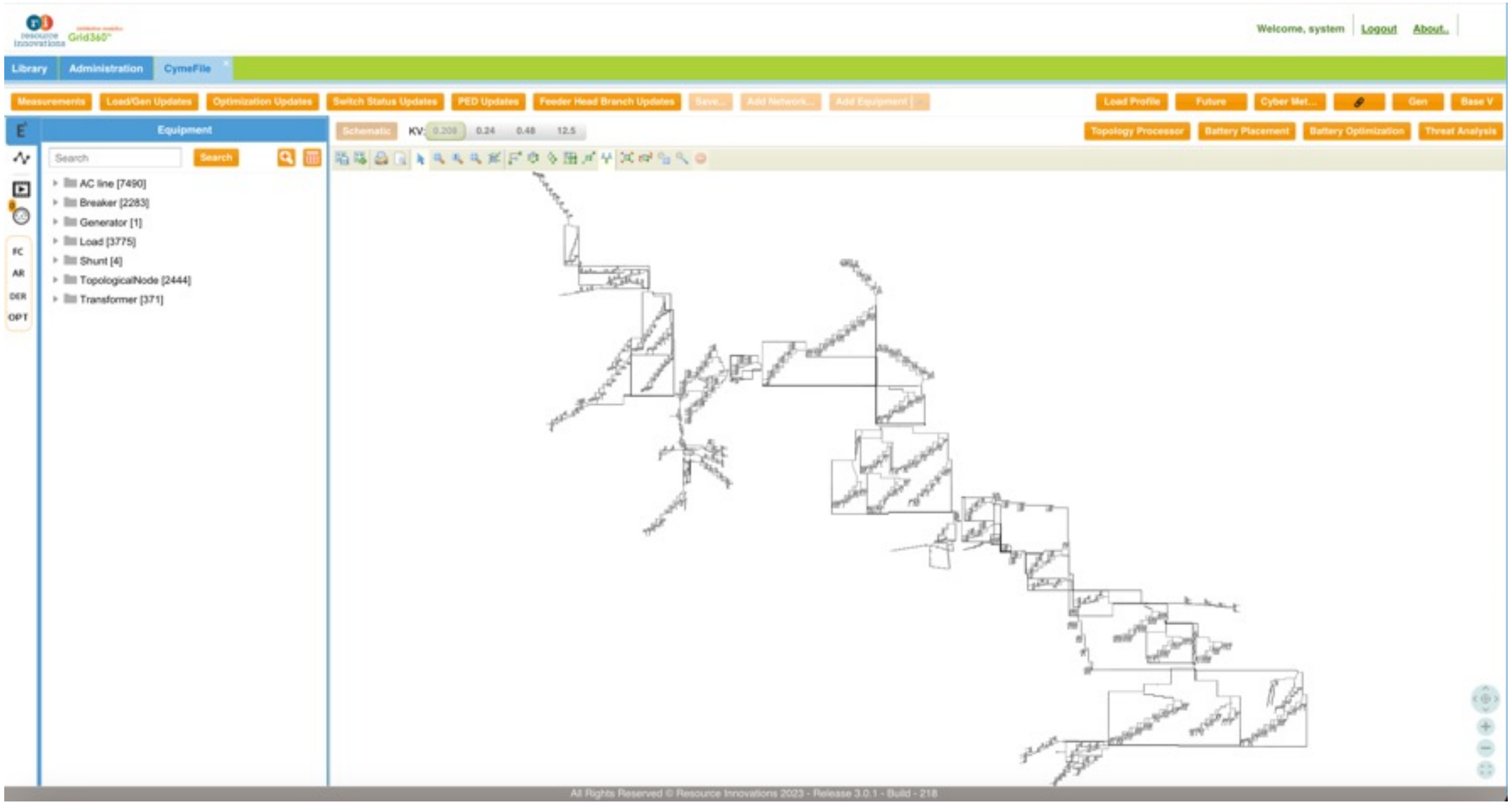




Testing at West Pennsylvania

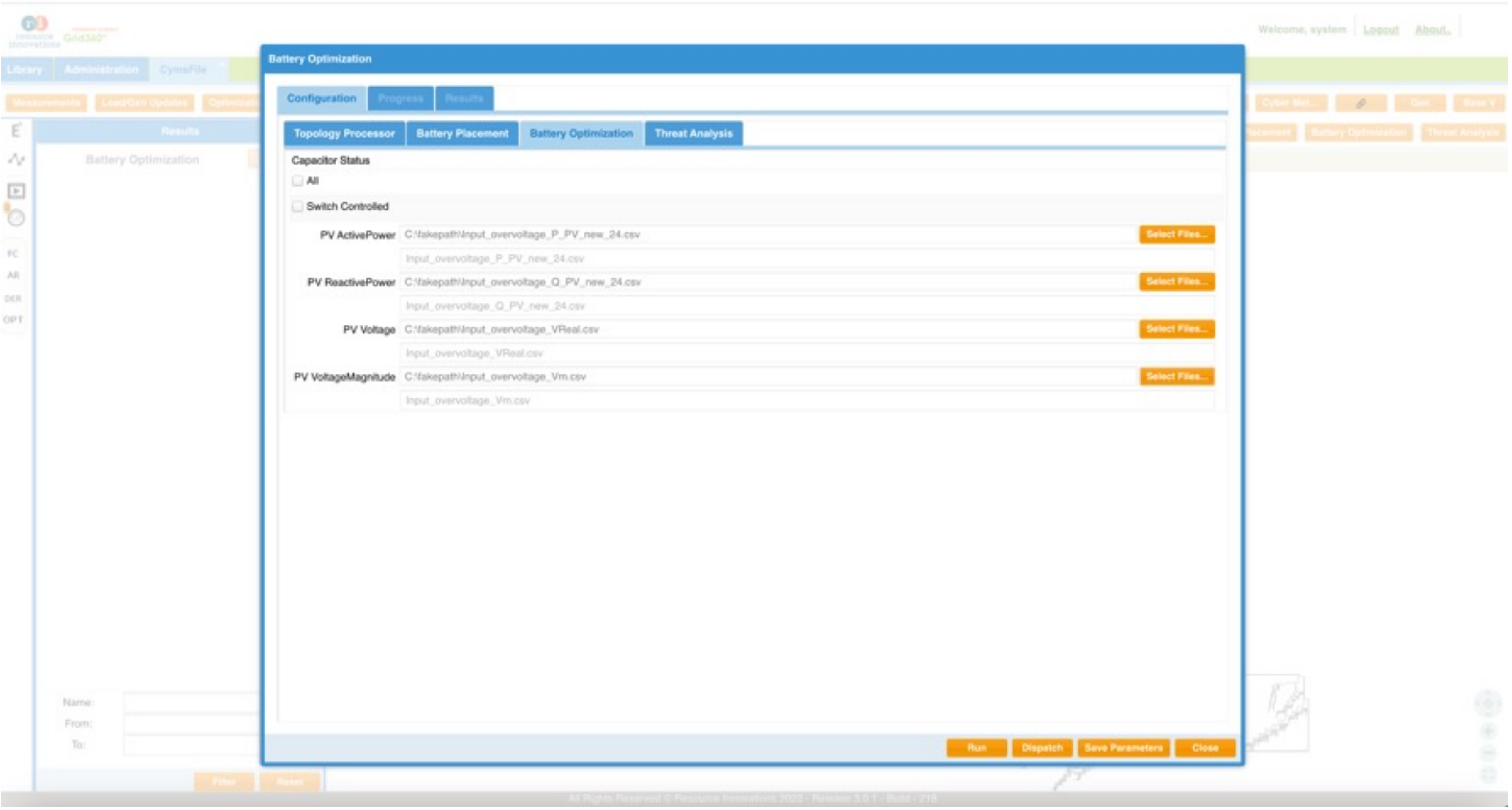


Commercialization Method



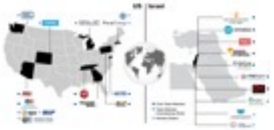
APS feeder data loaded into Grid360

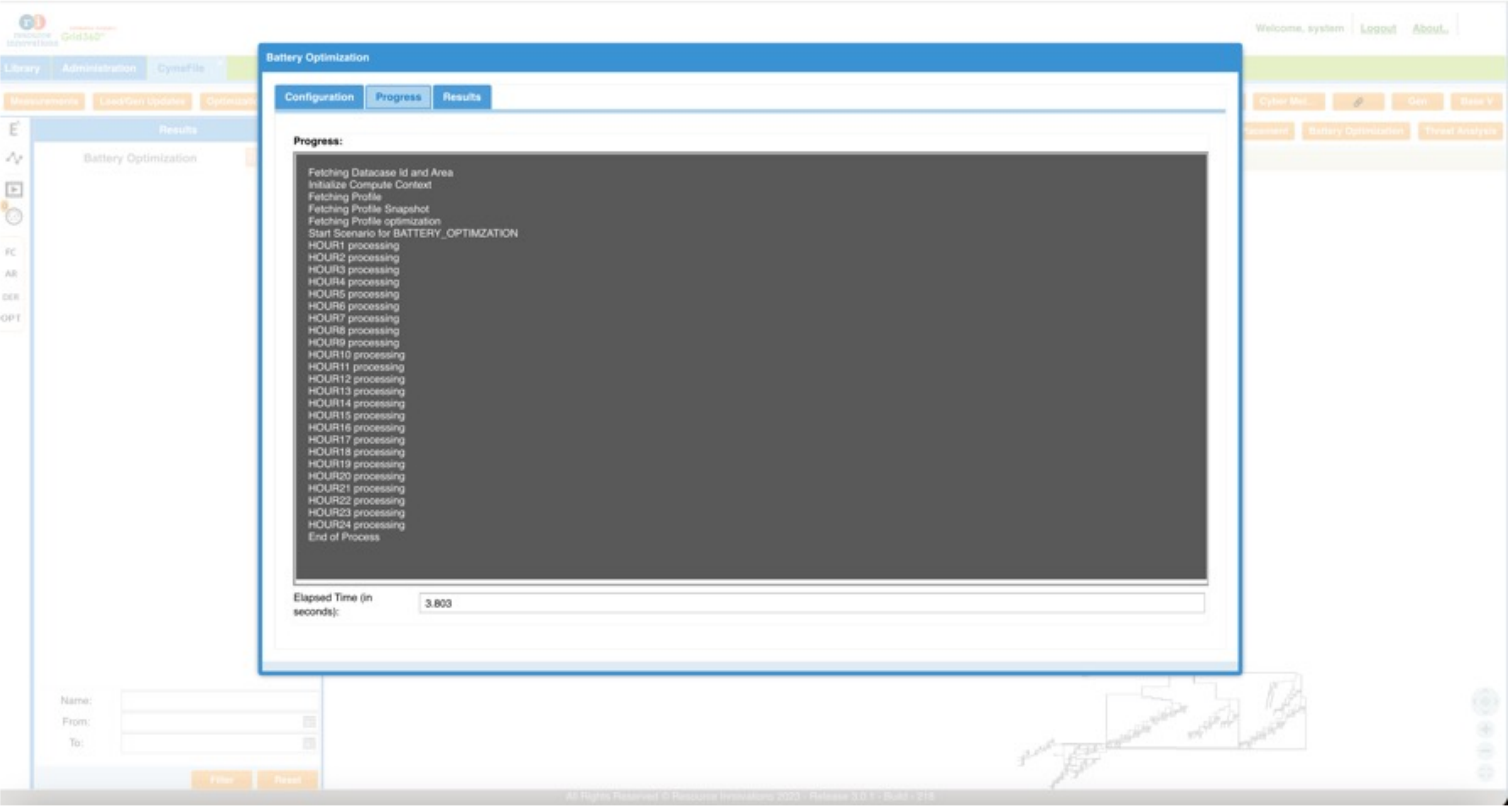
Commercialization Method



Battery Optimization input data loaded into Grid360

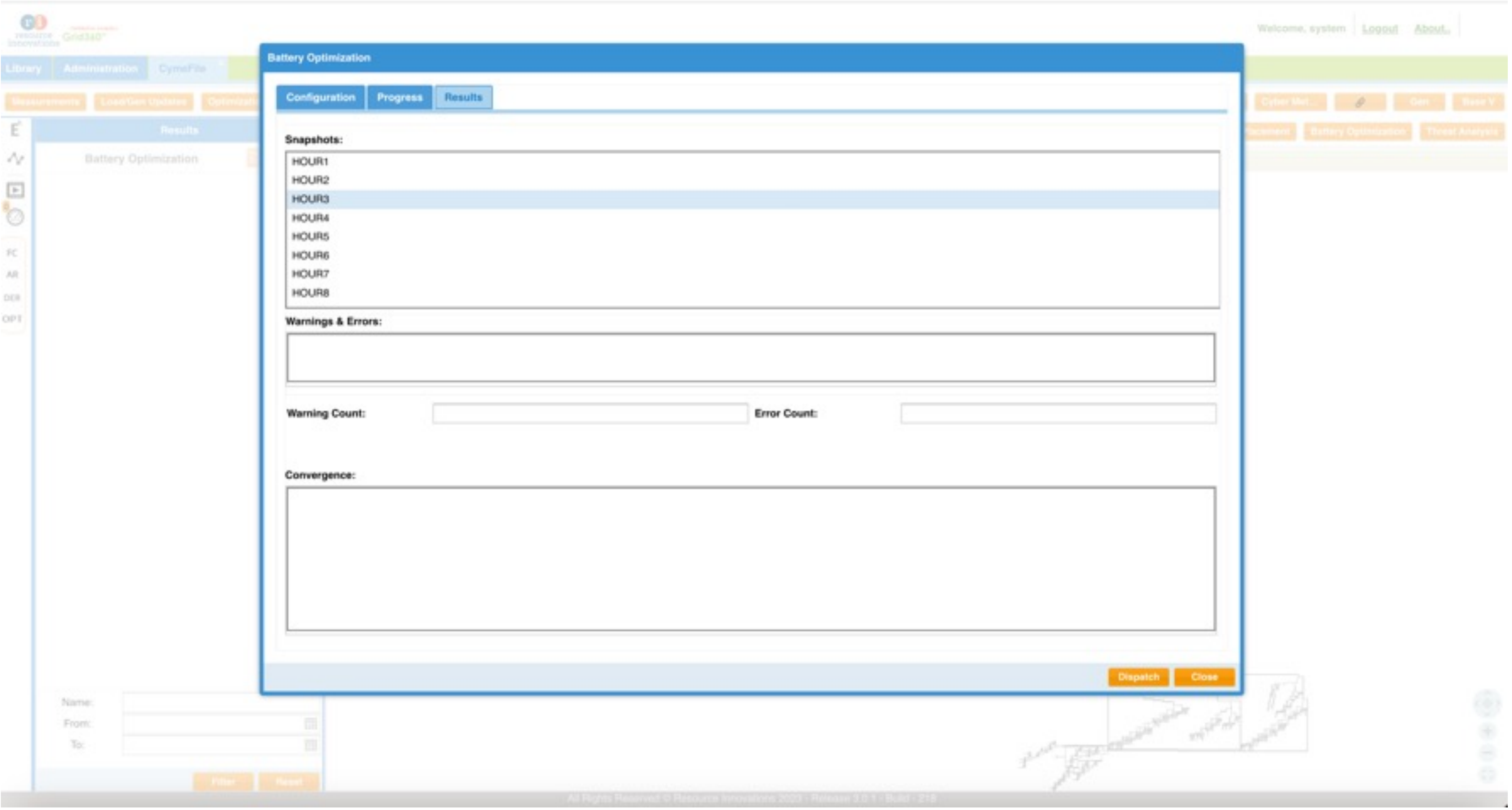
Commercialization Method





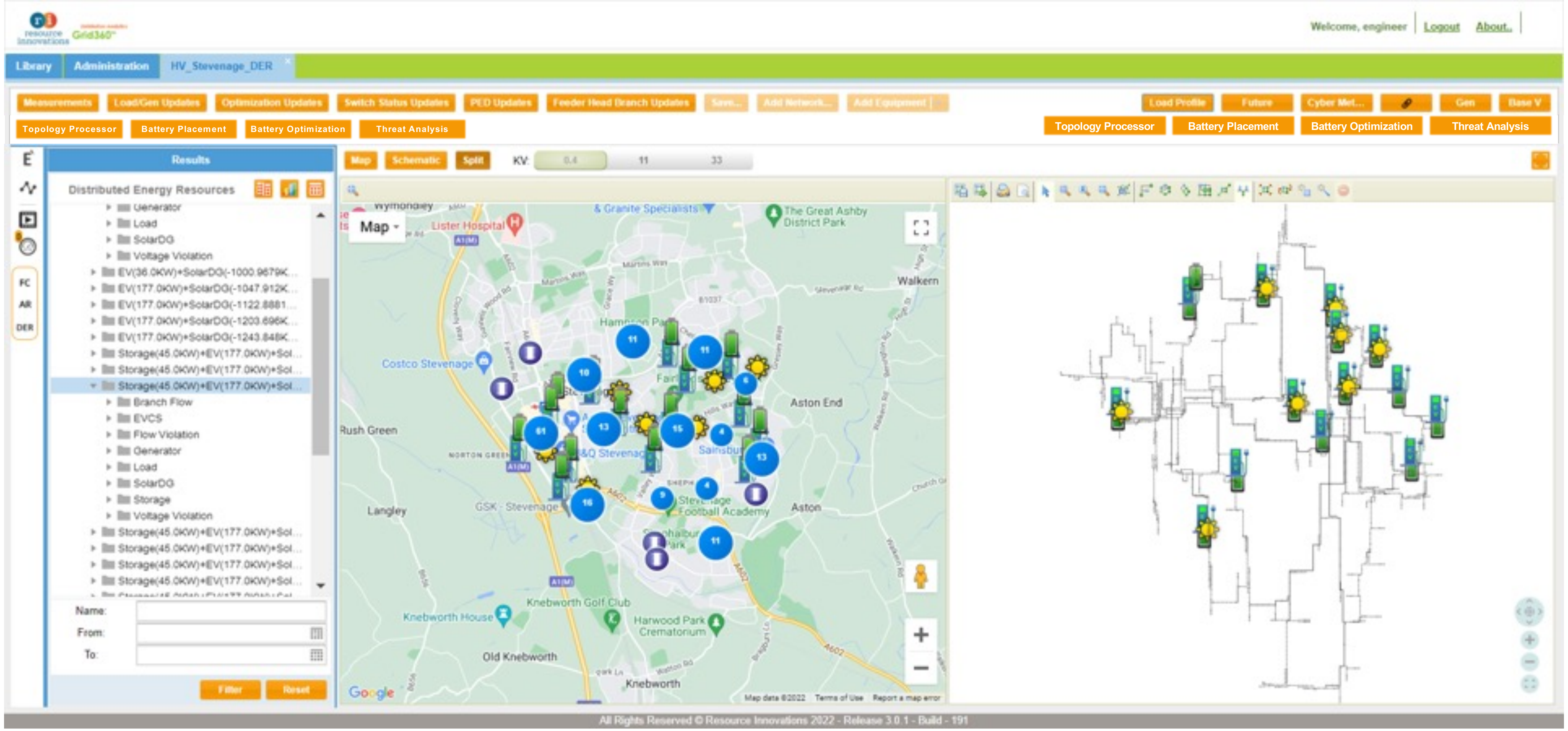
Battery Optimization code processing

Commercialization Method



Battery Optimization code hourly results

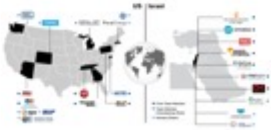
Commercialization Method



Next tasks:

1. Full visualization of results in map and schematic view
2. Use of Grid360 engines to calculate input data
3. Commercialization of Battery Placement code

Commercialization



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