

Task 1 Update: Realization of Advanced Energy Management Applications

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

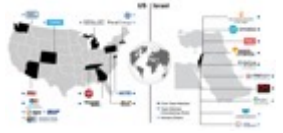


Yang Weng

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

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

Nathaniel Lee

WATCH LIVE

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 | @rebeleber | rebecca.leber@vox.com | Dec 27, 2022, 2:30pm EST

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 Halber

June 2, 2022

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

SPORT BUSINESS EVENTS ES MONEY CULTURE INSIDER THE ESCAPIST THE REVELLER

VIDEO ON ES LOG IN

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

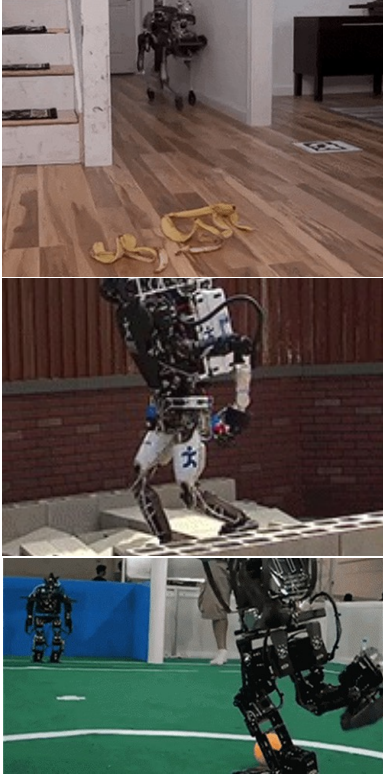


Critical Infrastructure?

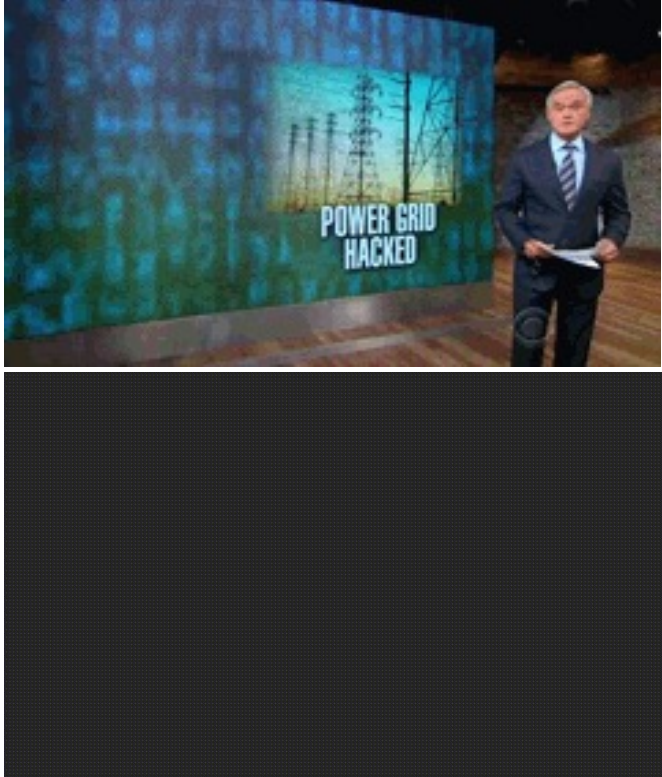
Not That Safe



Not That Robust

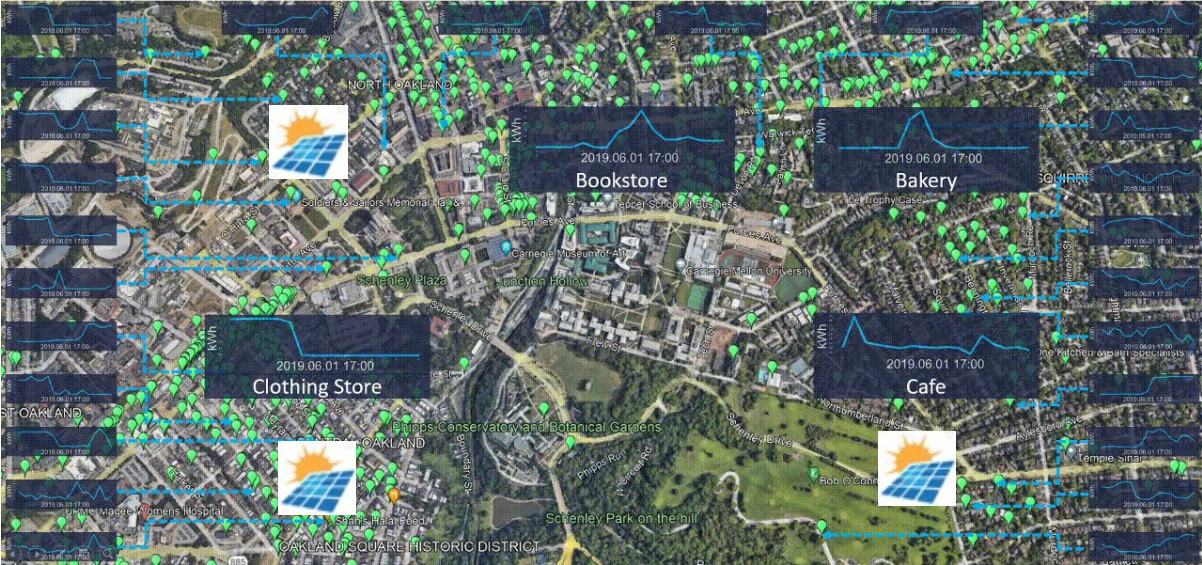


Can Cause Security Issues



Problem Setup: Learn the Power Flow Equation in Distribution Grids

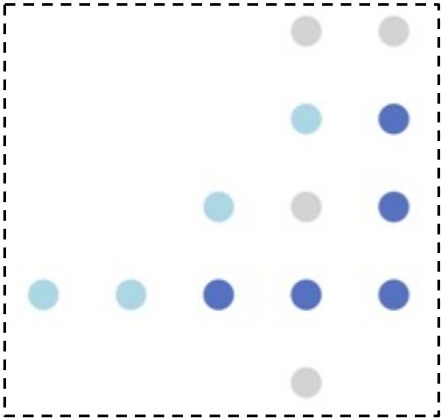
Why Today?



Pennsylvania Data

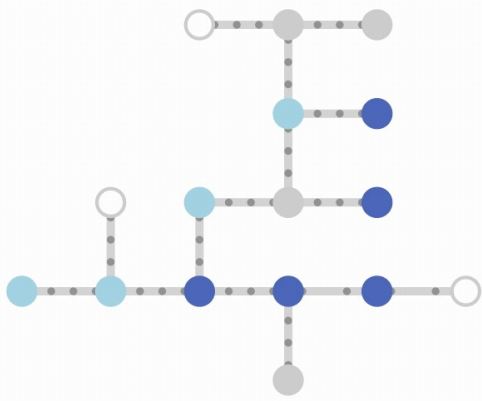


- Given: Sensor Data

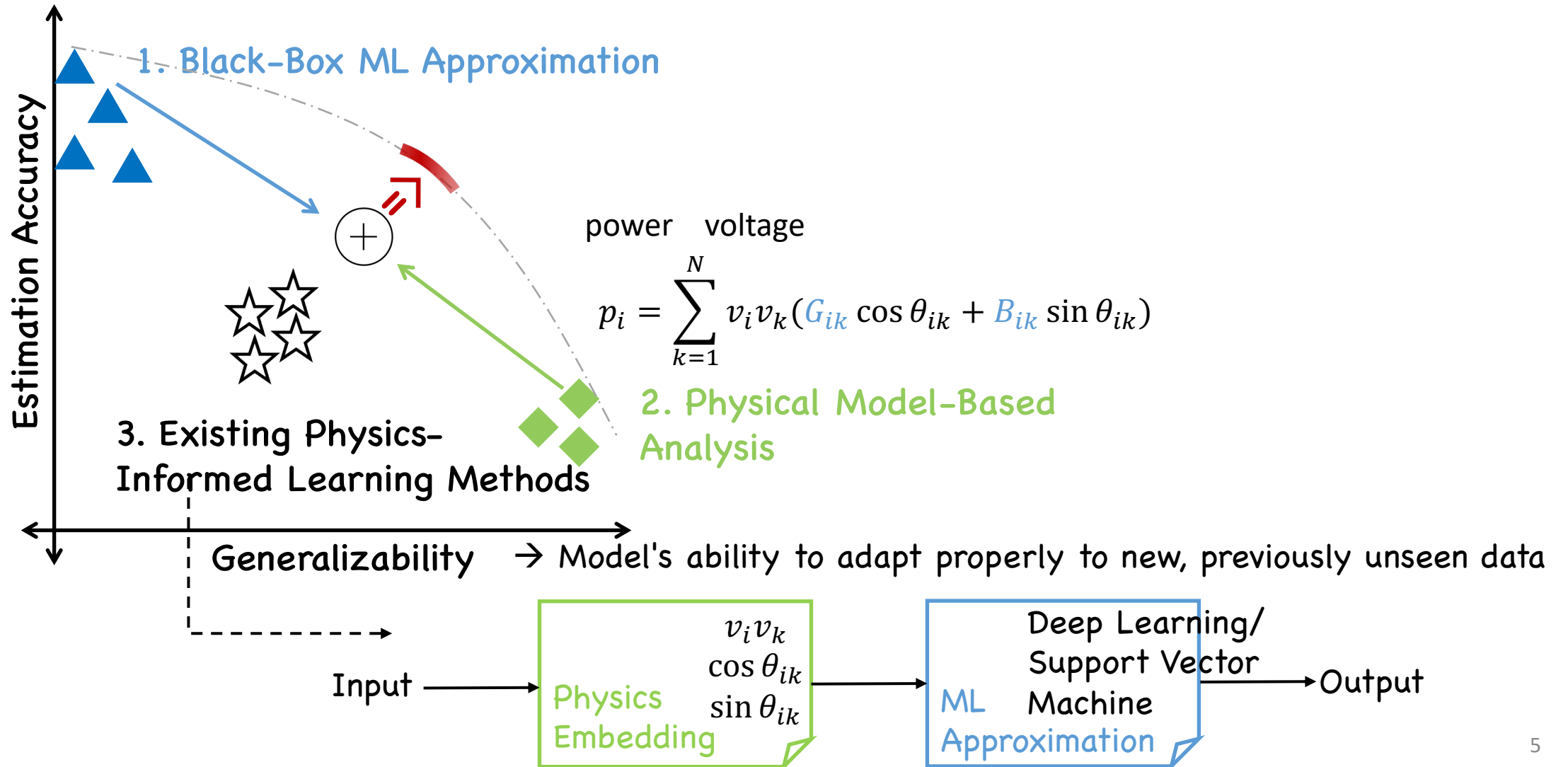
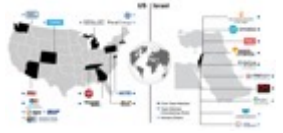


	voltage	power
	(v, p)	
● (dark blue)	✓	✓
● (light blue)	✓	X
● (grey)	X	✓
○ (white)	X	X

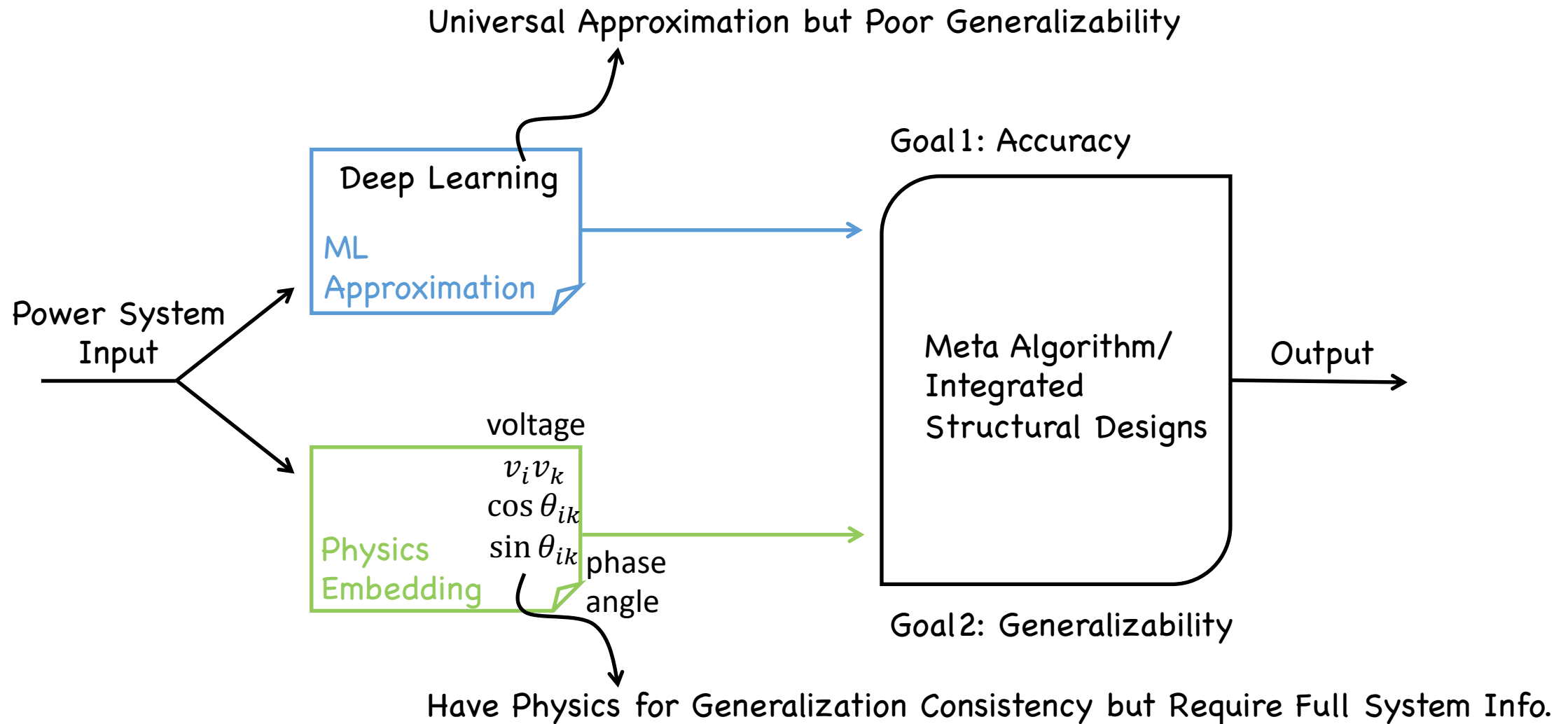
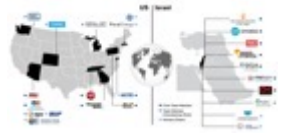
- Find: the Topology, Parameter, and Virtual Nodes for Power Flow Equation

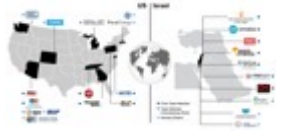


Past Methods



New Idea: Series to Parallel → Enable Flexibility





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

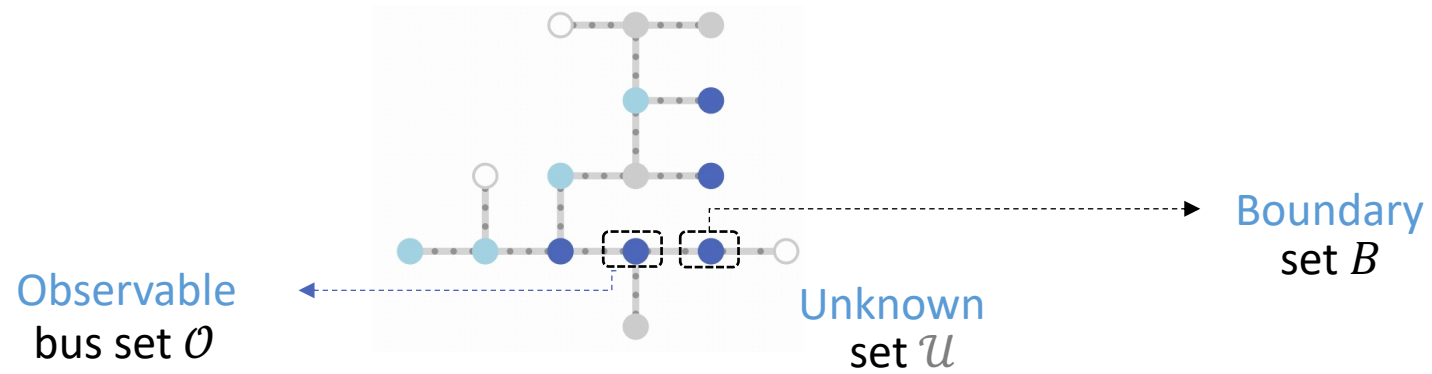
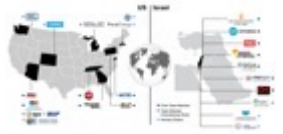
$$\mathbf{p} = \begin{pmatrix} p_i^{(1)} \\ \dots \\ p_i^{(T)} \end{pmatrix} = \begin{bmatrix} v_i^{(1)} v_1^{(1)} \cos \theta_{i1}^{(1)} & \dots & v_i^{(1)} v_N^{(1)} \cos \theta_{iN}^{(1)} & v_i^{(1)} v_1^{(1)} \sin \theta_{i1}^{(1)} & \dots & v_i^{(1)} v_N^{(1)} \sin \theta_{iN}^{(1)} \\ \dots & \dots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

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

$$\mathbf{p} = \phi \beta^*$$

$\mathbf{p} \in \mathbb{R}^T$: power injection at bus i up to time T , $V = (v_k^{(t)}) \in \mathbb{R}^{T \times N}$: 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



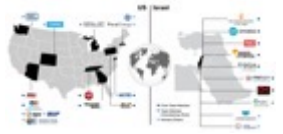
$$\mathbf{p} = \phi(\mathbf{V}, \Theta) \boldsymbol{\beta}^* = \underbrace{\begin{pmatrix} \phi(\mathbf{V}_O, \Theta_O) & \phi(\mathbf{V}_{OB}, \Theta_{OB}) \\ \phi(\mathbf{V}_{BU}, \Theta_{BU}) & \phi(\mathbf{V}_U, \Theta_U) \end{pmatrix}}_{\text{Unknown}} \begin{pmatrix} \boldsymbol{\beta}_{OO} \\ \boldsymbol{\beta}_{OB} \\ \boldsymbol{\beta}_{BU} \\ \boldsymbol{\beta}_{UU} \end{pmatrix}$$

(\mathbf{V}, Θ)

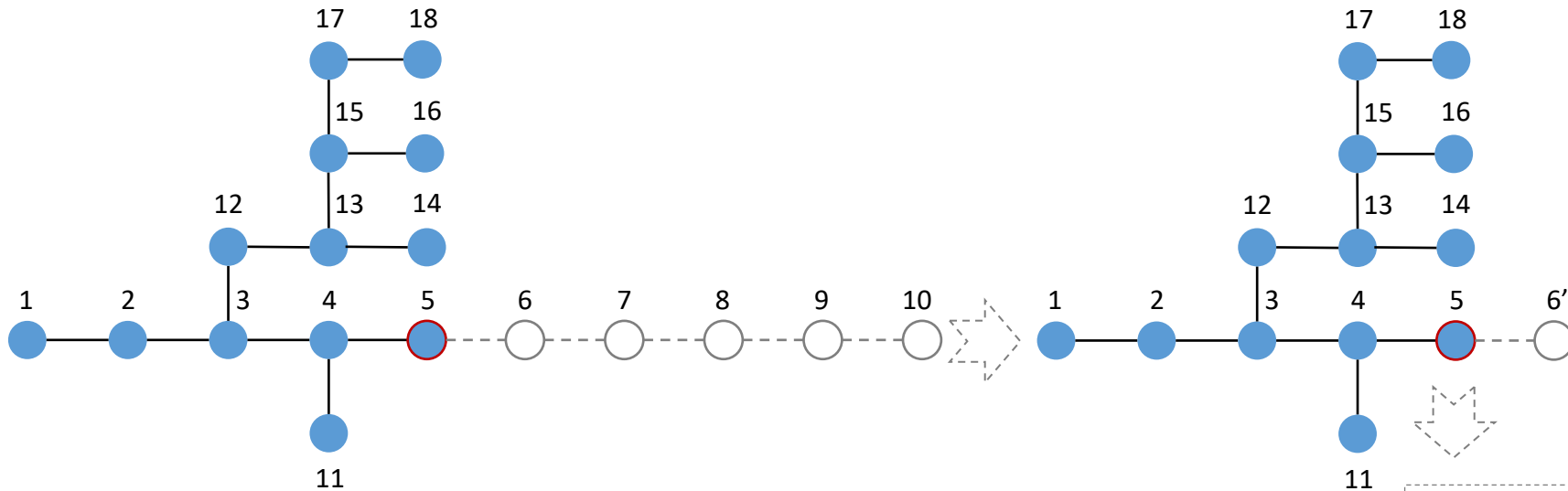
If Physically Learnable: $\mathbf{p} = \mathbf{h}_p(\phi(\mathbf{V}, \Theta))$ + $\mathbf{h}_v(\mathbf{V}, \Theta)$

Physical Contribution Borrow Use Blackbox Learning Methods

An Example: How Physics and Approximation Work Together?

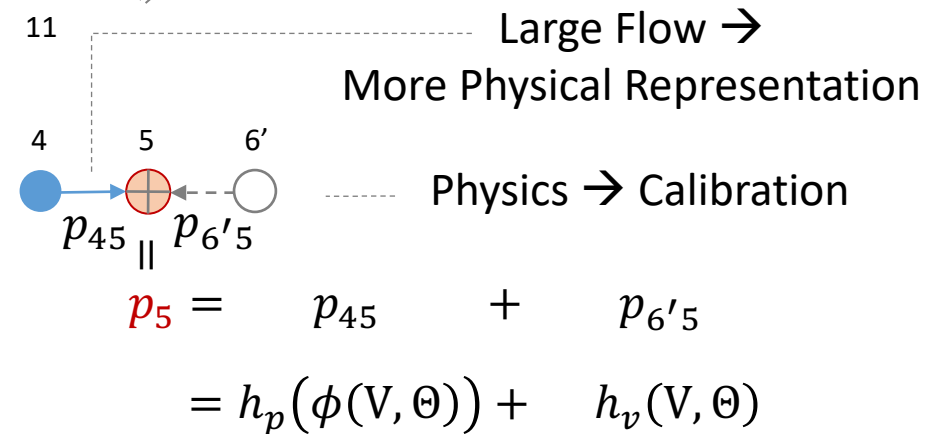


Target: Representation Learning for p_5

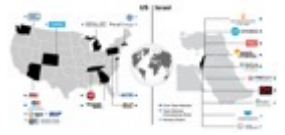


$$p_5 = \begin{pmatrix} v_5 v_4 \cos \theta_{54} \\ v_5 v_4 \sin \theta_{54} \\ v_5^2 \\ v_5 v_6 \cos \theta_{56} \\ v_5 v_6 \sin \theta_{56} \end{pmatrix}^T \begin{pmatrix} G_{54} \\ B_{54} \\ G_{55} \\ G_{56} \\ B_{56} \end{pmatrix} = \begin{pmatrix} v_5 v_4 \cos \theta_{54} \\ v_5 v_4 \sin \theta_{54}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

$h_v(V, \Theta)$



Learning Targets



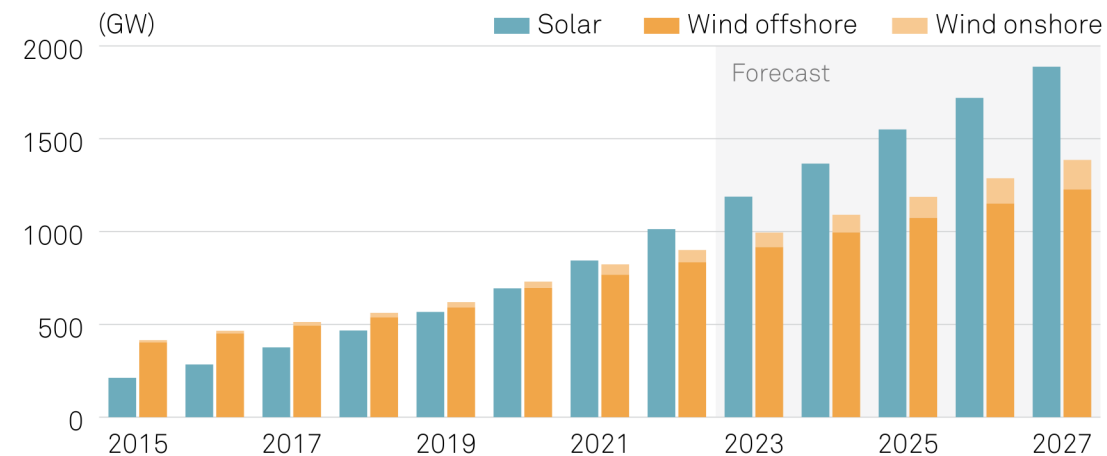
Minimize Error + Maximize Generalizability

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 \mathbf{p} . An approximator of power $f(\cdot)$ has an error as $\varepsilon_p = \frac{1}{T} \|\mathbf{p} - f(V, \Theta)\|_2$.

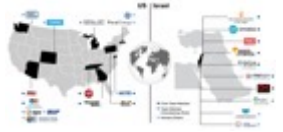
Definition 2. [Error of physical parameters] In a system with voltage data V, Θ and power data $\mathbf{p} = \phi(V, \Theta) \boldsymbol{\beta}^* \in \mathbb{R}^T$, an estimated physical parameter $\hat{\boldsymbol{\beta}}$ has an error $\varepsilon_\beta = \|\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^*\|_2$.

Generalizability, e.g.,
New Operating Point

Global installed solar, wind capacity (cumulative)



Twin Neural Network Model and the Objective



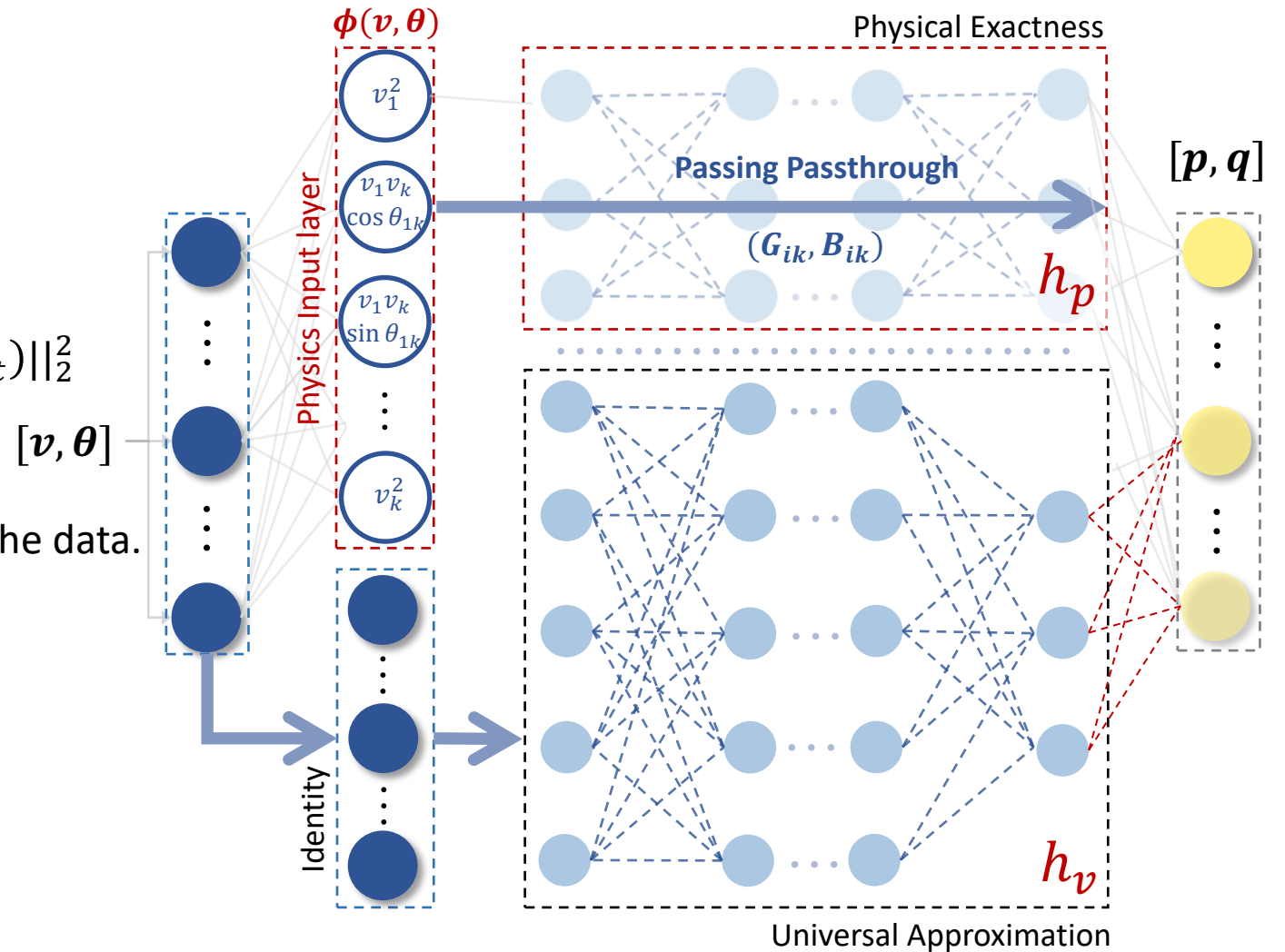
Optimization

$$\begin{aligned} & \min \varepsilon_p^2 \\ & = \min \frac{1}{T} \|\mathbf{p} - f(\mathbf{V}, \Theta)\|_2^2 \\ & = \min_{\beta, W_v} \frac{1}{T} \sum_{t=1}^T \|\mathbf{p}_t - h_p(\phi(\mathbf{v}_t, \boldsymbol{\theta}_t)) - h_v(\mathbf{v}_t, \boldsymbol{\theta}_t)\|_2^2 \end{aligned}$$

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

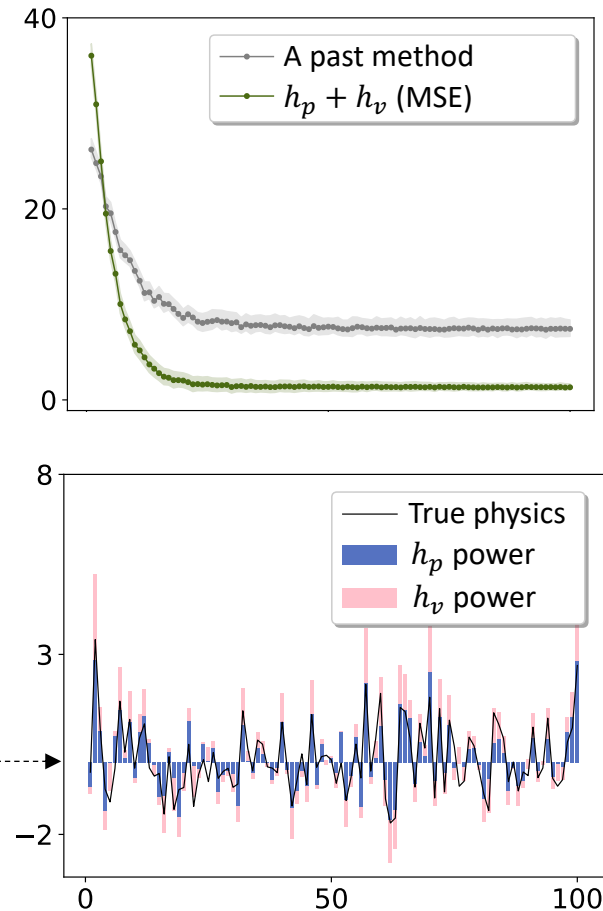
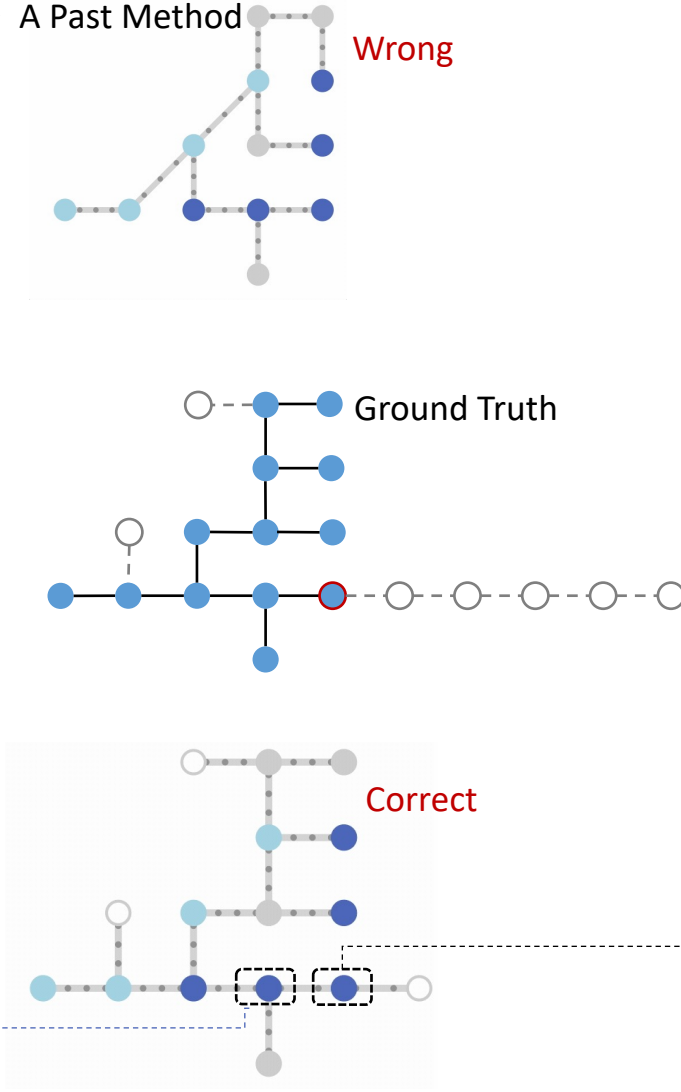
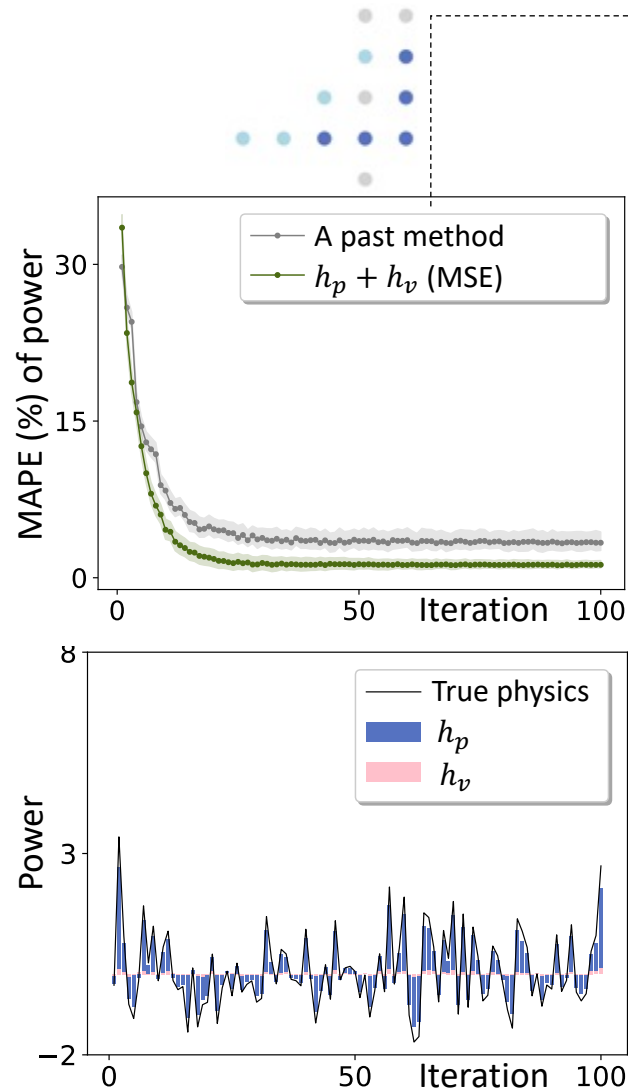
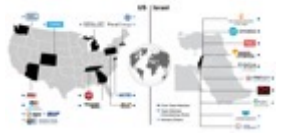
In the Rest of the Slides

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

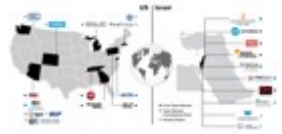


β : parameters of $h_p(\cdot)$, a linear layer. W_v : parameters of $h_v(\cdot)$, a deep neural network.

Numerical Result: Proposed Collaboration is Better

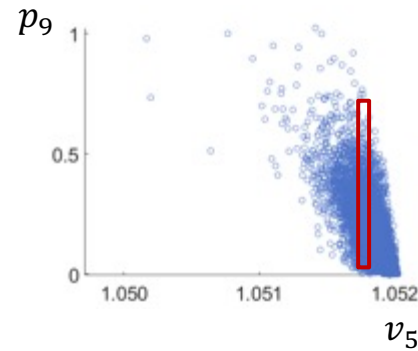
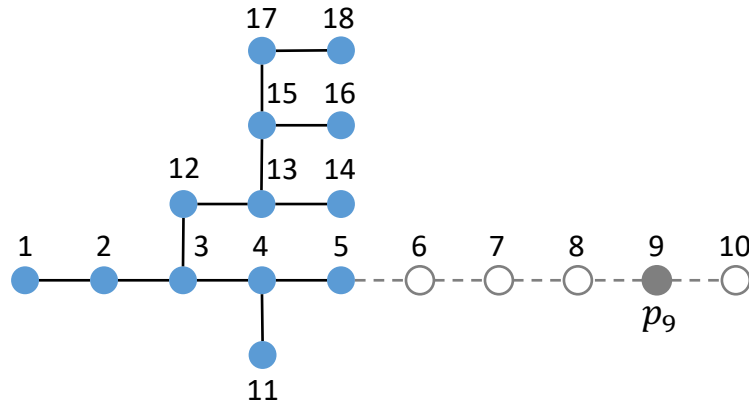


When Will the Method Have Bigger Errors?

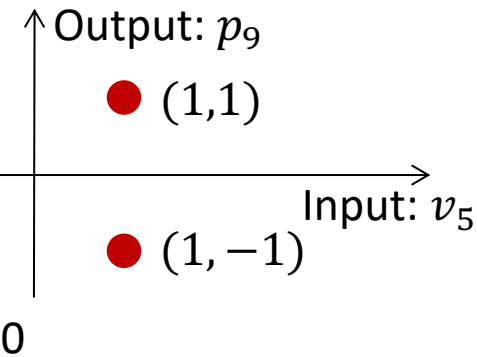


Assumption on universal approximation for h_v :

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



Ambiguity: Same Input \rightarrow Multiple Outputs

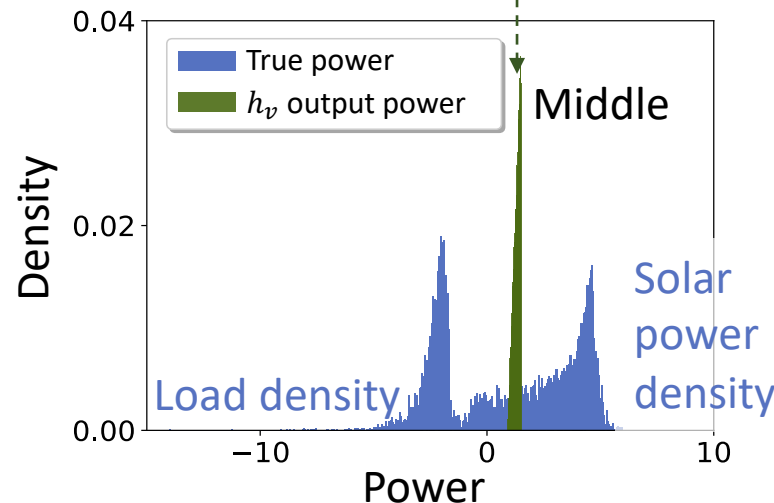


Correct Output: **1, -1**

Learning:

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

Incorrect Output: 0

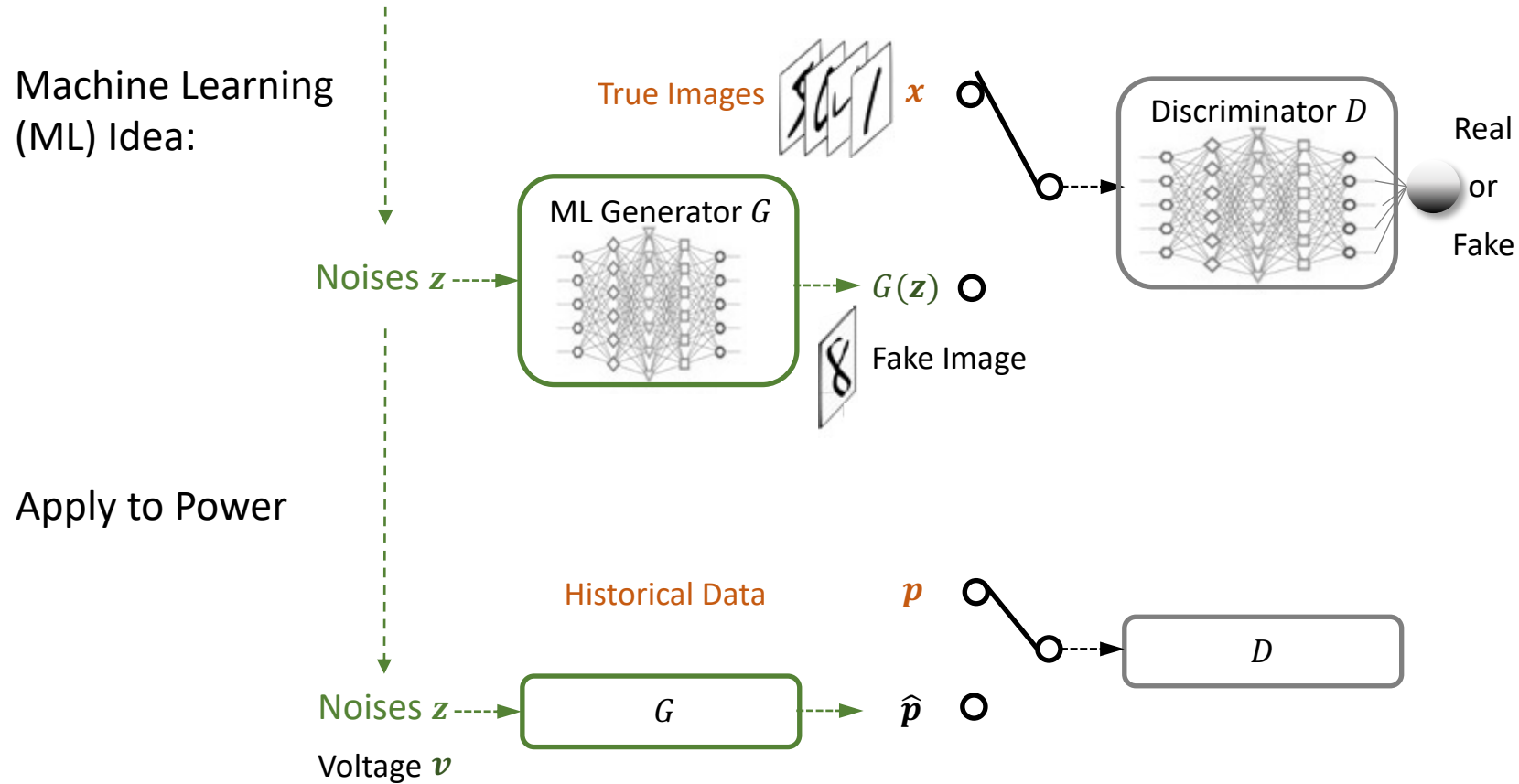


Ideas:

1. Keep the Uncertainty
2. Make a Choice Later

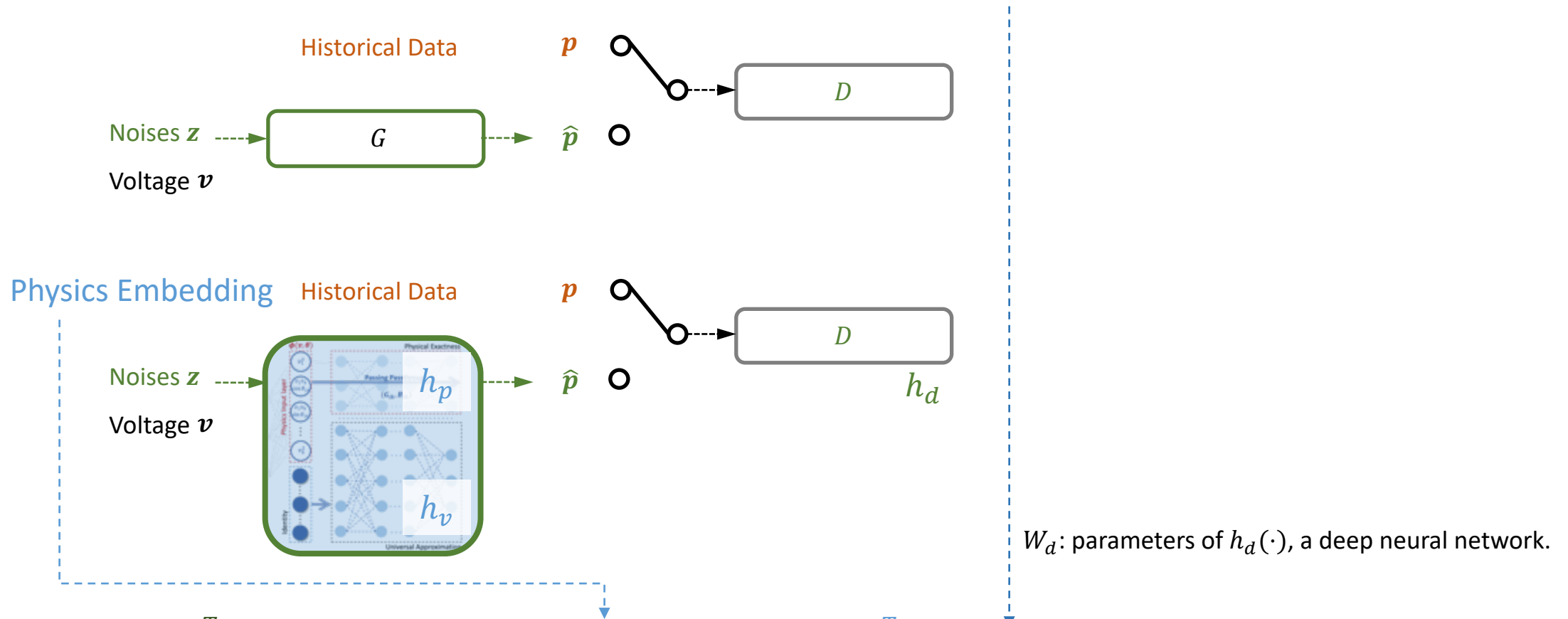
Model Design: Generative Adversarial Network with MSE Regularization

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



Robustness: Generative Adversarial Network with MSE Regularization

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

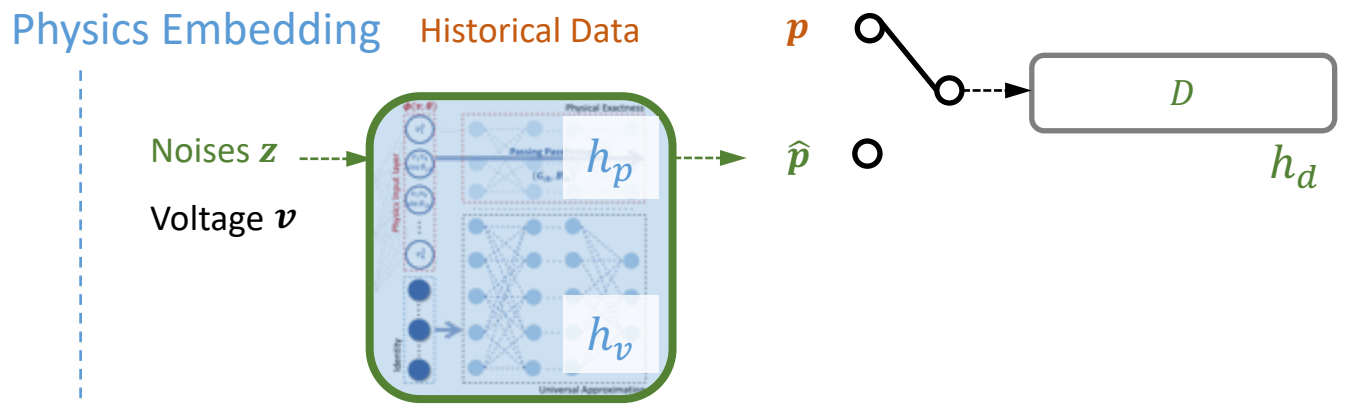
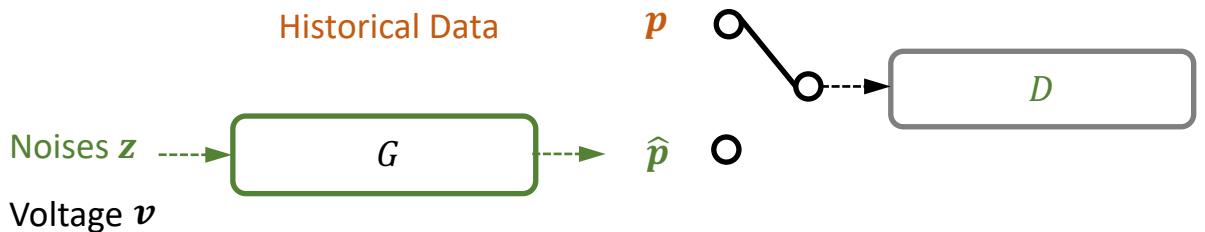


W_d : parameters of $h_d(\cdot)$, a deep neural network.

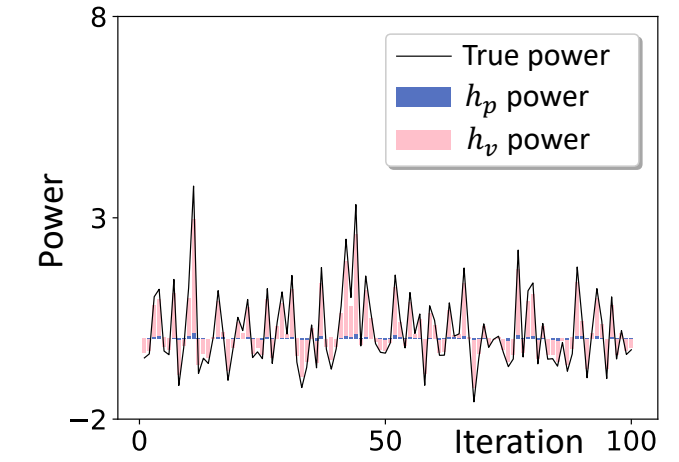
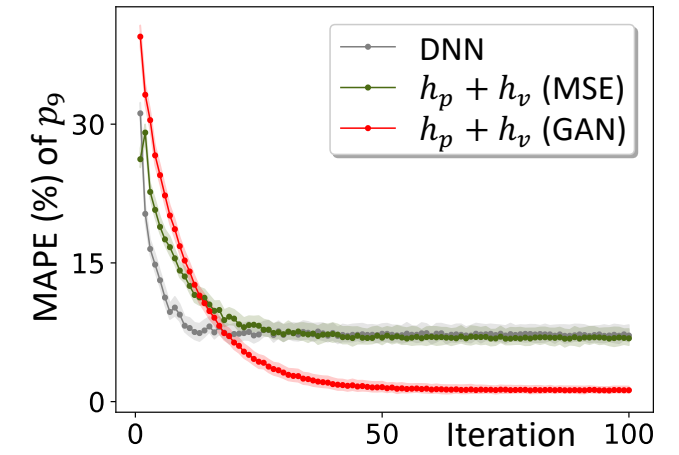
$$\min_{\beta, W_v} \max_{W_d} \frac{1}{T} \sum_t h_d(\mathbf{p}_t) - h_d(h_p(\phi(\mathbf{v}_t)) + h_v(\mathbf{v}_t, \mathbf{z}_t)) + \lambda \frac{1}{T} \sum_t (\mathbf{p}_t - h_p(\phi(\mathbf{v}_t)) - h_v(\mathbf{v}_t, \mathbf{z}_t))^2$$

Robustness: Generative Adversarial Network with MSE Regularization

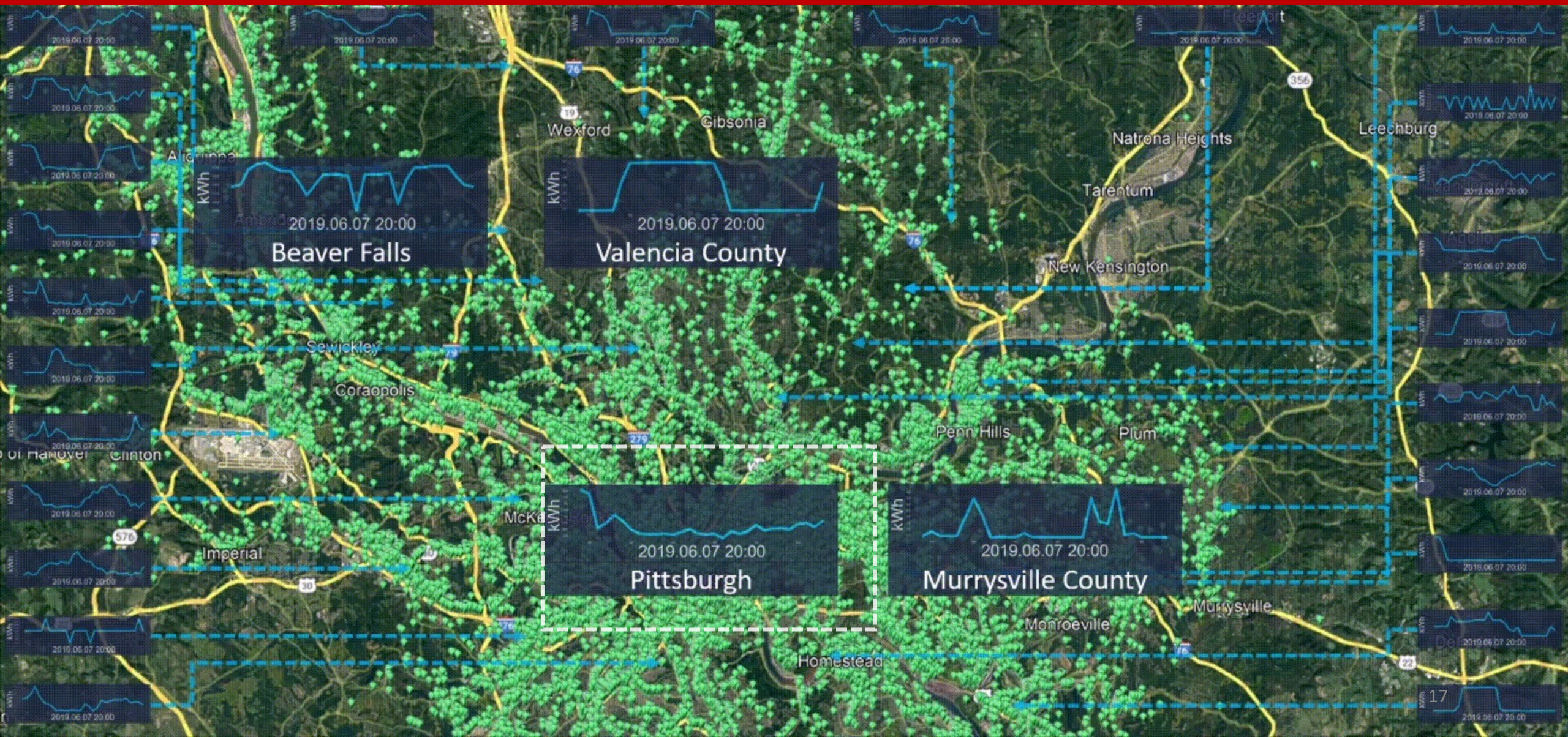
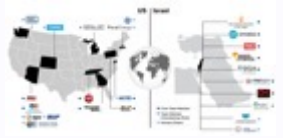
Goal: keep the **uncertainty** according to the **distribution** and **make a choice later**.



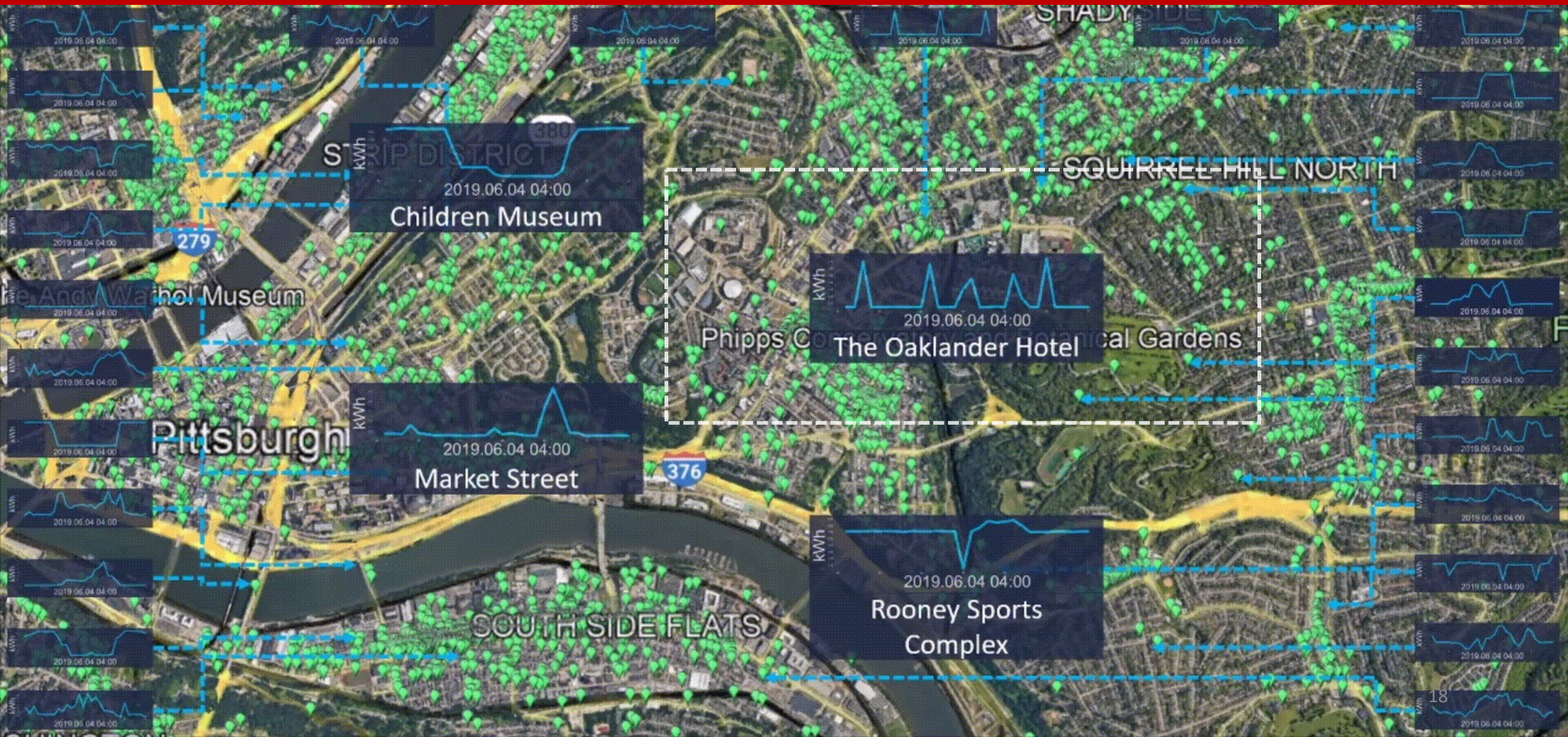
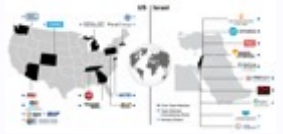
$$\min_{\beta, W_v} \max_{W_d} \frac{1}{T} \sum_t h_d(\mathbf{p}_t) - h_d(h_p(\phi(\mathbf{v}_t)) + h_v(\mathbf{v}_t, \mathbf{z}_t)) + \frac{\lambda}{T} \sum_t (\mathbf{p}_t - h_p(\phi(\mathbf{v}_t)) - h_v(\mathbf{v}_t, \mathbf{z}_t))^2$$



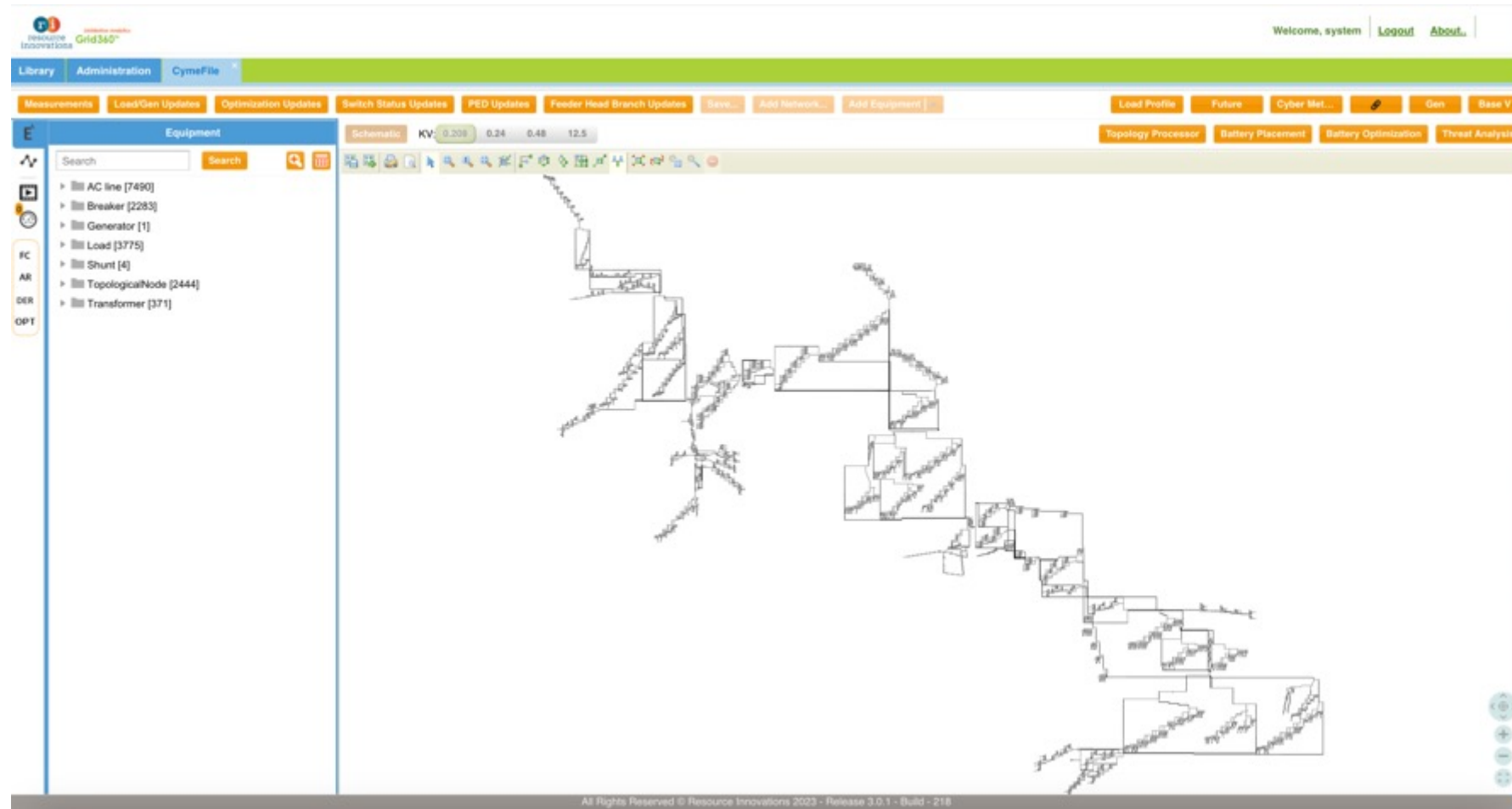
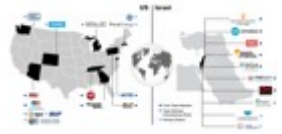
Testing at West Pennsylvania



Testing at West Pennsylvania

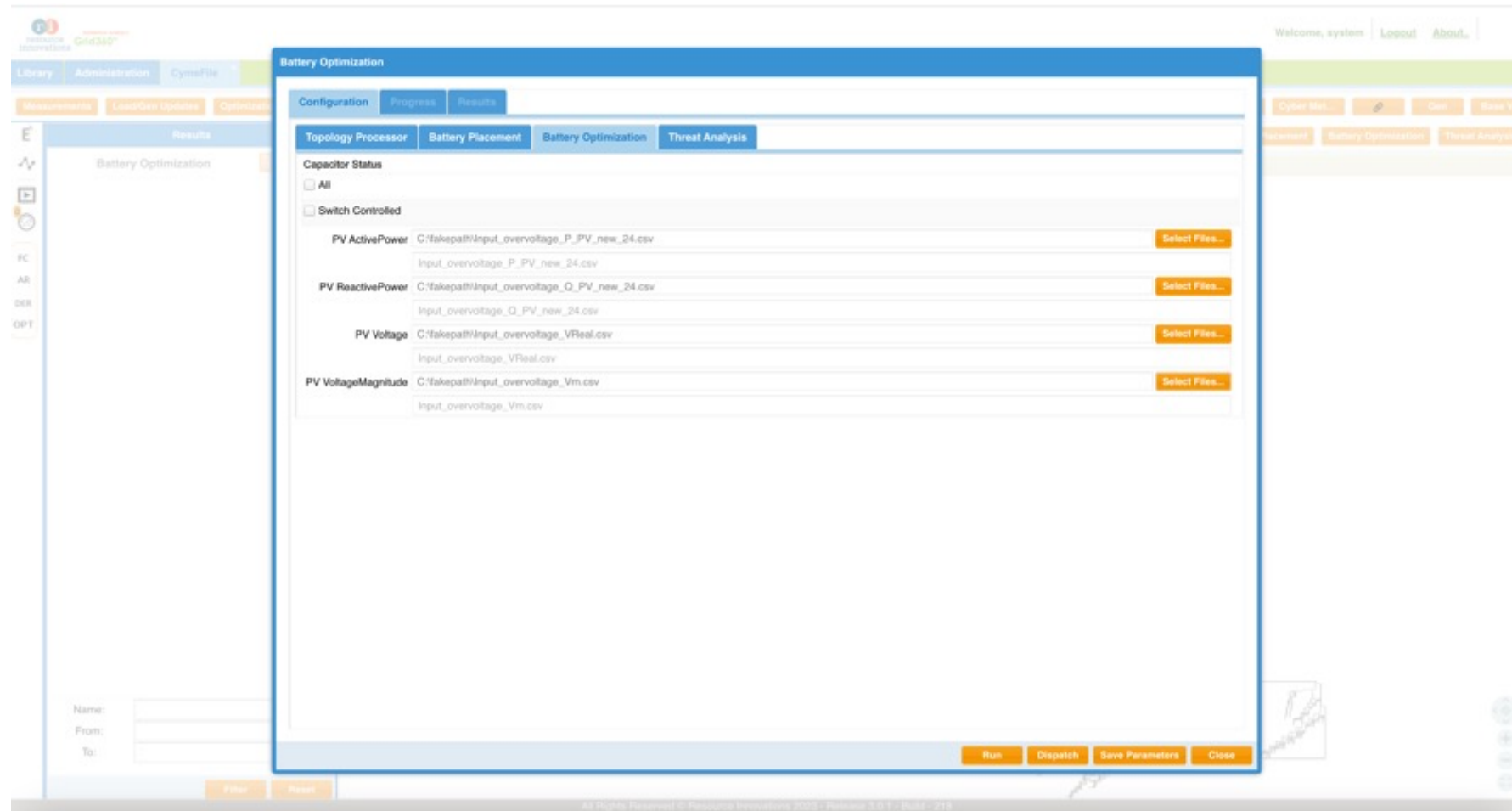
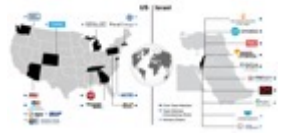


Commercialization Method



APS feeder data loaded into Grid360

Commercialization Method



Grid360
Welcome, system | Logout | About

Library Administration CymFile

Measurements Load/Gen Updates Optimization

Results

Battery Optimization

Configuration Progress Results

Topology Processor Battery Placement Battery Optimization Threat Analysis

Capacitor Status

All

Switch Controlled

PV ActivePower C:\fakepath\input_overnoltage_P_PV_new_24.csv Select Files...

Input_overnoltage_P_PV_new_24.csv

PV ReactivePower C:\fakepath\input_overnoltage_Q_PV_new_24.csv Select Files...

Input_overnoltage_Q_PV_new_24.csv

PV Voltage C:\fakepath\input_overnoltage_VReal.csv Select Files...

Input_overnoltage_VReal.csv

PV VoltageMagnitude C:\fakepath\input_overnoltage_Vm.csv Select Files...

Input_overnoltage_Vm.csv

Run Dispatch Save Parameters Close

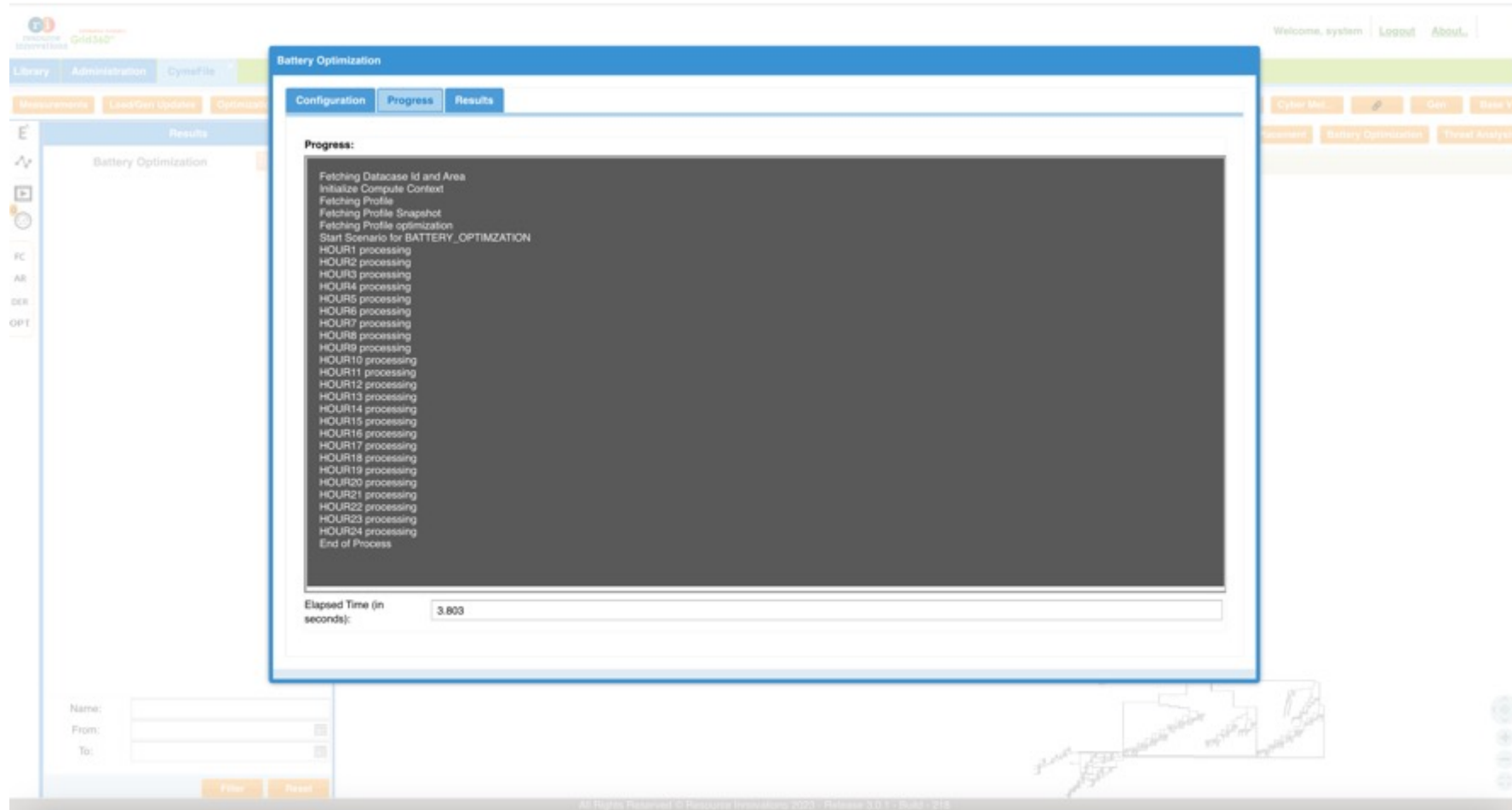
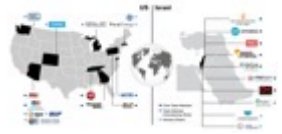
Name: From: To:

Filter Reset

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Battery Optimization input data loaded into Grid360

Commercialization Method



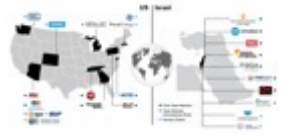
The screenshot displays a web application interface for 'Battery Optimization'. The main window is titled 'Battery Optimization' and has three tabs: 'Configuration', 'Progress', and 'Results'. The 'Progress' tab is active, showing a list of tasks and their status. The tasks are:

- Fetching Database Id and Area
- Initialize Compute Context
- Fetching Profile
- Fetching Profile Snapshot
- Fetching Profile optimization
- Start Scenario for BATTERY_OPTIMIZATION
- HOUR1 processing
- HOUR2 processing
- HOUR3 processing
- HOUR4 processing
- HOUR5 processing
- HOUR6 processing
- HOUR7 processing
- HOUR8 processing
- HOUR9 processing
- HOUR10 processing
- HOUR11 processing
- HOUR12 processing
- HOUR13 processing
- HOUR14 processing
- HOUR15 processing
- HOUR16 processing
- HOUR17 processing
- HOUR18 processing
- HOUR19 processing
- HOUR20 processing
- HOUR21 processing
- HOUR22 processing
- HOUR23 processing
- HOUR24 processing
- End of Process

Below the list, the 'Elapsed Time (in seconds):' is displayed as 3.603. The interface also includes a sidebar with navigation options like 'Library', 'Administration', and 'Cycles/Files', and a top navigation bar with 'Welcome, system', 'Logout', and 'About...'.

Battery Optimization code processing

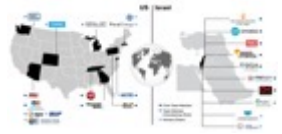
Commercialization Method



A screenshot of a web application interface. The main window is titled "Battery Optimization" and has three tabs: "Configuration", "Progress", and "Results". The "Results" tab is active. Under "Snapshots:", there is a list of hours from HOUR1 to HOUR8, with HOUR3 highlighted. Below this is a section for "Warnings & Errors:" with an empty text box. Further down are two input fields for "Warning Count:" and "Error Count:". At the bottom of the window are "Dispatch" and "Close" buttons. The background shows a sidebar with navigation options like "Library", "Administration", and "Cymd File", and a top navigation bar with "Welcome, system", "Logout", and "About...".

Battery Optimization code hourly results

Commercialization Method

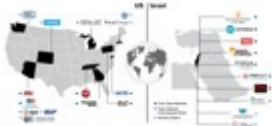


The screenshot displays the Grid360 software interface. At the top, there is a navigation bar with 'Library' and 'Administration' tabs, and a user profile 'Welcome, engineer' with 'Logout' and 'About...' links. Below this is a menu of functional buttons: 'Measurements', 'Load/Gen Updates', 'Optimization Updates', 'Switch Status Updates', 'PED Updates', 'Feeder Head Branch Updates', 'Save...', 'Add Network...', and 'Add Equipment...'. A secondary row of buttons includes 'Topology Processor', 'Battery Placement', 'Battery Optimization', and 'Threat Analysis'. On the right side, there are buttons for 'Load Profile', 'Future', 'Cyber Met...', 'Gen', and 'Base V'. The main interface is divided into three sections: a left sidebar with a 'Results' panel listing various energy resources like 'Generator', 'Load', 'SolarDG', 'EV', and 'Storage'; a central map view showing a geographical area with a network of nodes and lines overlaid; and a right-hand schematic view showing a detailed network topology. The map view includes labels for locations like 'Lister Hospital', 'The Great Ashby District Park', 'Astons End', and 'Knebworth'. The schematic view shows a complex network of nodes and connecting lines. At the bottom of the interface, there is a footer with the text 'All Rights Reserved © Resource Innovations 2022 - Release 3.0.1 - Build - 191'.

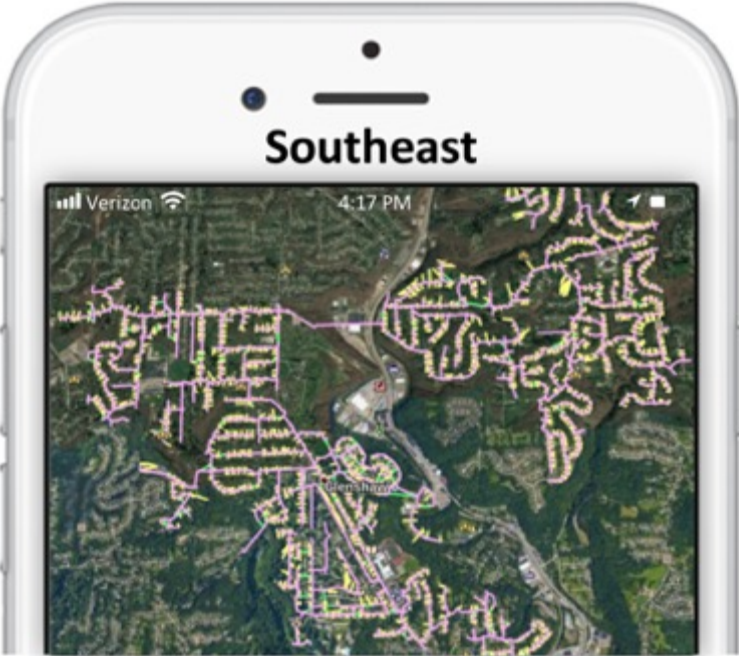
Next tasks:

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



resource innovations
Reimagining tomorrow with *Nexant* today



Smart Meter kWh
kWh
2019.06.01 01:00