# Pattanun Chanpiwat

## September 12, 2022

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# Agenda

- Self-Introduction
- Previous Experience
  - Teaching Experience
  - (Selected) Research Projects
- Projects at Aalto University

# Self-Introduction

# Education and Background

**Educations:**

- Ph.D. Candidate in Mechanical Engineering, University of Maryland, College Park, Maryland, USA, 2017-Present
- M.S. in Mechanical Engineering, University of Maryland, College Park, Maryland, USA, 2021
- M.S. in Civil Engineering, Virginia Tech, Blacksburg, Virginia, USA, 2014
- B.S. in Civil Engineering, Virginia Military Institute (VMI), Lexington, Virginia, USA, 2012

**Professional Licenses / Career:**

- Engineer-in-Training (E.I.T.) License, State of Virginia, USA, 2012-Present
- Associate Engineer License, Kingdom of Thailand, 2015-Present

# Previous Experience

# Teaching Experience
## Via Teaching Assistantship

**Graduate Courses:**

- ENME 610: Engineering Optimization
- ENME 741: Operations Research Models in Engineering
- ENME 809E Probability-Based Design (graduate)

**Undergraduate Courses:**

- ENES 102: Mechanics I
- ENES 220: Mechanics II
- ENME 392: Statistical Methods for Product and Processes Development
- CEE 4014: Estimating, Production and Cost Engineering

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

**Objectives:**

- Develop means to analyze and cluster residential households into homogeneous groups based on the electricity load
- Require a metric to determine the financial benefits of homogeneous groups of customers and Aim to enter each customer into as few DR events as possible to reduce their discomfort.

**Methodologies:**

- Dynamic program schedules DR events for a customer cluster throughout the day [3]
- Cluster Analysis (partitioning around medoids (PAM), i.e., k-medoids)
  - First, it allows REPs more profitable control of existing customers.
  - Second, it permits a more informed selection of which customers to enroll in DR programs.

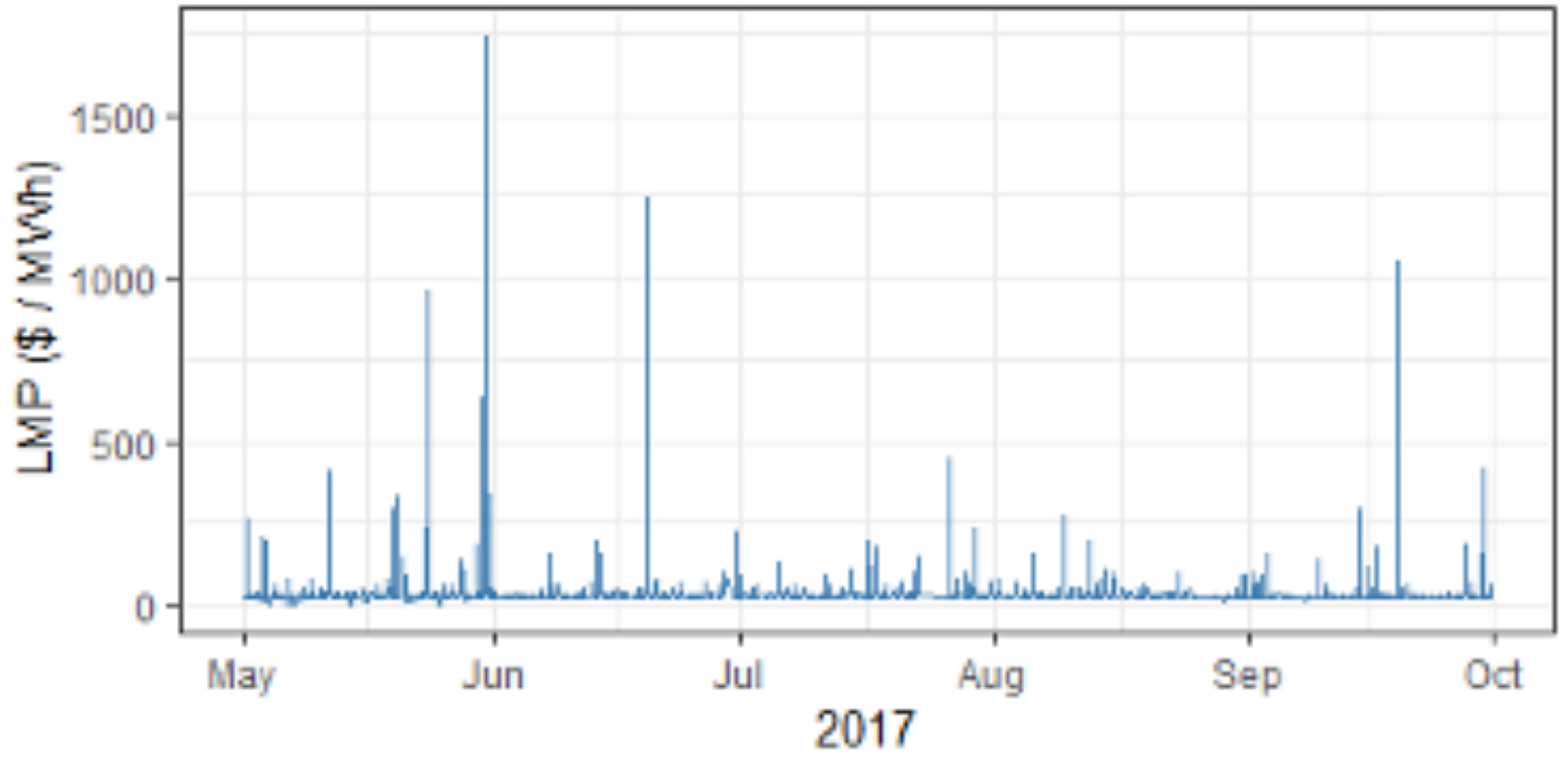


Fig: Hourly LMPs of Texas between May 1 - Sep. 30, 2017 from the Electric Reliability Council of Texas (ERCOT) [2]

Table: Household Electricity Load and LMPs Data [2]

| # | Date & Time | LMP ($/MWh) | Electricity Load (kWh) #1 | #2 | ... | #10000 |
|---|---|---|---|---|---|---|
| 1 | 05/01/17 00:00 | 20.87 | 0.35 | 0.62 | ... | 1.15 |
| 2 | 05/01/17 01:00 | 18.73 | 0.34 | 0.51 | ... | 0.62 |
| 3 | 05/01/17 02:00 | 17.85 | 0.35 | 0.36 | ... | 0.41 |
| ... | ... | ... | ... | ... | ... | ... |
| 3552 | 09/30/17 23:00 | 1.72 | 1.19 | 1.15 | ... | 0.83 |

**Related Publications**

[2] P. Chanpiwat, S. A. Gabriel, R. L. Moglen, and M. Siemann, "Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes," ASME Journal of Engineering for Sustainable Buildings and Cities, vol. 1, no. 1, Feb., 2020.

[3] R. L. Moglen, P. Chanpiwat, S. A. Gabriel, and Blohm A., "Optimal Thermostatically-Controlled Residential Demand Response for Retail Electric Providers," Energy Systems, Aug., 2020.

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

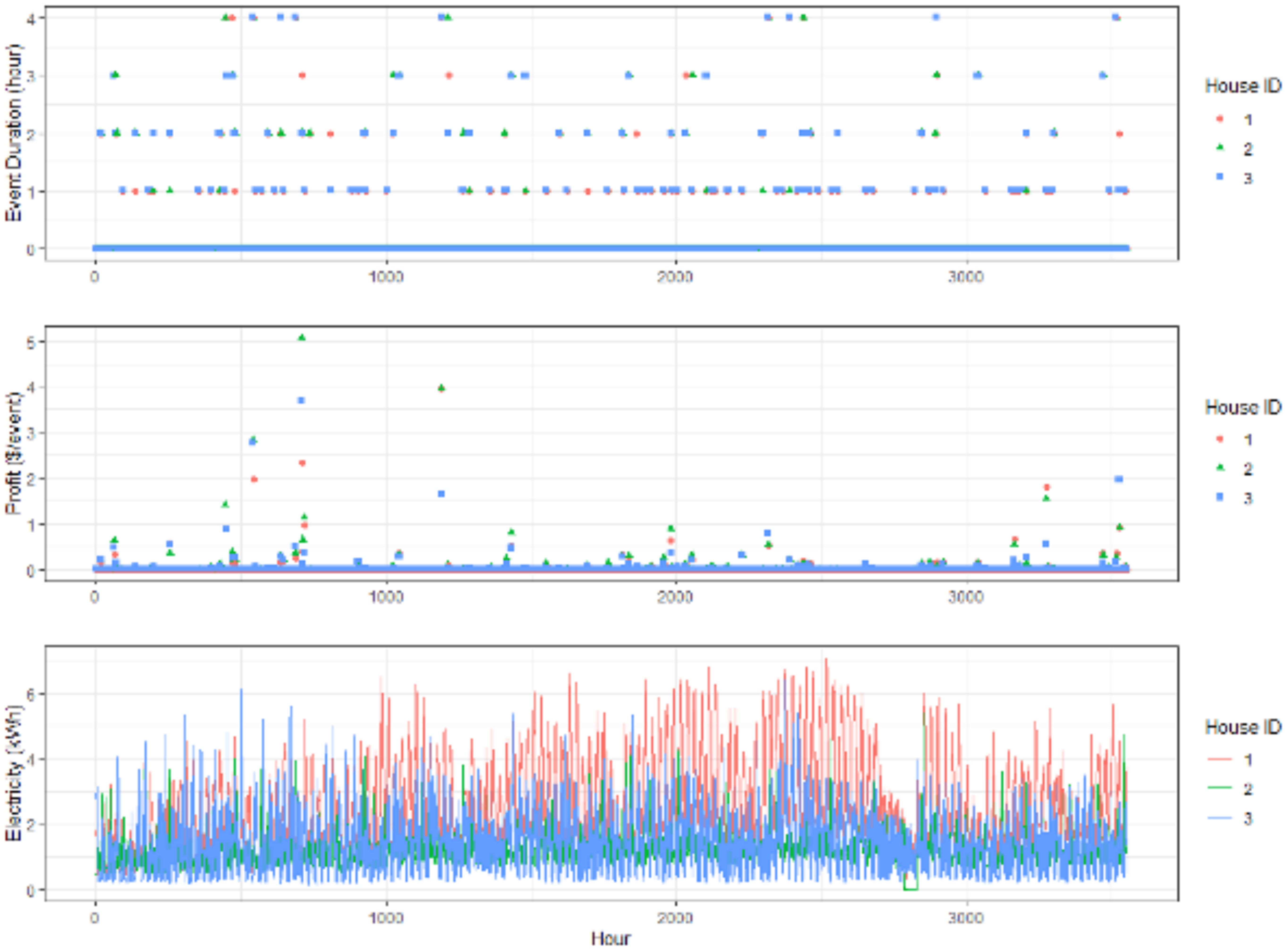


Fig. 2. Three randomly selected households with DP event duration, DR profit, electricity load profile between May 1 to Sep. 30, 2017 [2]

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

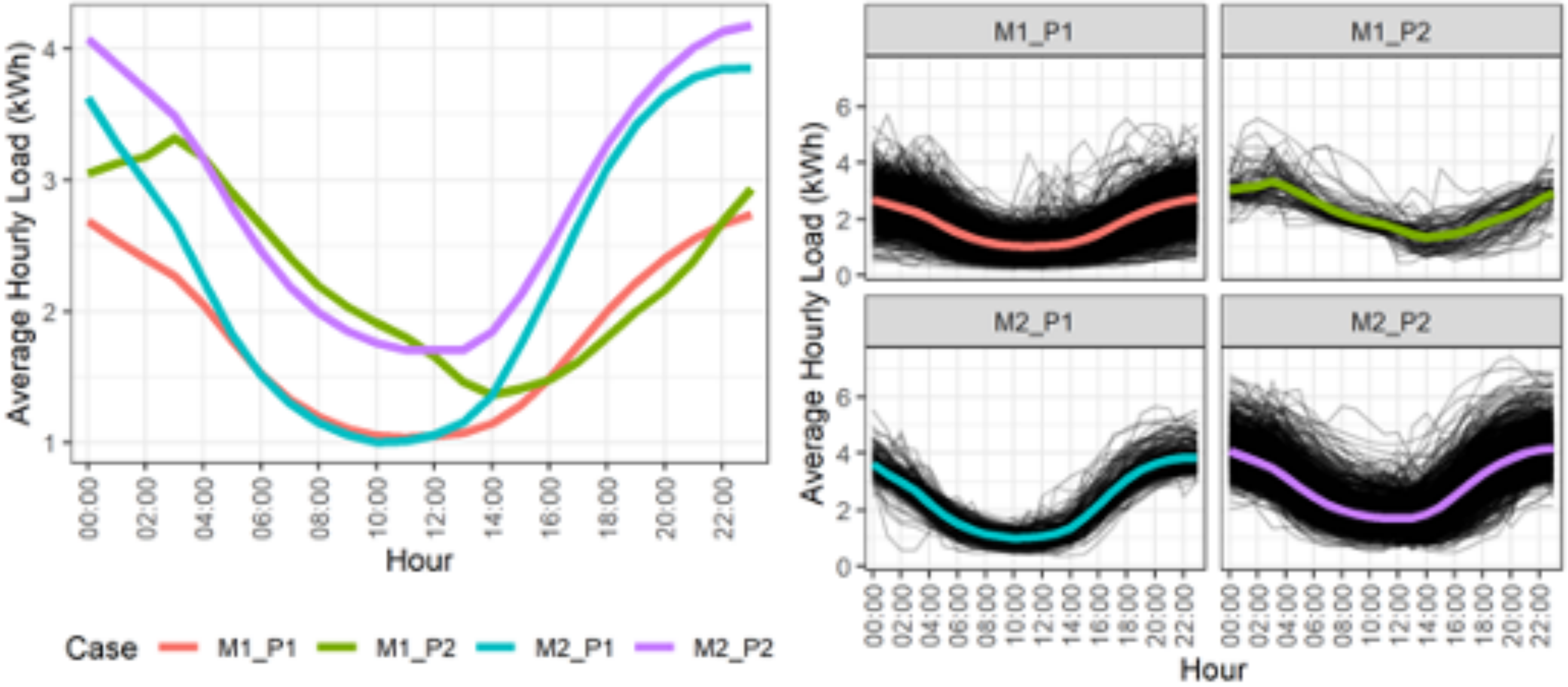


Fig: Four load cases of randomly selected 3,000 households with two $k_m$ and two $k_p$ by CLPM with left) cumulative cases, right) individual cases [2]

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

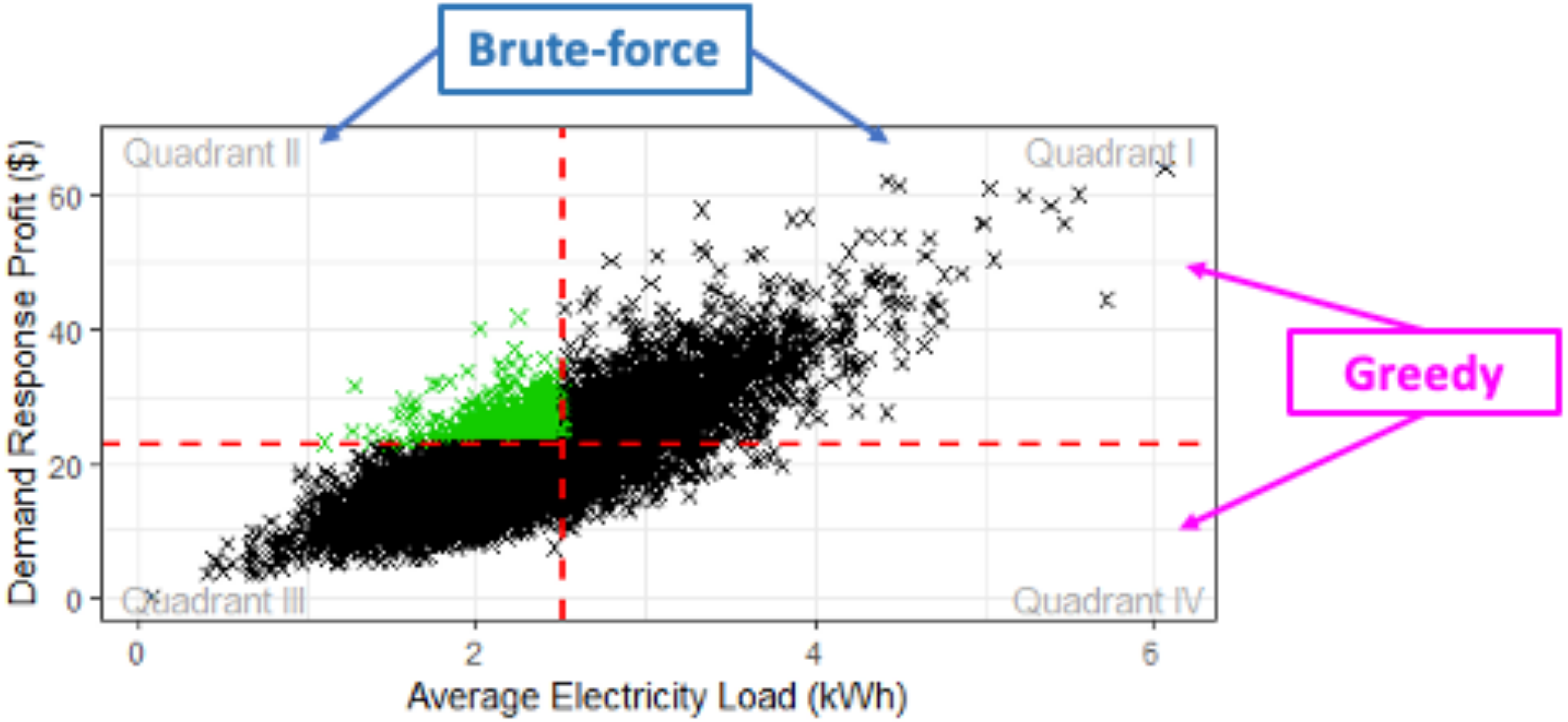


Fig: Estimated DR profits using DP by the brute-force method between May 1 to Sep. 30, 2017 [2]

$$Opportunity\ \ Cost\ \ Ratio = \frac{[(\sum_{hou.\in Q_2} Profit_{hou.}) - (\sum_{hou.\in Q_4} Profit_{hou.})] \cdot 100}{[(\sum_{hou.\in Q_1} Profit_{hou.}) + (\sum_{hou.\in Q_4} Profit_{hou.})]}$$

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

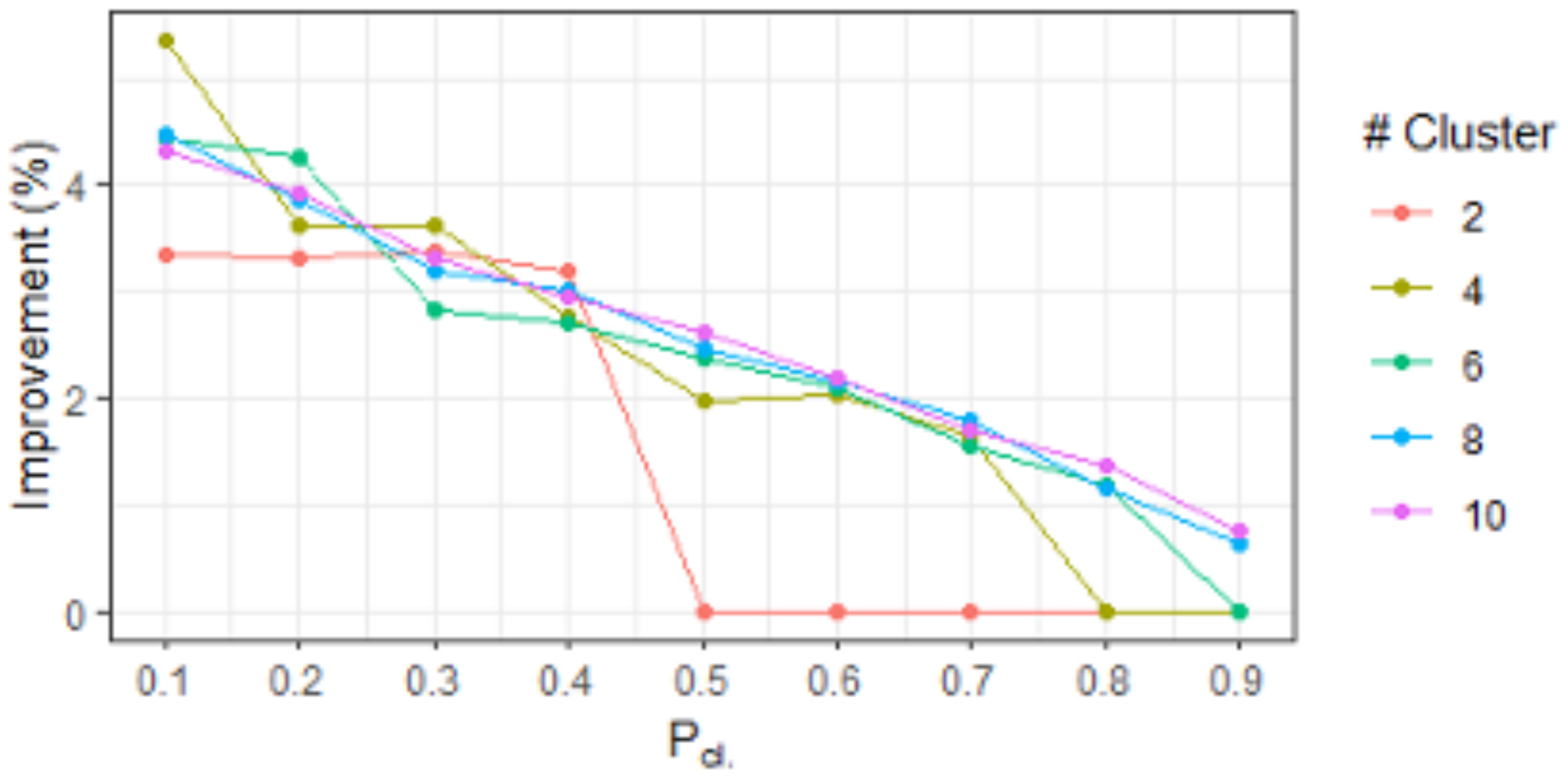


Fig: Opportunity for profitability improvement (%) with the clustered load-profile method over the greedy method [2]

- **The Figure indicates a positive improvement of proposed method over the greedy method**
  - **The improvement (%) is calculated by the amount of DR profits the CLPM attained less the profits of the greedy method.**
- **Two clusters (i.e., two $k_m$ and two $k_p$) yield the highest percent improvement approximately 3.18% at 0.4 $P_{cl.}$**
- **Below 0.4 $P_{cl.}$, the optimal number of clusters varies with the value of $P_{cl.}$**

# Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes [2]

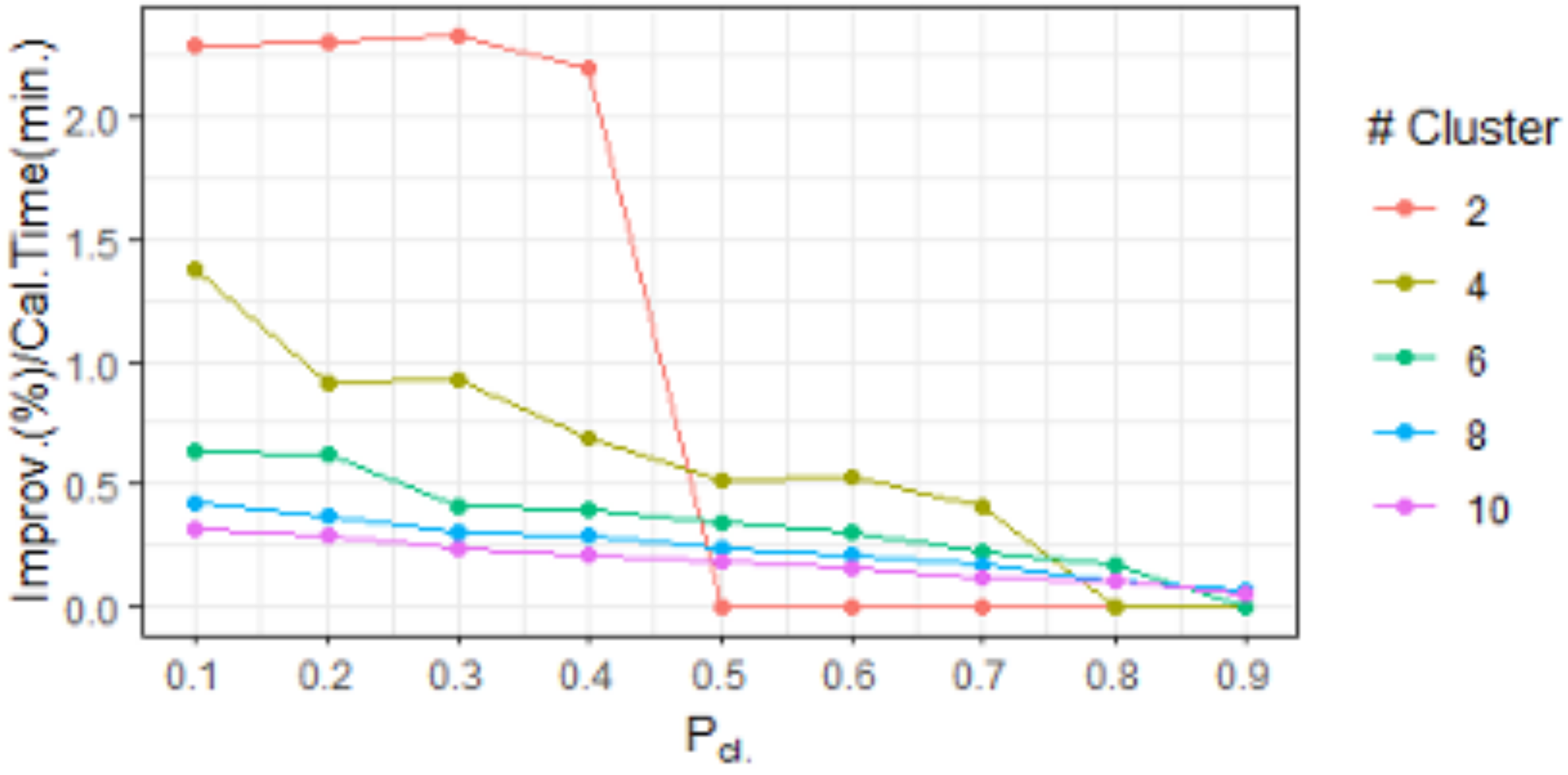


Figure: Ratio of profitability improvement (%) over calculation time (min.) of the clustered load-profile method [2]

- **When looking at the ratio of improvement percentage over the computational time, two clusters are still optimal up to 0.4 $P_{cl.}$**
- **The proposed method (the clustered load-profile method (CLPM)) is always better than or equal to the greedy method (i.e., easiest ways for DR)**
- **Implementation of the CLPM is beneficial to REPs in terms of potential success in near real-time DR programs with improvement in the optimization accuracy (over the greedy method) and computational efficiency (over the brute-force method)**

# Multi-Stage Modeling with Recourse Decisions for Solving Stochastic Complementarity Problems with an Application in Energy

Pattanun Chanpiwat, Steven A. Gabriel, and Maxwell Brown

**Motivations:**

- Capture benefits of variable renewable energy (VRE) resources
- Overcome challenges due to the intermittent nature of VRE
- Various generators' startup times in some power plants create issues for implementing VRE resources into the system that affect the reliability and operations of the electric grid.

**Objectives:**

- Assess the value of variable renewable energy (VRE) and battery storage from multiple perspectives of uncertainty.
    - Analyze from a market equilibrium perspective as opposed to just a single optimization problem.
    - Compare the results of the stochastic solutions with the deterministic ones
- Investigate the interaction of players in the electricity market
- Use the recourse problem that mimics a practical order in which decisions are taken and random events are unveiled

# Multi-Stage Modeling with Recourse Decisions for Solving Stochastic Complementarity Problems with an Application in Energy

**Pattanun Chanpiwat, Steven A. Gabriel, and Maxwell Brown**

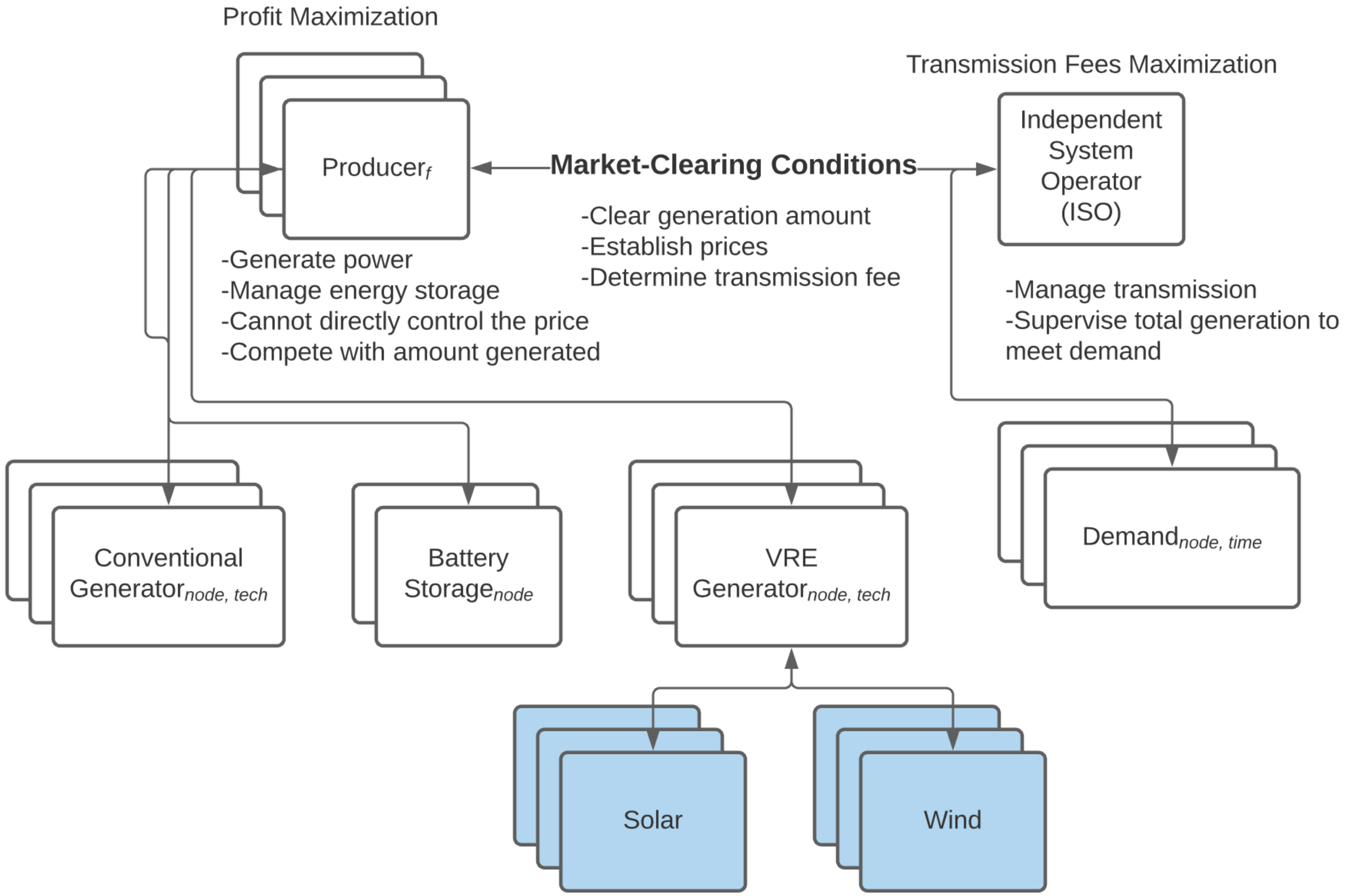


Fig: Schematic illustrating the power market for solving stochastic mixed complementarity problem (MCP)

# U.S. National Renewable Energy Laboratory (NREL) Internship

## Regional Energy Deployment System (ReEDS)

- ReEDS is a large, complex optimization model with many inputs, outputs, variables, and constraints.
- Simulate electricity sector investment decisions based on system constraints and demands for energy and ancillary services.
- Unique in its high-spatial resolution and advanced algorithms for representing the cost, value, and technical characteristics of integrating renewable energy technologies.

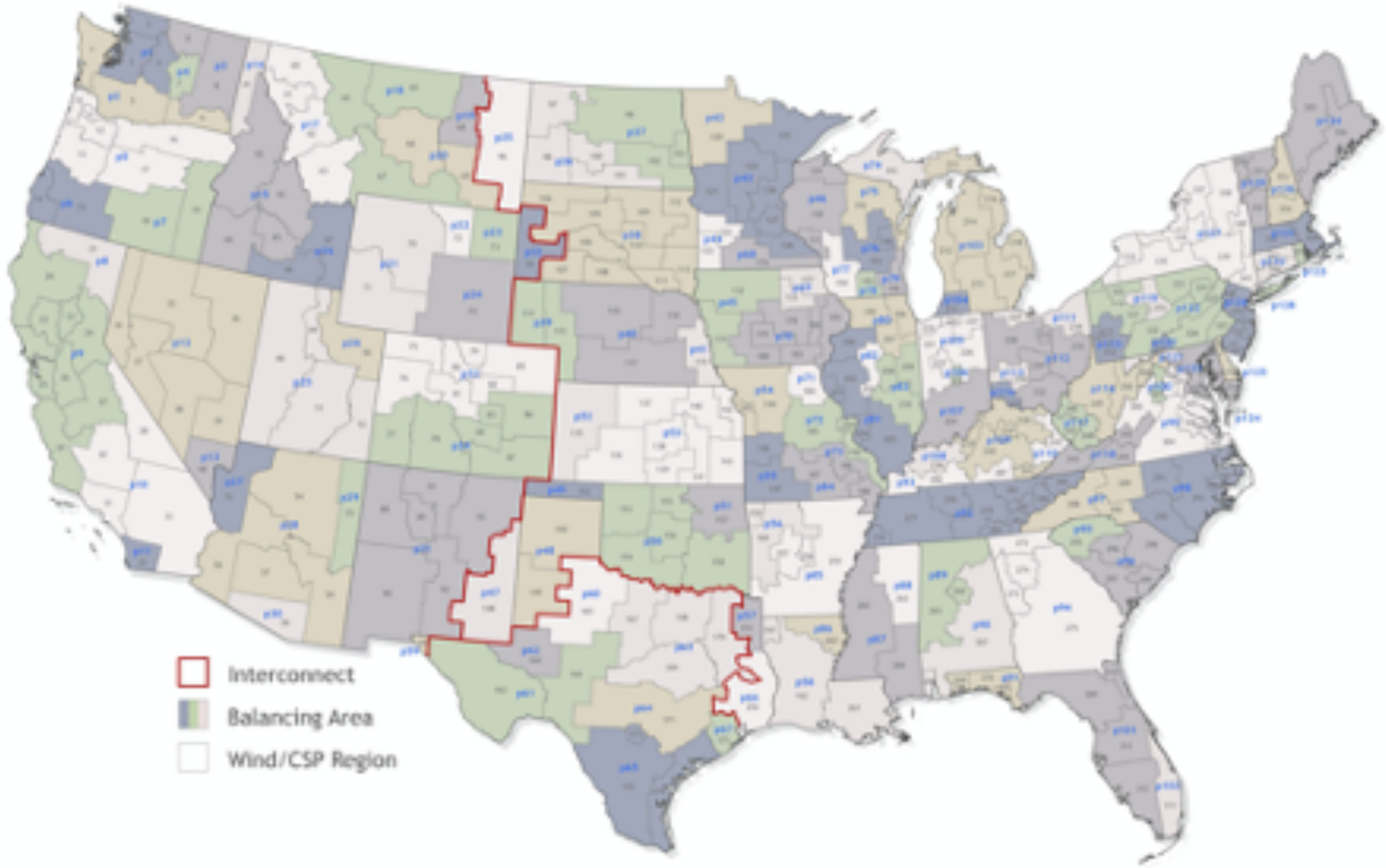


Figure: ReEDS U.S. regions map [NREL]

NATIONAL RENEWABLE ENERGY LABORATORY

# U.S. National Renewable Energy Laboratory (NREL) Internship

## Regional Energy Deployment System (ReEDS)

- Title: Graduate Internship — Power Sector Modeling, and Economic Analysis,
- Department: Economics and Forecasting Group, the Grid Planning and Analysis Center (GPAC)
- Period: Summer 2020, Summer 2021

- Developed GAMS representative models for temporal flexibility, both nationwide and for a subset of regions
  - Increase from 17 timeslices to 8,760 timeslices for greater temporal resolution and scope to more accurately capture operational dynamics driven by resource availability, load patterns, transmission, constraints, storage use
- Proposed temporal aggregation and distribution fitting methods to estimate the most-representative sets of days, weeks, and months

NATIONAL RENEWABLE ENERGY LABORATORY

# Other Research Projects

L. Wang, T. Hensel, **P. Chanpiwat**, S. Zhu and J. Srebric, "Occupant-centric Control of Building Systems based on Real-time Optimization by Extremum Seeking," 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), 2022, pp. 1-6, doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854615.

J.C. Huemme, S.A. Gabriel, **P. Chanpiwat**, and T. Shu,“An analysis of the U.S. - China Trade War’s impact on global natural gas markets and the U.S. Coast Guard’s LNG inspection workforce,” Journal of Natural Gas Science and Engineering, Nov., 2021, https://doi.org/10.1016/j.jngse.2021.104198.

W. Idewu, **P. Chanpiwat,** and H. Naghawi,“Identifying Optimum Taper Lengths for Zipper Merging Applications using Real Data and Microscopic Simulation,” Periodica Polytechnica Transportation Engineering, June, 2019, https://doi.org/10.3311/PPtr.13044.

**P. Chanpiwat** and S. Sinha, “Quantitative Approach to Select Energy Benchmarking Parameters for Drinking Water Utilities,” In Proc. Pipelines, 2014, pp. 1237-1253, https://doi.org/10.1061/9780784413692.112.

**P. Chanpiwat** and W. Idewu, “Joint Merge Taper Length Variations for Use in Construction Zones,” New Horizons, vol. 6, no. 1, Apr., pp. 20-46, 2012.

# Projects at Aalto University

# EasyDR

- Motivations: Providing demand flexibility (e.g., demand response) to the power system through the optimal grid control system.
- Develops the demand response algorithm based on reinforcement learning for residential households under uncertainty in electricity prices, weather conditions, and load demand.
    - Does not require computationally intensive, calibration, prediction, and optimization processes at the end-user device
    - Capable to able to learn optimal load-shifting strategies for the operation of the demand response of an isolated micro-grid during peak electricity prices

# Actor-Critic RL

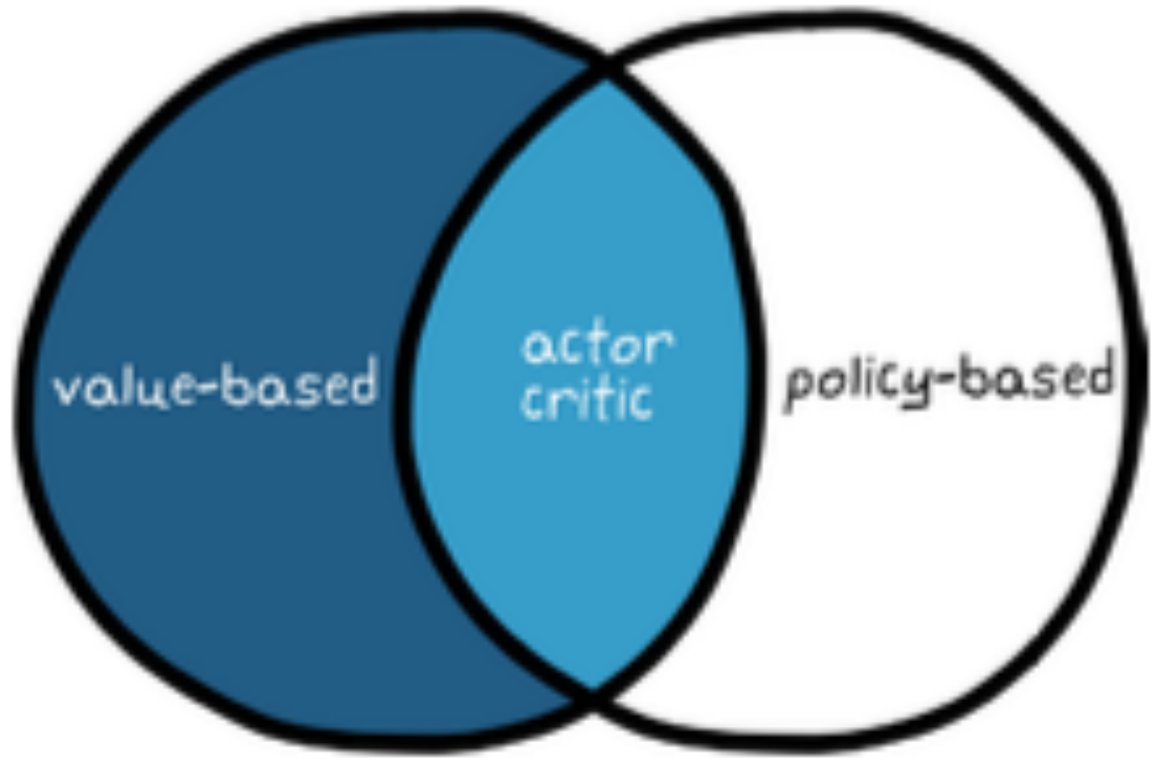


Fig: Actor-Critic RL [4]

## “Value” Function-Based Learning:

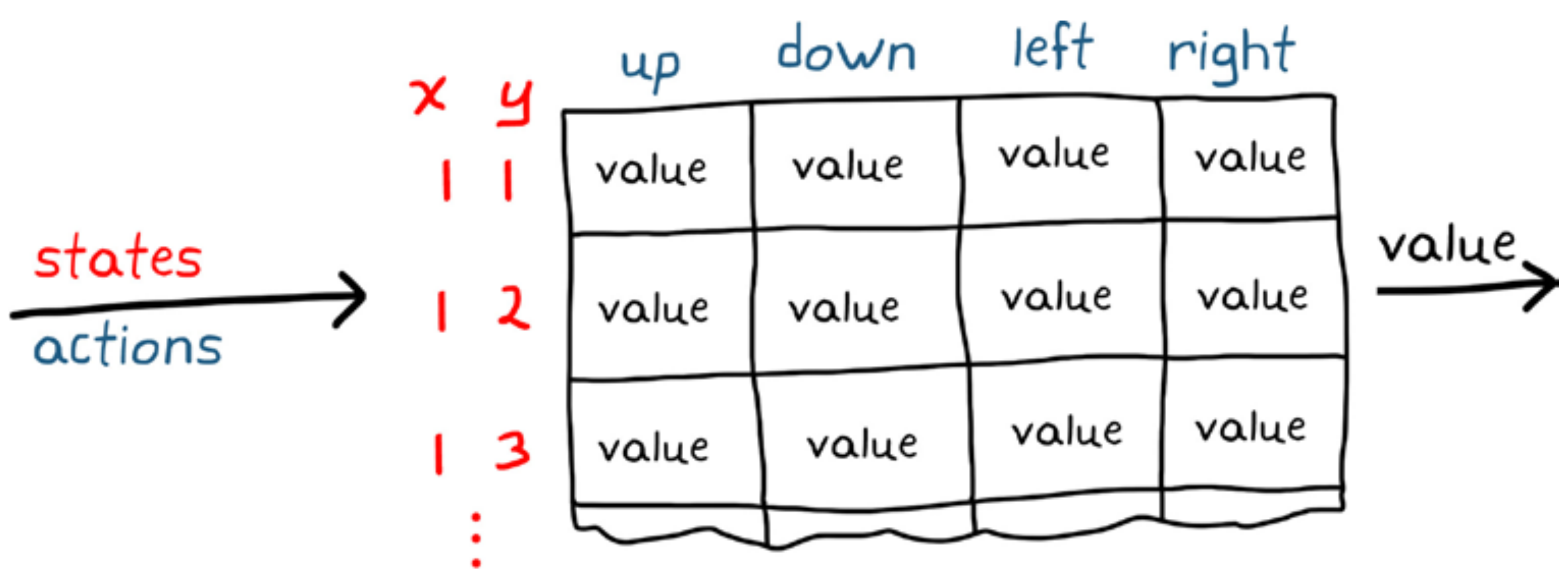


Fig: “Value” Function-Based Learning [4]

## “Policy” Function-Based Learning:

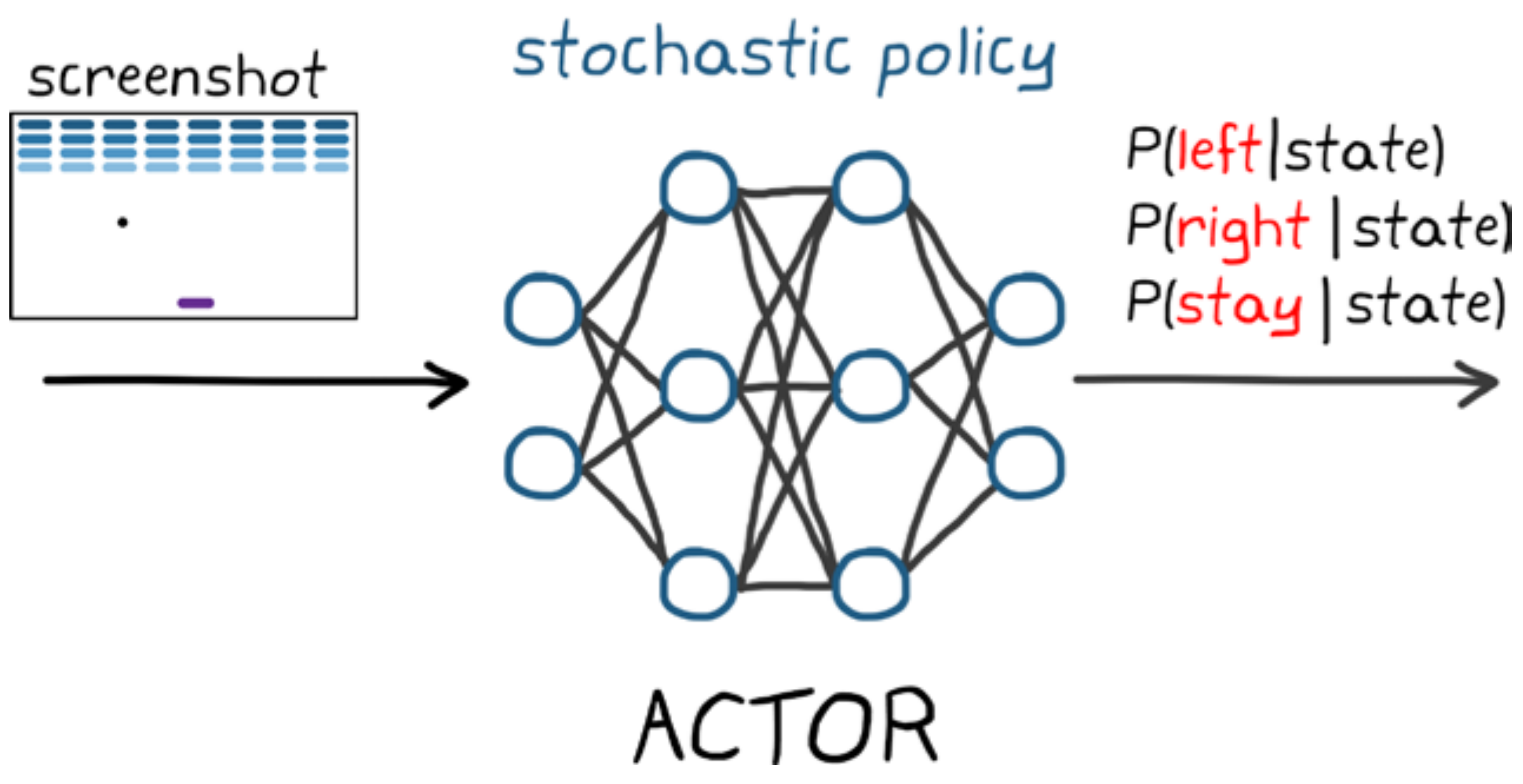


Fig: “Pollicy” Function-Based Learning [4]

# Actor-Critic RL

## The combination of both “value” and “policy” function methods.

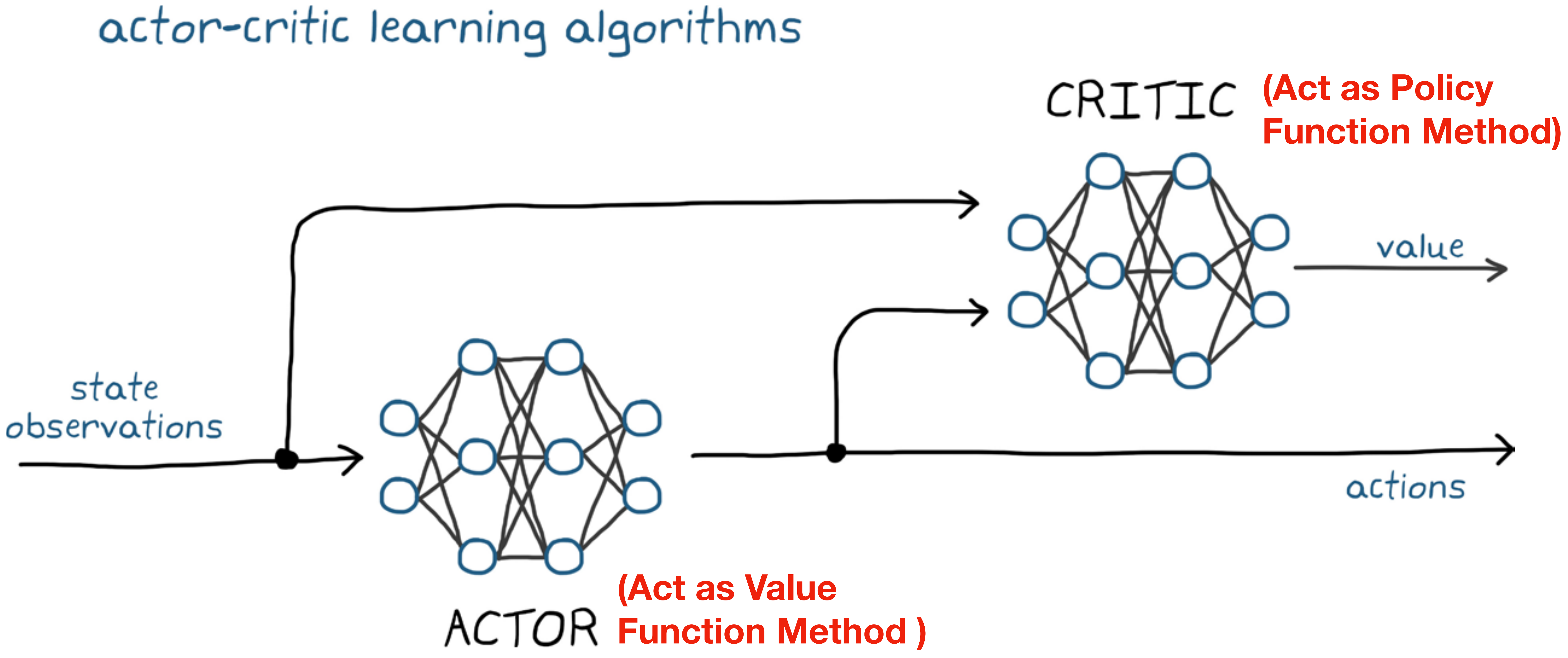


Fig: Actor-Critic RL [4]

- Handle both continuous state and action spaces
- Speed up learning when the returned reward has high variance

# Actor-Critic RL Learning Cycle

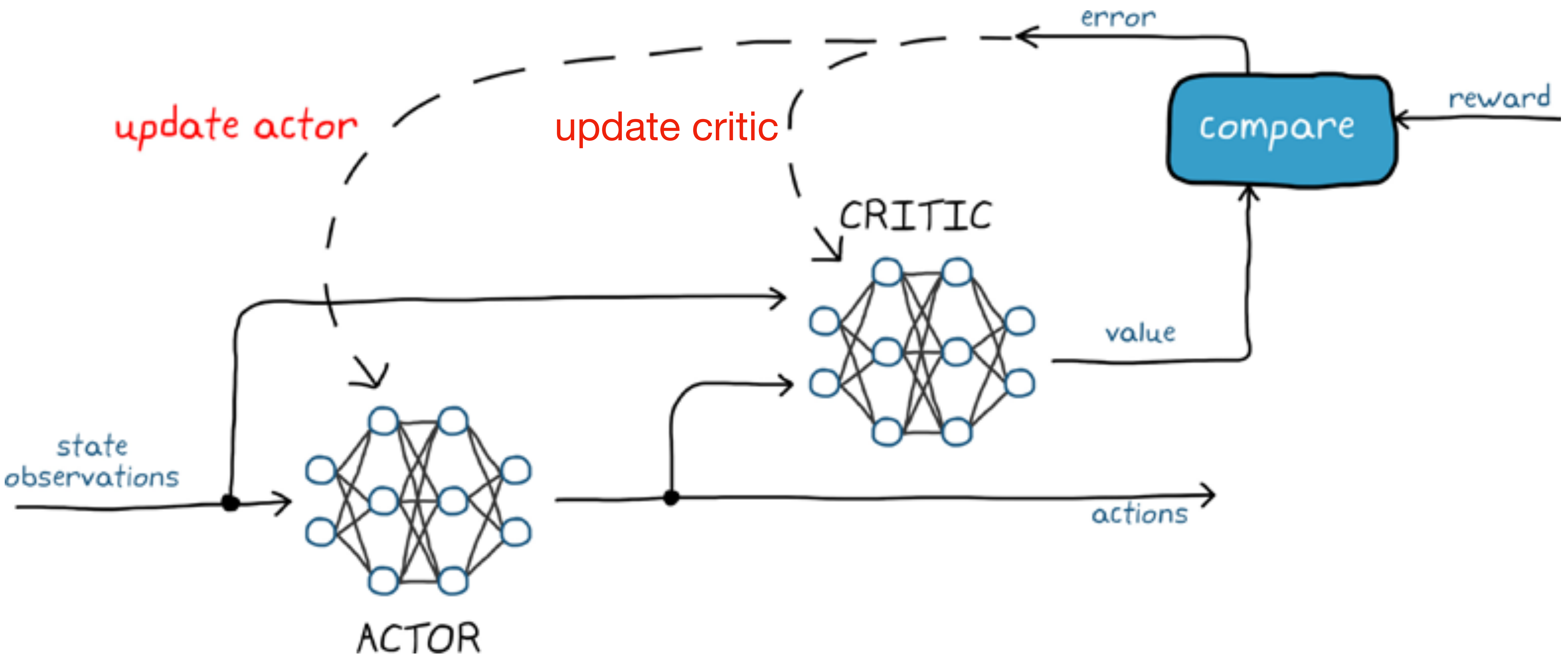


Fig: Actor-Critic RL [4]

# Thank You

## Questions, Comments, Suggestions

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Phone: +358 50 577 6368

# References

1. Reinforcement Learning and Simulink [link]

2. P. Chanpiwat, S. A. Gabriel, R. L. Moglen, and M. Siemann, ”Using Cluster Analysis and Dynamic Programming for Demand Response Applied to Electricity Load in Residential Homes,” ASME Journal of Engineering for Sustainable Buildings and Cities, vol. 1, no. 1, Feb., 2020.

3. R. L. Moglen, P. Chanpiwat, S. A. Gabriel, and Blohm A., ”Optimal Thermostatically-Controlled Residential Demand Response for Retail Electric Providers,” Energy Systems, Aug., 2020.

4. Reinforcement Learning with MATLAB and Simulink [link]