Evolving Robust and Reconfigurable Multi-Objective Controllers for Advanced Power Systems

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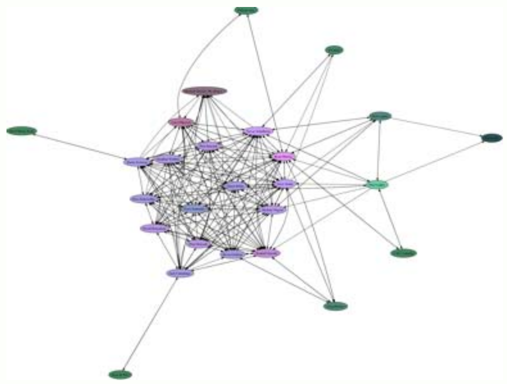
Motivation: Energy Systems

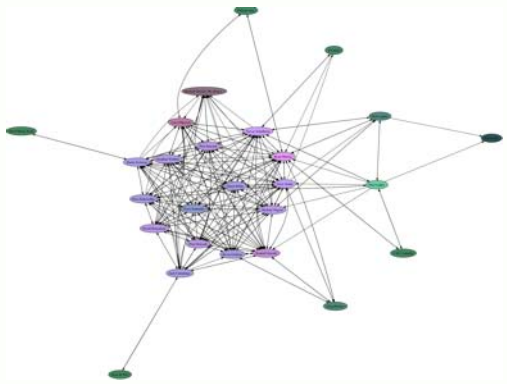
- Where are we?
  - Advanced energy systems becoming more interconnected
  - Computation pushed further down the pipe
  - More powerful, cheaper, smaller devices



- Where are we going?
  - Hybrid systems
  - Competing objectives
  - Smart sensors, actuators

Motivation: Energy Systems

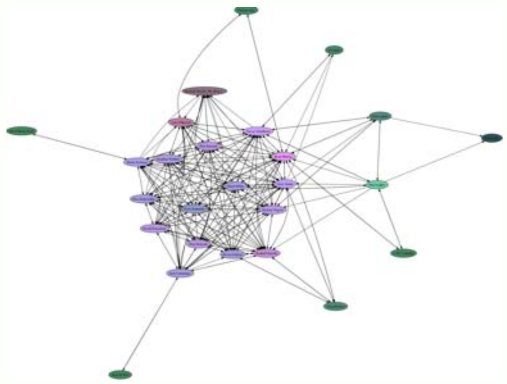
- Where are we?
  - Difficult to model
  - Distributed decision making
  - Need Scaling



- Where are we going?
  - Even more difficult to model
  - Even more distributed decision making
  - Even more scaling

Motivation: Energy Systems

- We need to account for?
  - Model inaccuracies (or lack of models)
  - Thousands of actors (sensors, controllers, users)
  - Failing components
  - Competing objectives
  - Dynamic and stochastic environments



  - And still control systems to result in safe, efficient operation

Distributed multi-objective Control?

Multiagent control

Many agents, one objective

- Who does what ?

Many agents , many objectives

Outline

- Motivation: multiagent, multi-objective control in complex systems
- Roadmap & objectives

- Key Milestones for last year
  - M 1: Develop abstract simulator
  - M 4: Develop multi-objective controller

- Summary & Project Status

Roadmap and Objectives

- Learning-Based Control

Objective 1

- Multiagent
  - Biomimetic distributed subsystem-level control
  - System-level results

Objective 2

- Multi-objective
  - Simultaneously optimize multiple competing objectives

Objective 3

- Reconfigurable
  - Adapt to changing power system needs
  - Develop new policies with previously unconsidered objectives

Data driven, fast simulator

Project Milestones

Milestone Number	Milestone Title	Planned Completion Date	Actual Completion Date
1	Develop an abstract simulator for advanced power systems	June 2014	June 2014 ✓ Ongoing
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Milestone 1: Abstract Simulator

- Use data from real HyPer runs to train abstract simulator
  - Neural network maps current plant state and control actions to next plant state
  - Can use neural network to make a time domain simulator of the plant
- Are we claiming you can replace high-fidelity simulator ???

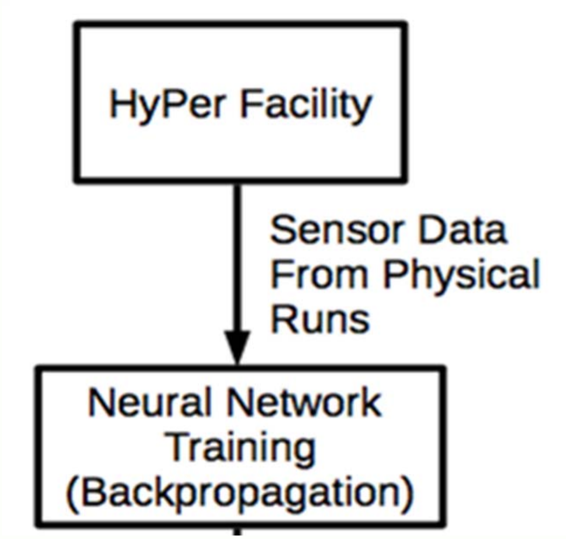
ABSOLUTELY NOT

Claim: You can approximate high-fidelity simulator in parts of state space to develop policies.

You can then tune policies on high-fidelity simulator and test in hardware

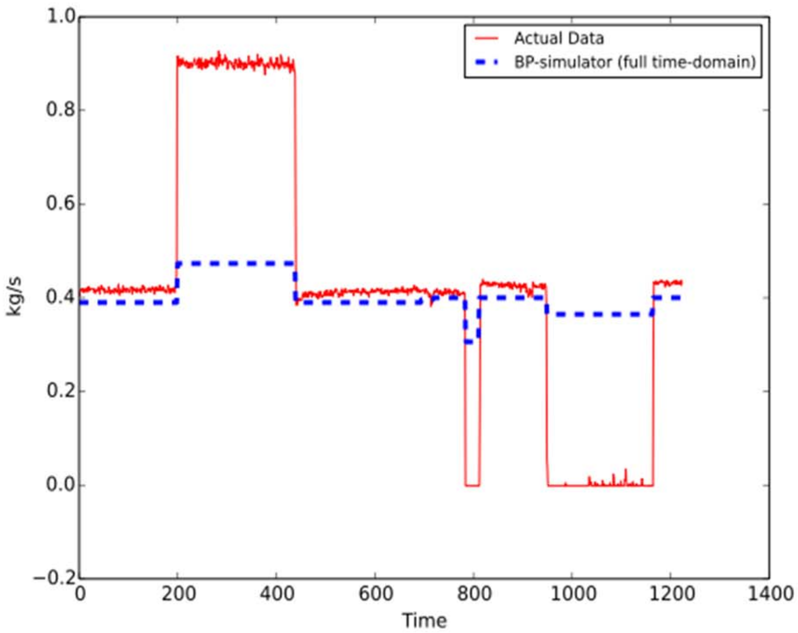
Training 1.0

- We have labeled data
- Backpropagation!

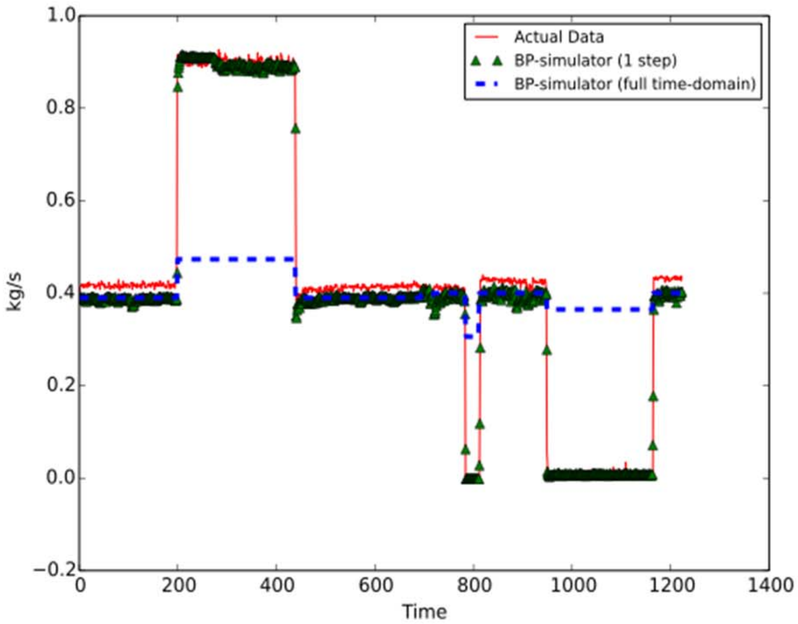


- What can possibly go wrong???

Results: Backpropagation (BP)



Results: Backpropagation 1-time step

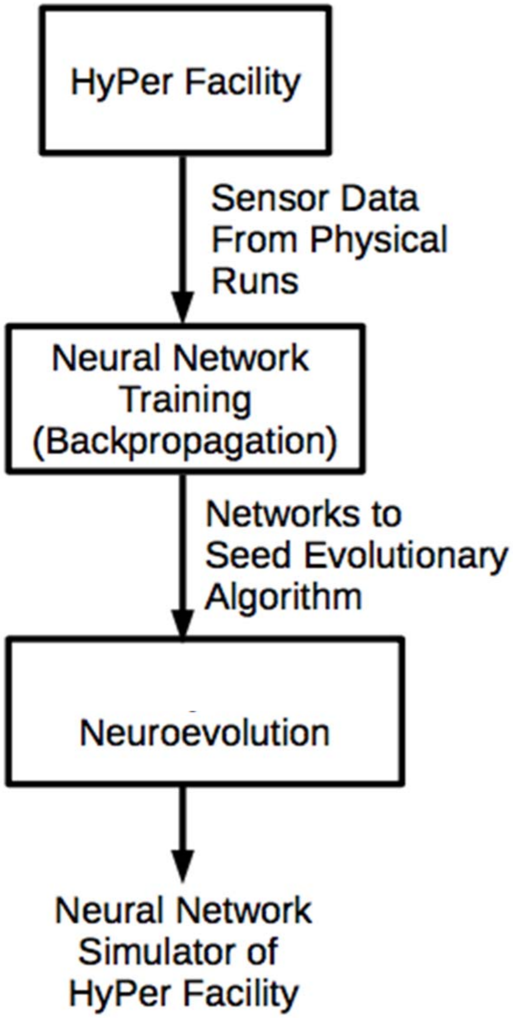


What is going on?

- Backpropagation inadequate
  - 1-time step training is good
  - Error propagates through time
- Solution: Evolutionary Algorithm with “bigger picture” view

Training 2.0

- Backpropagation inadequate
  - 1-time step training is good
  - Error propagates through time
- Solution: Evolutionary Algorithms
  - Key: Fitness metric



Weakness based search

$$w = \frac{1}{t_o} \sum_{i}^{k} \Big(\sum_{t=1}^{t_o} |t_i - y_i| \Big)^2$$

- Weakness metric (anti-fitness)
- 25,000 generations
- Population size: 100

Weakness based search

$$w = \frac{1}{t_o} \sum_{i}^{k} \left(\sum_{t=1}^{t_o} |t_i - y_i| \right)^2$$

- Error at each point

Weakness based search

$$w = \frac{1}{t_o} \sum_{i}^{k} \Big(\sum_{t=1}^{t_o} |t_i - y_i| \Big)^2$$

- Total time steps

Weakness based search

$$w = \frac{1}{t_o} \sum_{i}^{k} \Big(\underbrace{\boxed{\sum_{t=1}^{t_o} |t_i - y_i|}}_{E_i} \Big)^2$$

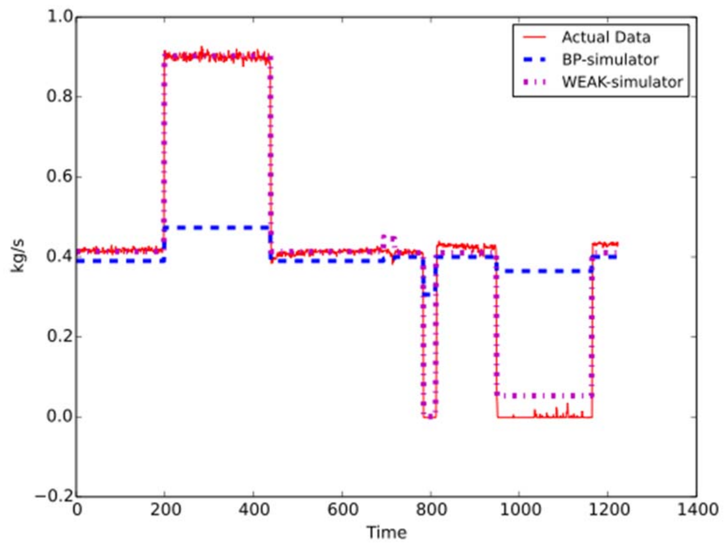
- Aggregate L1 norm of error for each sensor

Weakness based search

$$w = \frac{1}{t_o} \boxed{\sum_{i}^{k} \Bigg(\underbrace{\sum_{t=1}^{t_o} |t_i - y_i|}_{E_i} \Bigg)^2}$$

- L2 norm of time aggregate error distribution
- Error distribution is important

Results: Weakness-based neuro-evolution



What happened?

- Improved performance tremendously
- But: Solutions are sensitive to starting point

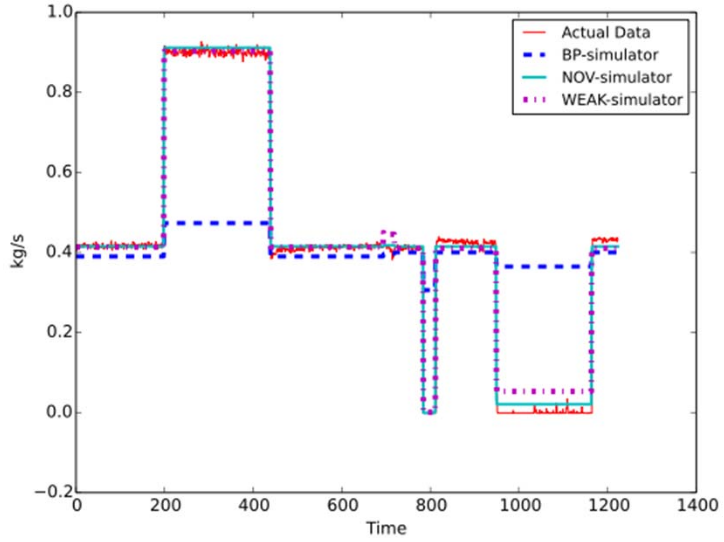
Training 3.0

- Use Novelty
  - Use sparcity of error vector
  - Average k-neighbor distance

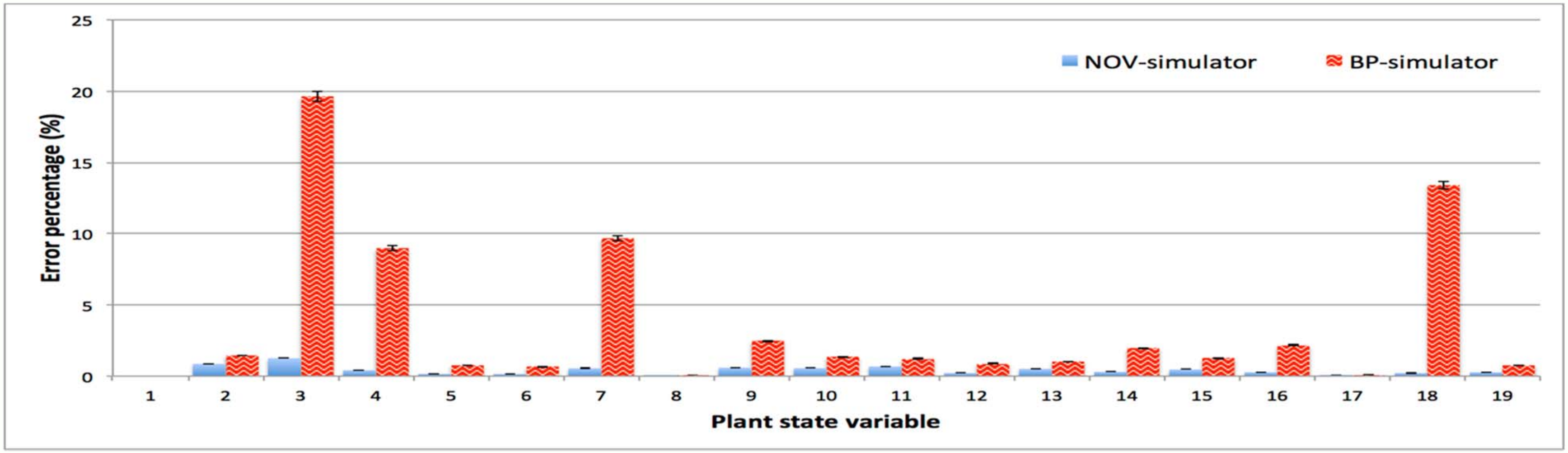
$$E = \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_k \end{bmatrix}$$

So ...

Results: Adding Novelty-based Neuro-evolution



Results: Error histograms



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Key Issue in many Real World Problems

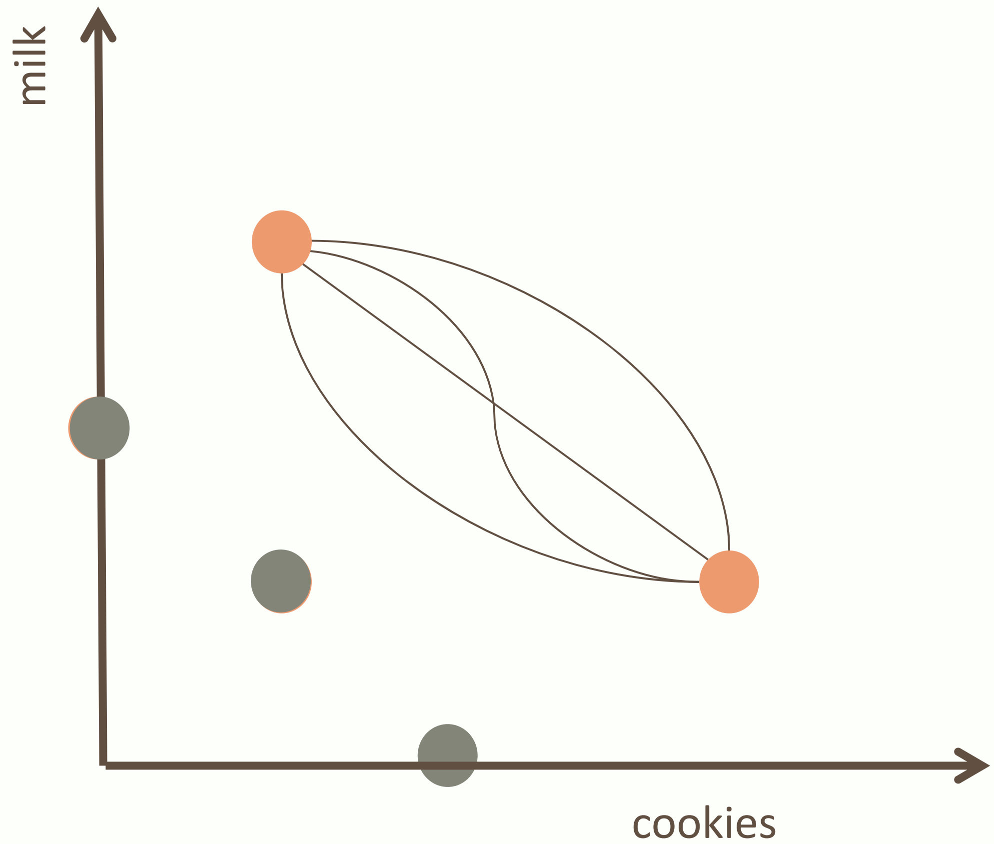
- You have one than one objective

- How do you trade-off one for the other

Key Issue in many Real World Problems

- You like milk and cookies
  - Choose:
  - No milk 2 cookies
  - 2 glasses of milk , no cookies
  - 1 cookie, 1 glass of milk
  - 1 cookie, 3 glasses of milk
  - 1 glass of milk, 4 cookies

Key Issue in many Real World Problems



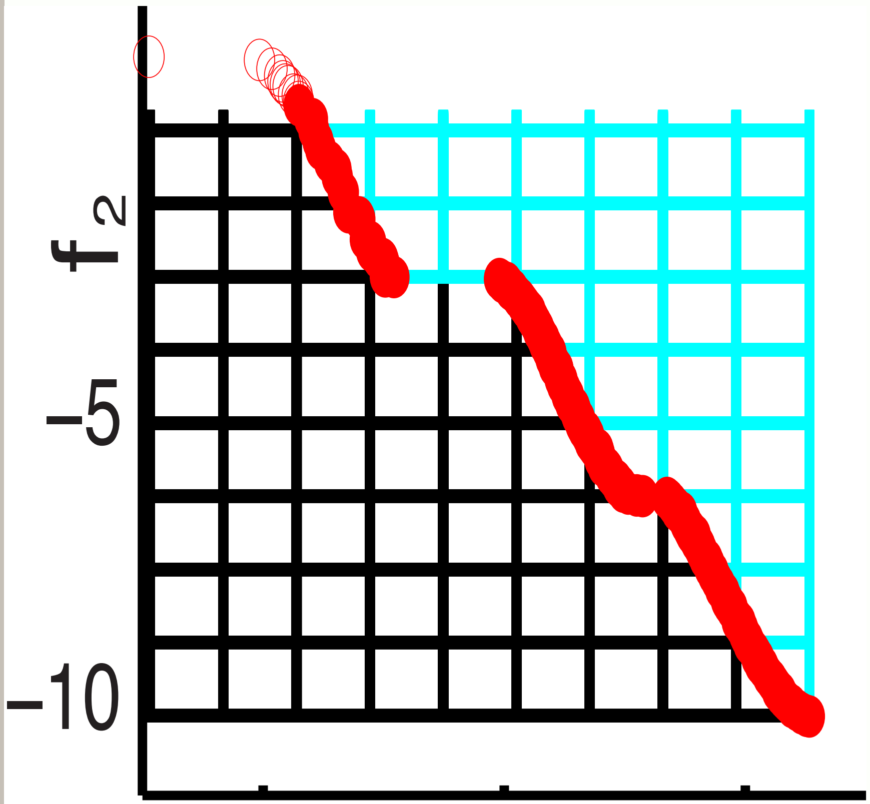
Key Points

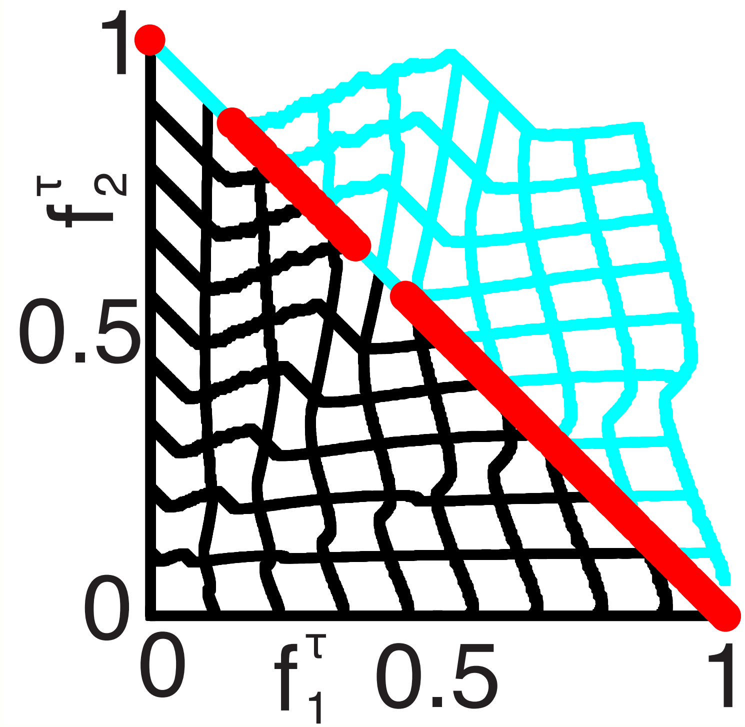
- “Seeing” the performance is easy with two objectives
- With higher than three objectives, it is very difficult

- Linear combination misses entire areas of search space
  - Suboptimal
  - Poor trade-offs

- Population based searches are slow. Very, very slow

PaCcET Result





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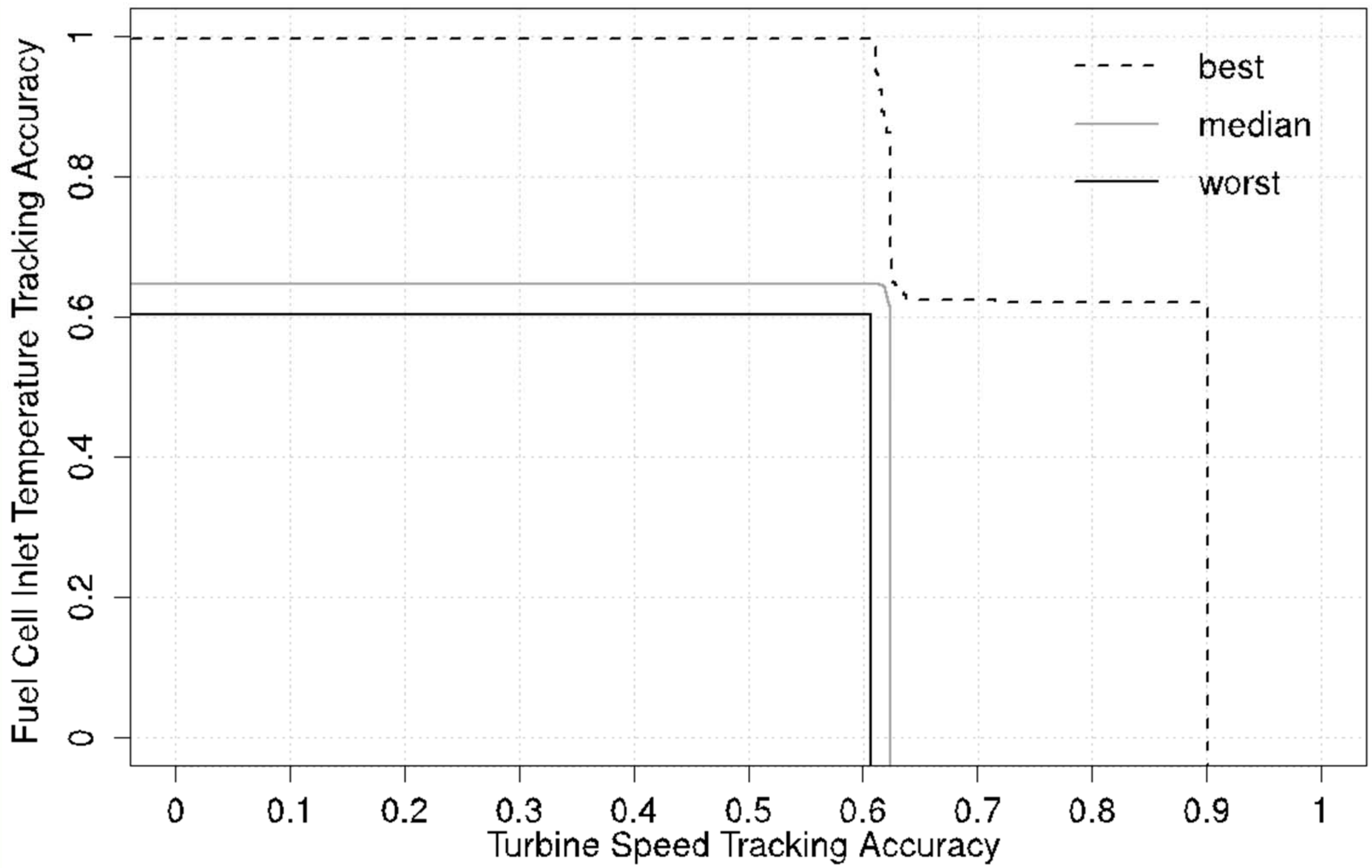
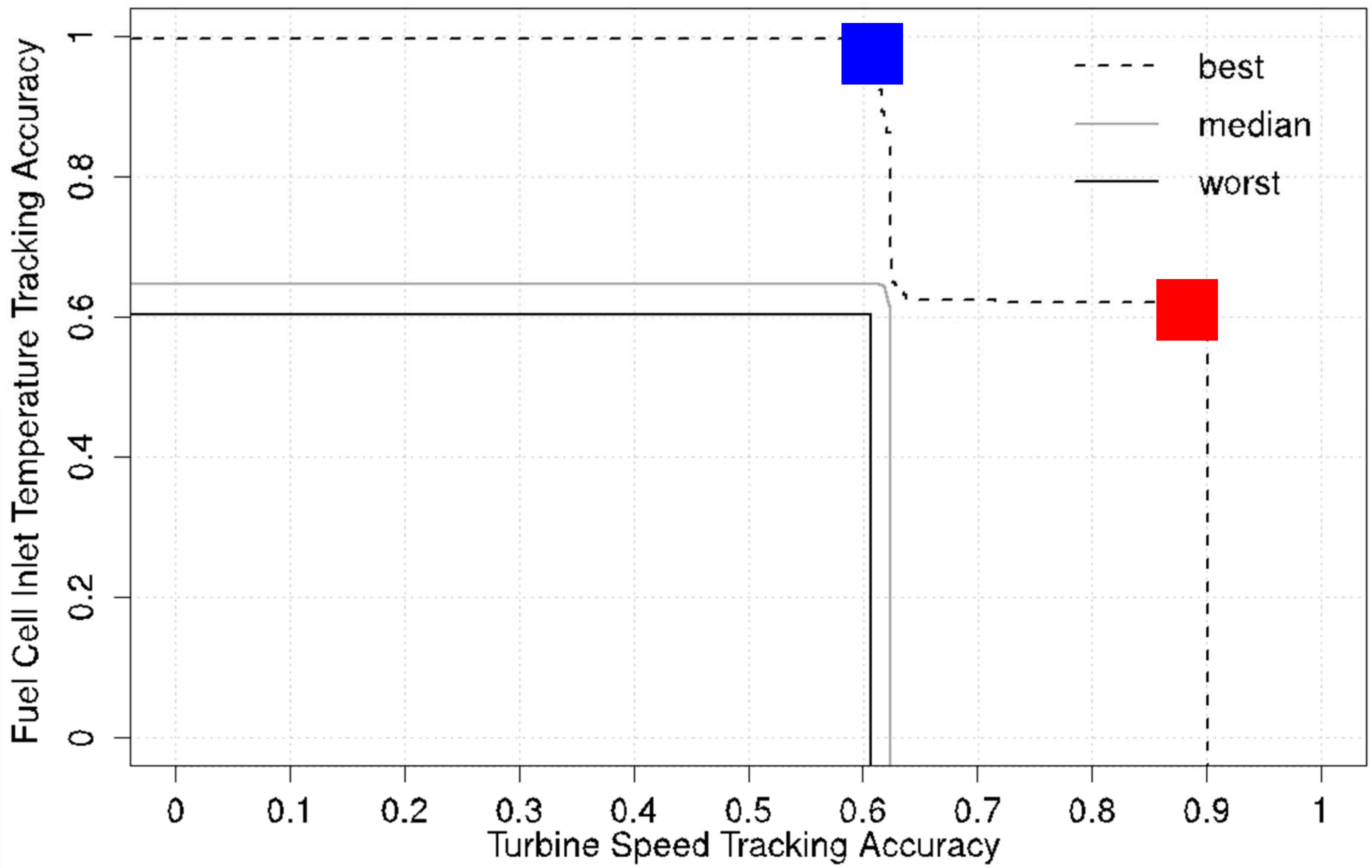
Multi-Objective Control

- Sample control policies
  - Maximize fuel cell inlet temperature accuracy
  - Maximize turbine speed tracking accuracy

Empirical Attainment Function



Endpoint Profile Locations



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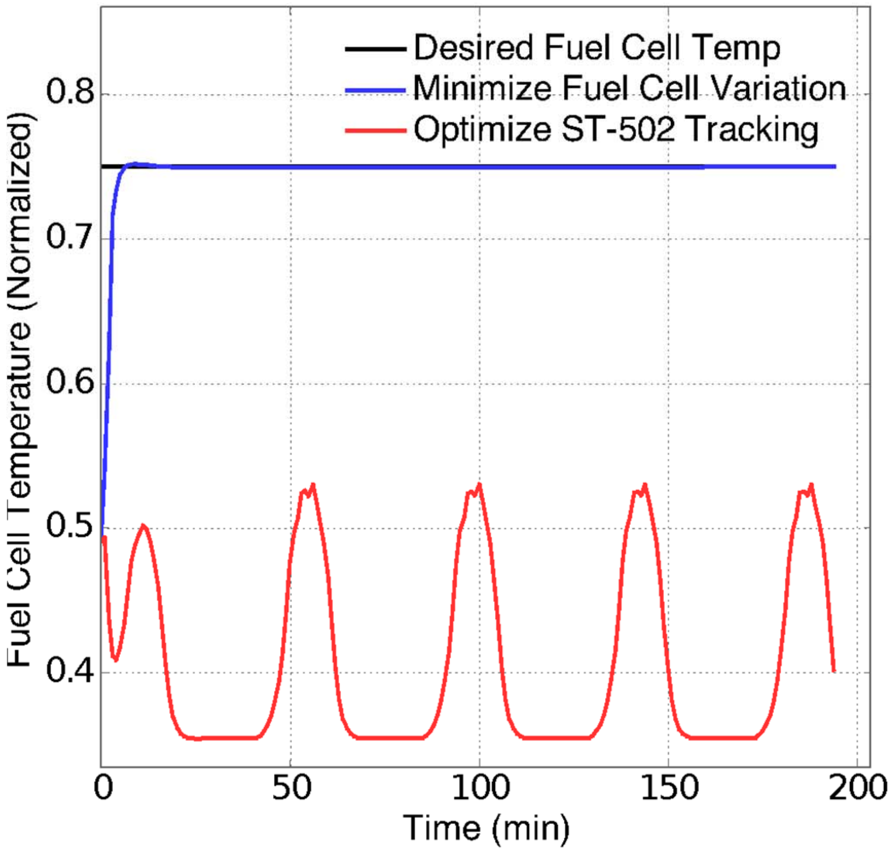
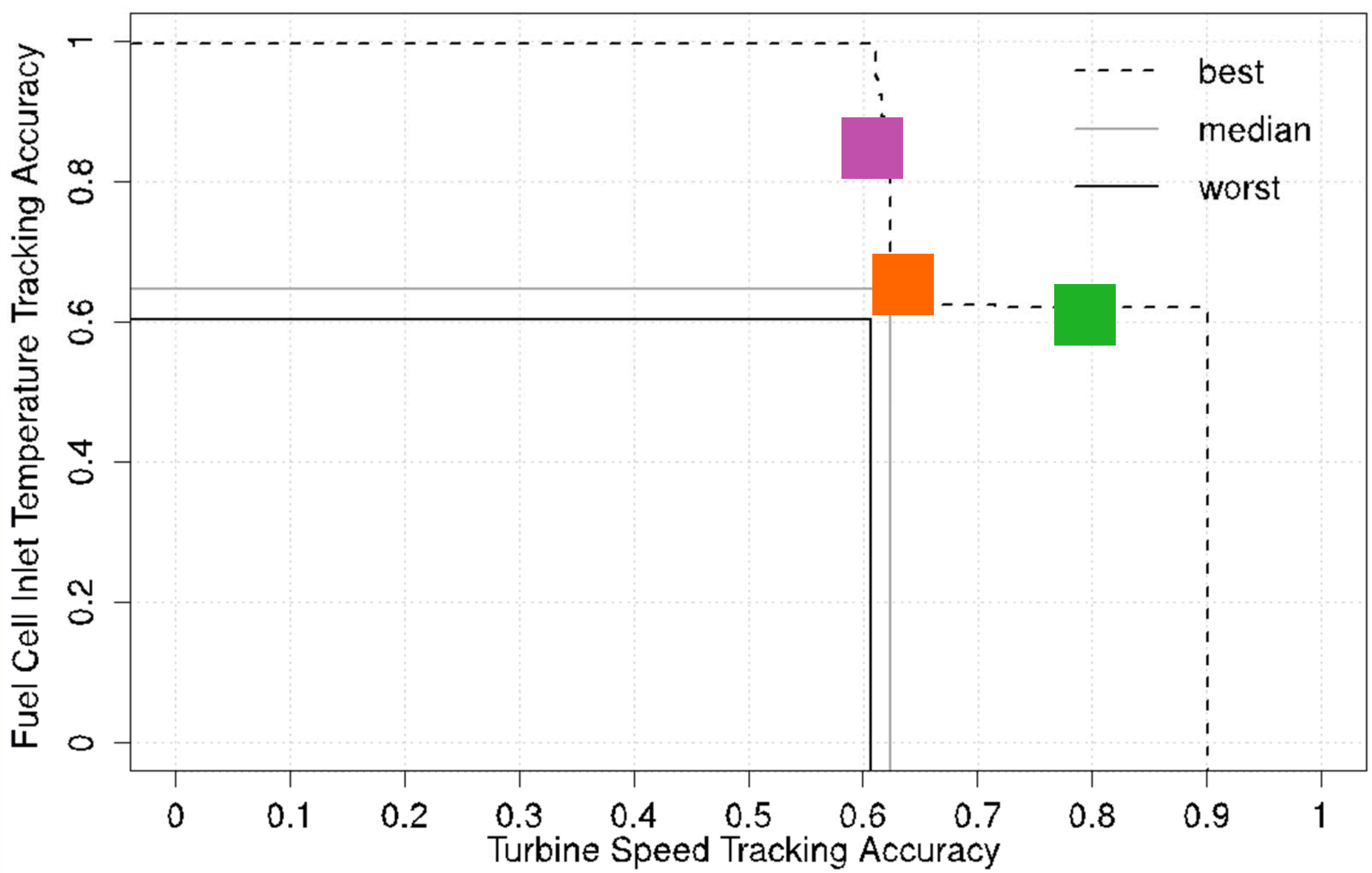
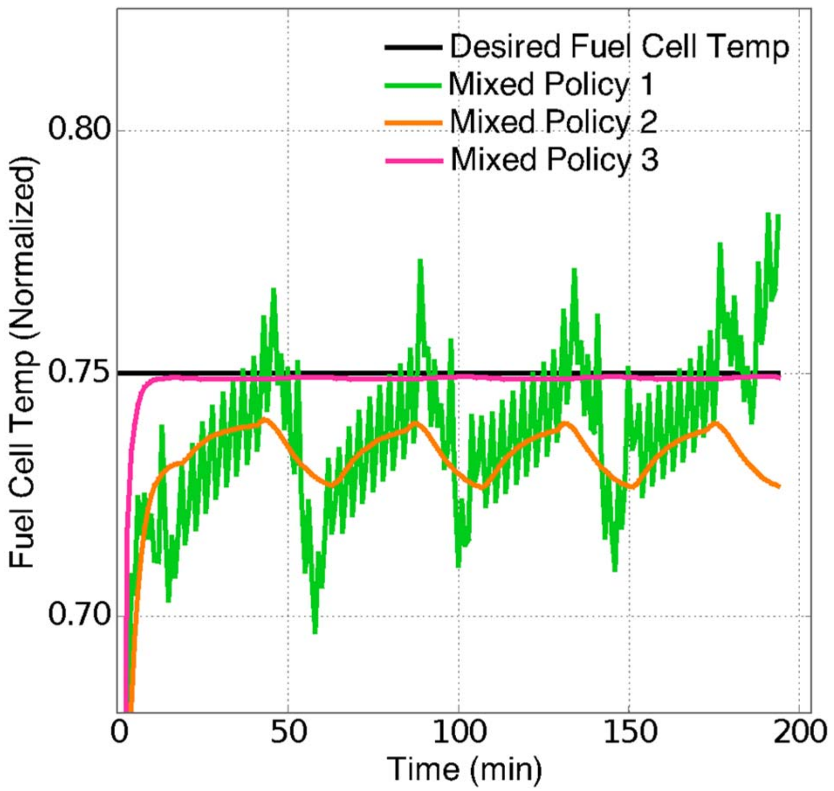


Tradeoff Profile Locations



Tradeoff Profiles



What do Results mean?

- Orange policy:
  - moderate match of the desired turbine profile and target fuel cell temperature
  - It does not optimize either objective of the plant, it does well at finding a middle ground between the policies which only consider one plant objective
  - These are not tradeoffs that are obvious with linear combination

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Publications

1. **Neuroevolution of a Hybrid Power Plant Simulator.**
   S. Khadka, K. Tumer, M. Colby, D. Tucker, P. Pezzini, K.M. Bryden. In Proceedings of Genetic and Evolutionary Computation Conference (GECCO) 2016, Denver, CO. July 2016.

1. **Multi-objective Neuro-evolutionary Control for a Fuel Cell Turbine Hybrid Energy System.**
   M. Colby, L Yliniemi, P. Pezzini, D. Tucker, K.M. Bryden, K. Tumer. In Proceedings of Genetic and Evolutionary Computation Conference (GECCO) 2016, Denver, CO. July 2016.

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- Postdoc: Mitchell Colby

Phd, 2014

- Dave Tucker, NETL
- Paolo Pezzini, Kenneth Mark Bryden, Ames laboratory

Questions?

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