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

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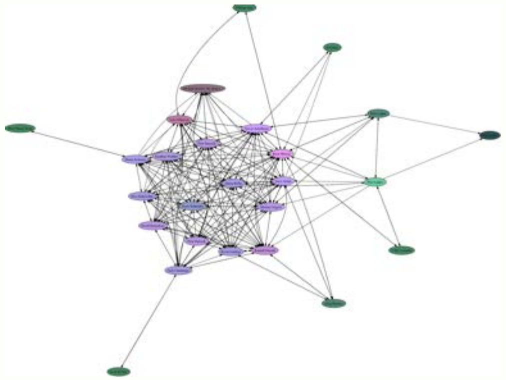
DE-FE0012302

March 22, 2017

Motivation: Energy Systems

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



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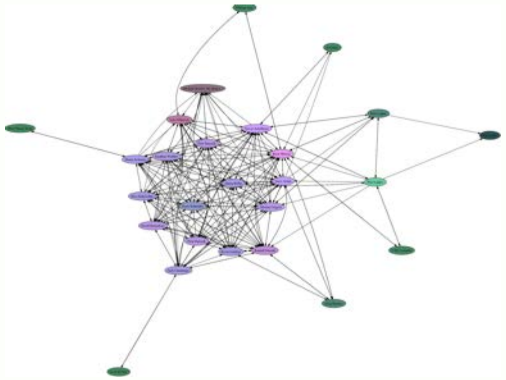
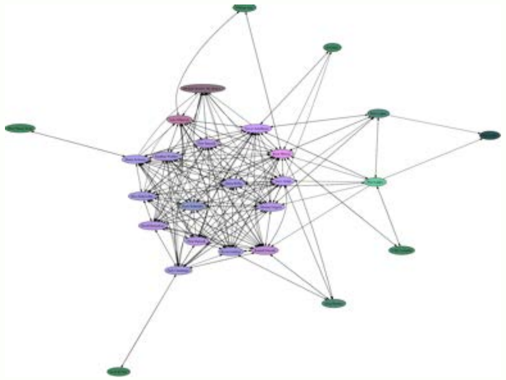


- Where are we going?
  - Hybrid systems (eg. Hyper)
  - Competing objectives
  - Smart sensors, actuators

Motivation: Energy Systems

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



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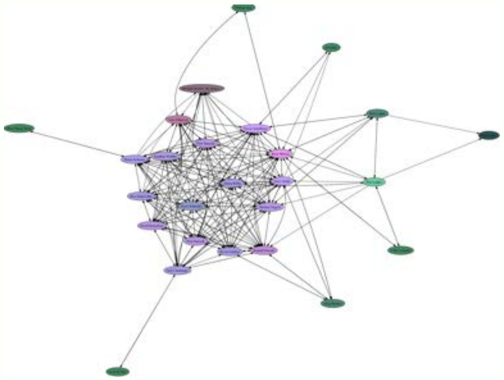
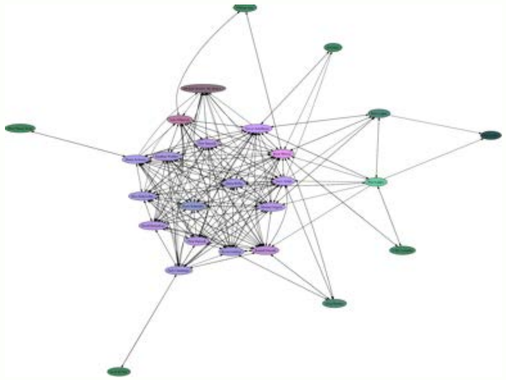


- Where are we going?
  - Even more difficult to model
  - Even more distributed decision making
  - Even more scaling

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

Outline

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

- Key Milestones for last year
  - M 5: Develop robust controller
  - M 6: Develop reconfigurable controller

- Summary & Project Status

Roadmap and Objectives

- Learning-Based Control: **multiagent, multi-objective control in complex systems**

Objective 1

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

Objective 2

- Multi-objective Optimization
  - Simultaneously optimize multiple competing objective functions

Objective 3

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

Data driven, fast simulator

Roadmap and Goals

- Learning-Based Control: **multiagent, multi-objective control in complex systems**

Goal 1

- Multiagent
  - Biomimetic distributed subsystem-level control
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Goal 3

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 ✓
2	Develop bio-mimetic control algorithm for advanced power systems	Sept. 2014	Sept. 2014 ✓
3	Develop system metrics to measure tradeoffs of plant objectives	March 2015	March 2015 ✓
4	Develop multi-objective control algorithm for advanced power systems	Sept. 2015	Sept. 2015 ✓
5	Develop robust controller for advanced power system	June 2016	June 2017 Ongoing
6	Develop reconfigurable, multi-objective controller for advanced power system	Sept. 2016	September 2017 Ongoing

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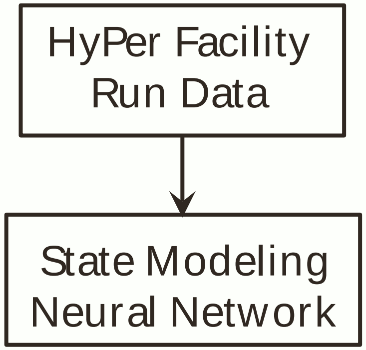
Project Overview



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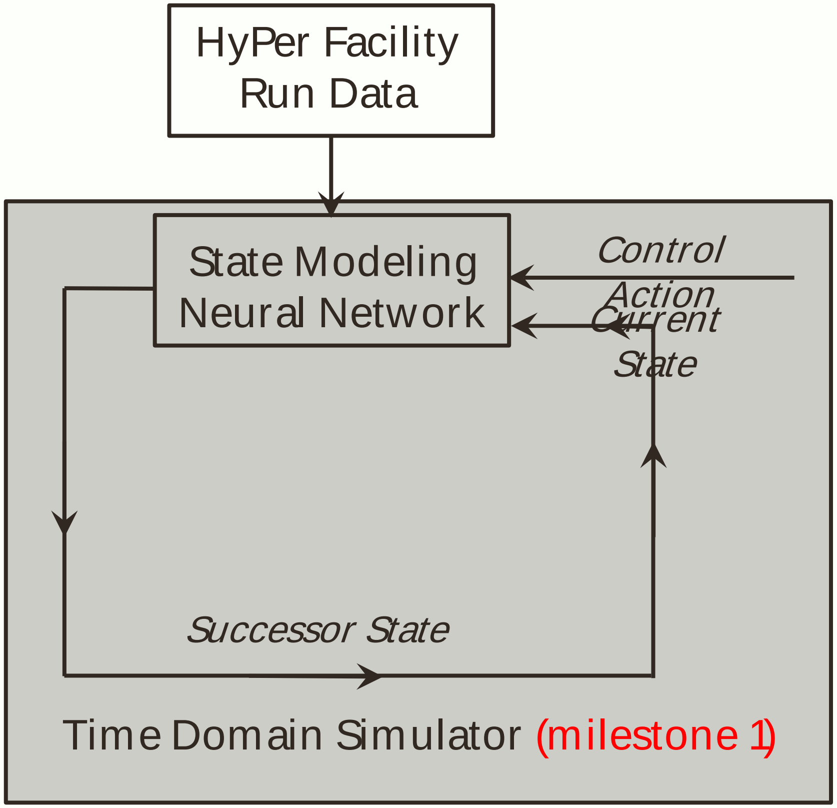

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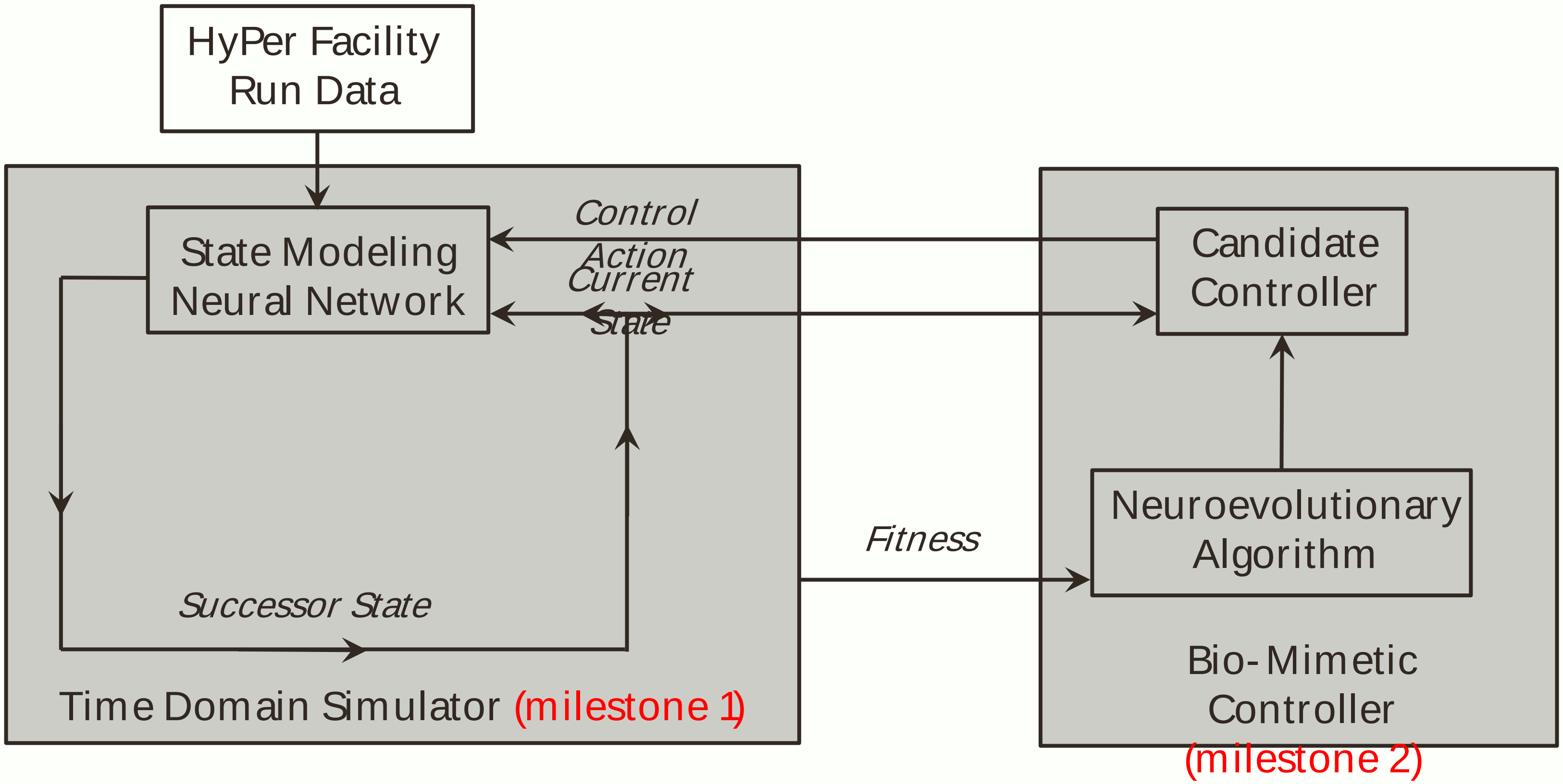

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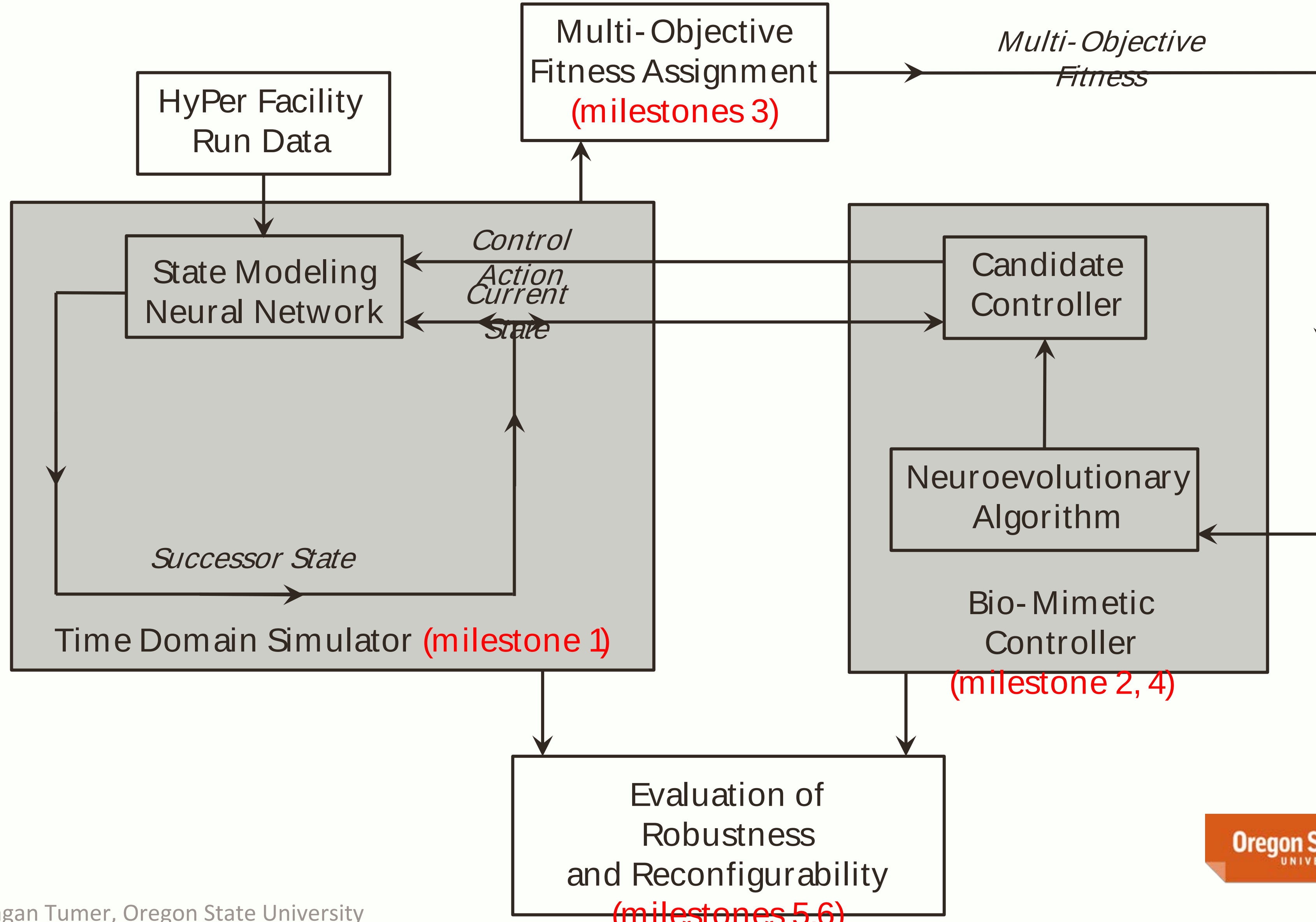

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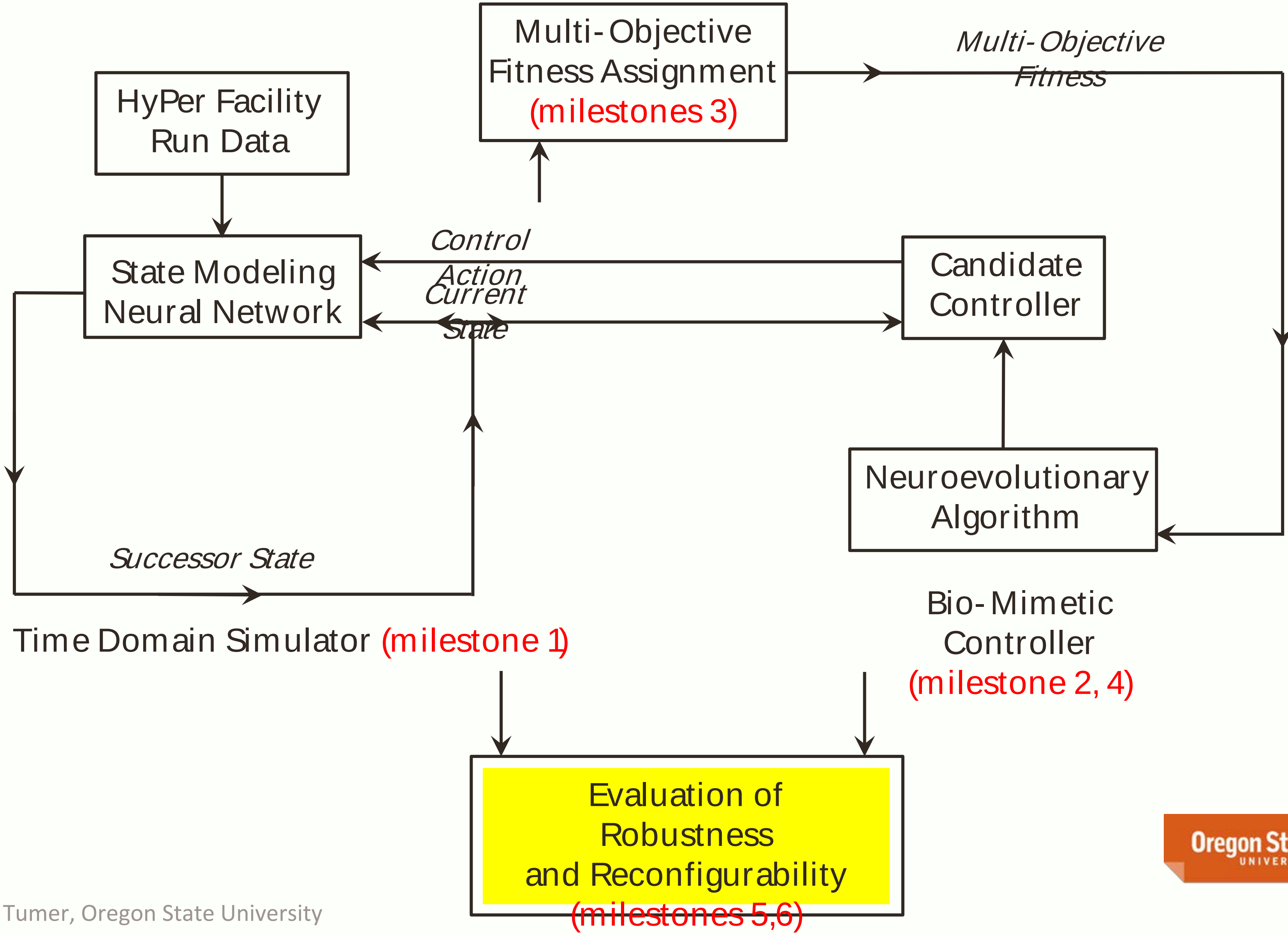

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Milestone 5: Robust Controller

- Train the controller for robustness to noise
  - Neural networks are known to be more robust to noisy inputs
  - Translate this robustness onto the controller

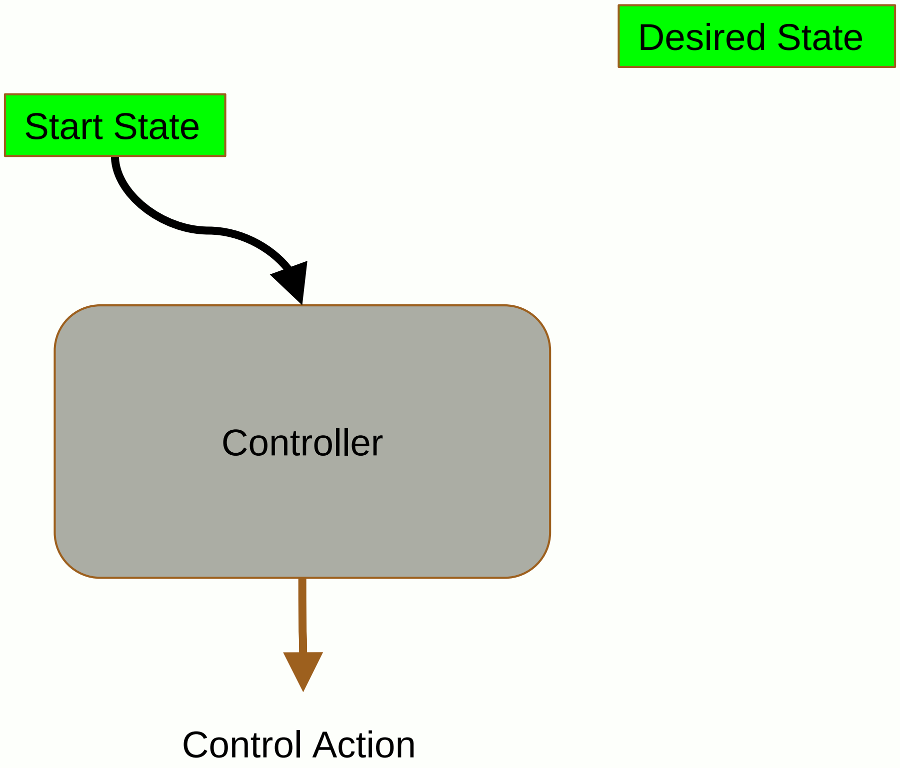
Deliverable: Train controller that are robust to actuator and sensor noise

Input and desired State trajectory

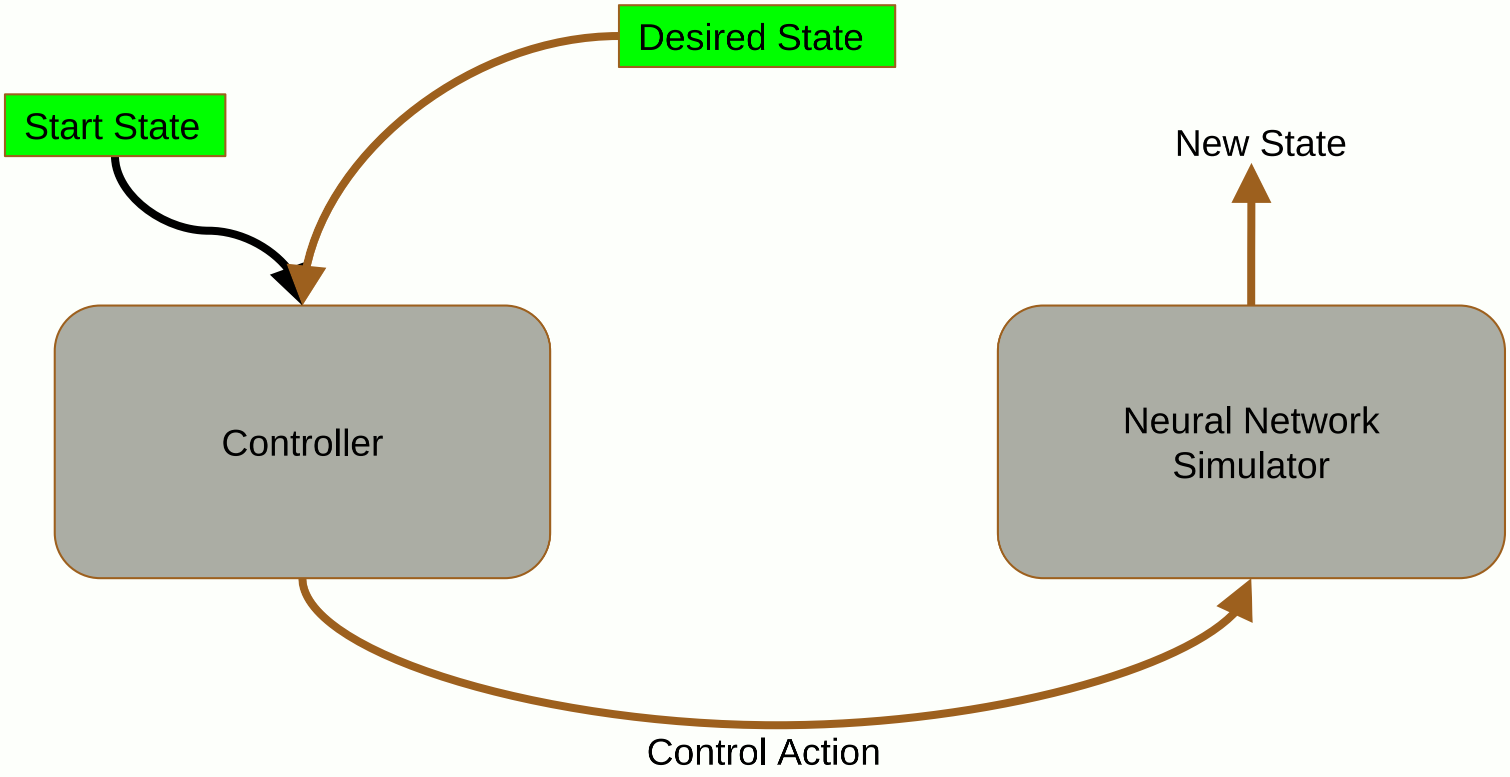
Desired State

Start State

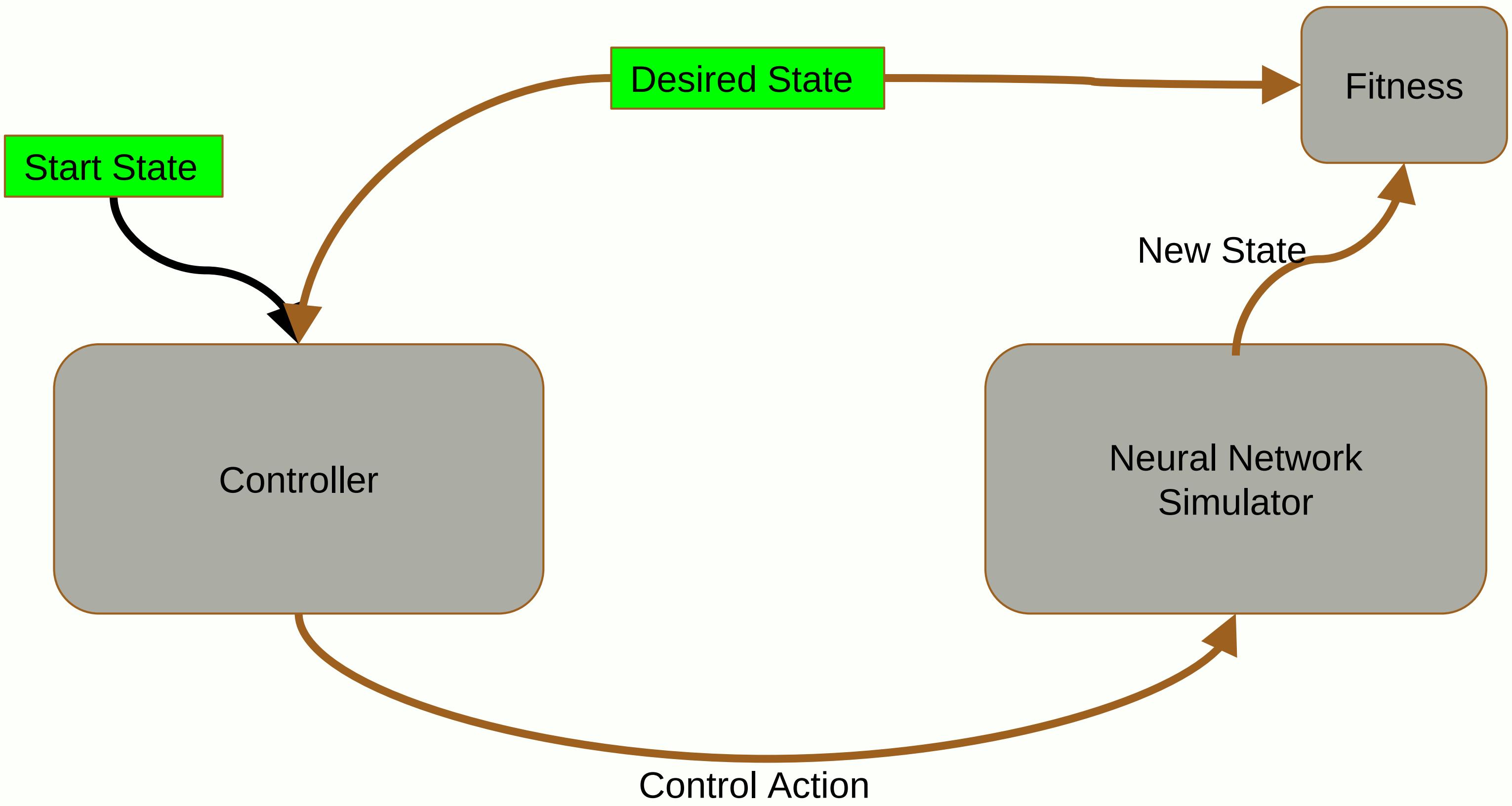
Add controller



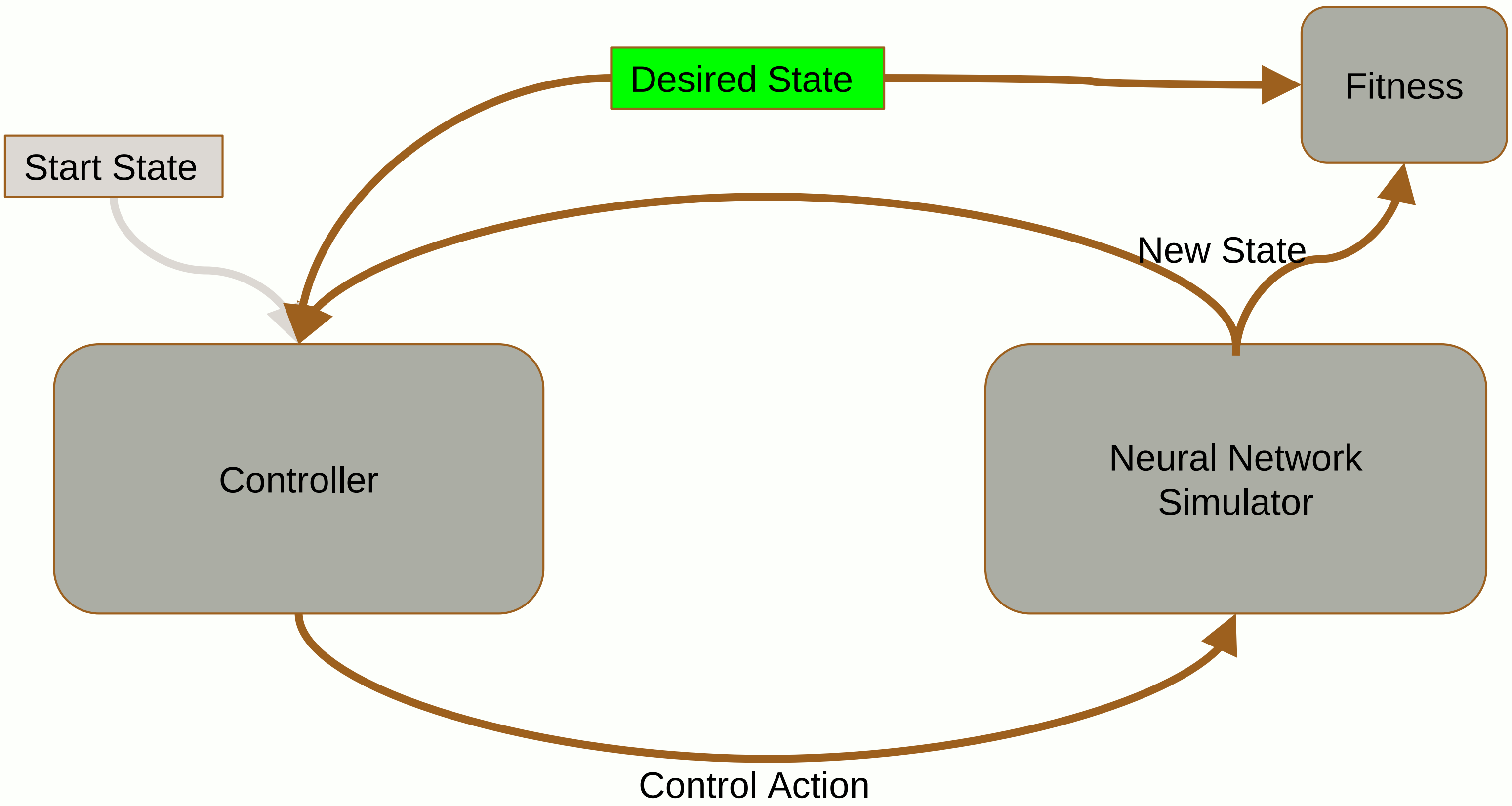
Add Simulator



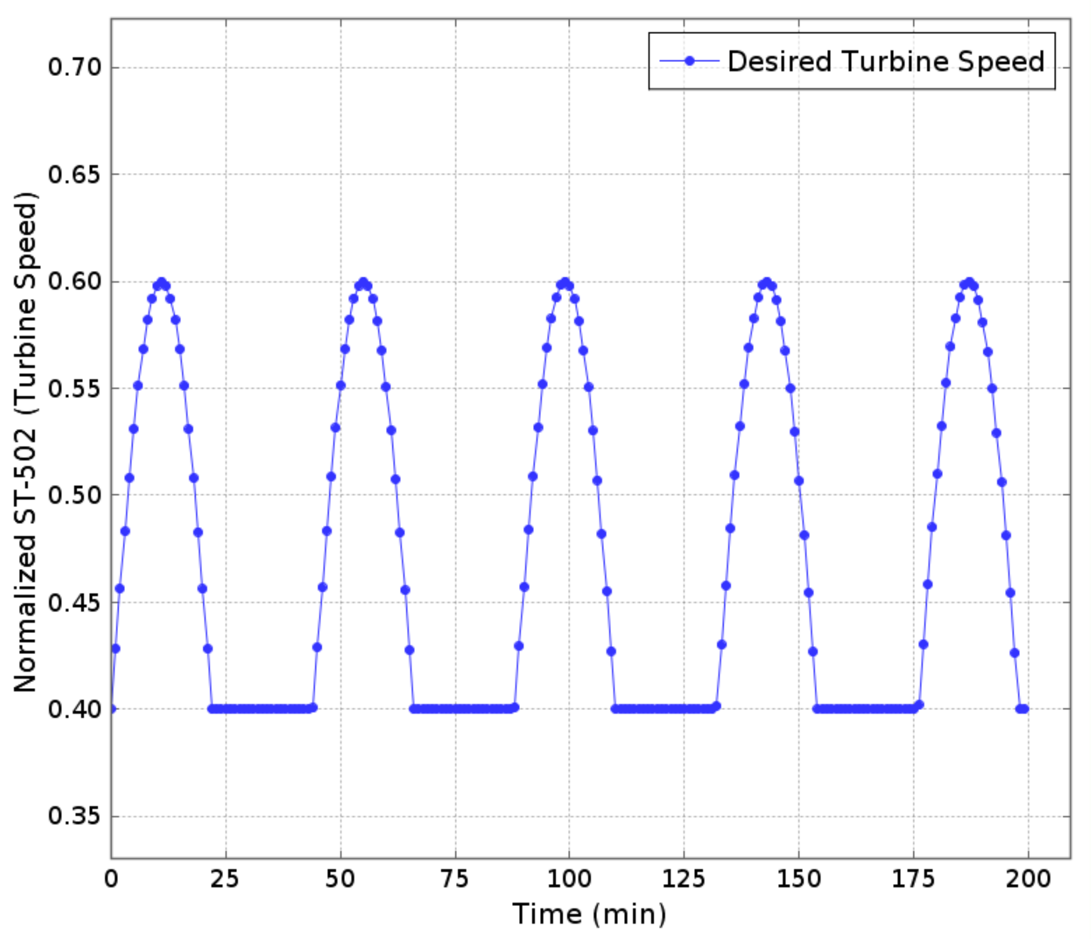
Compute fitness



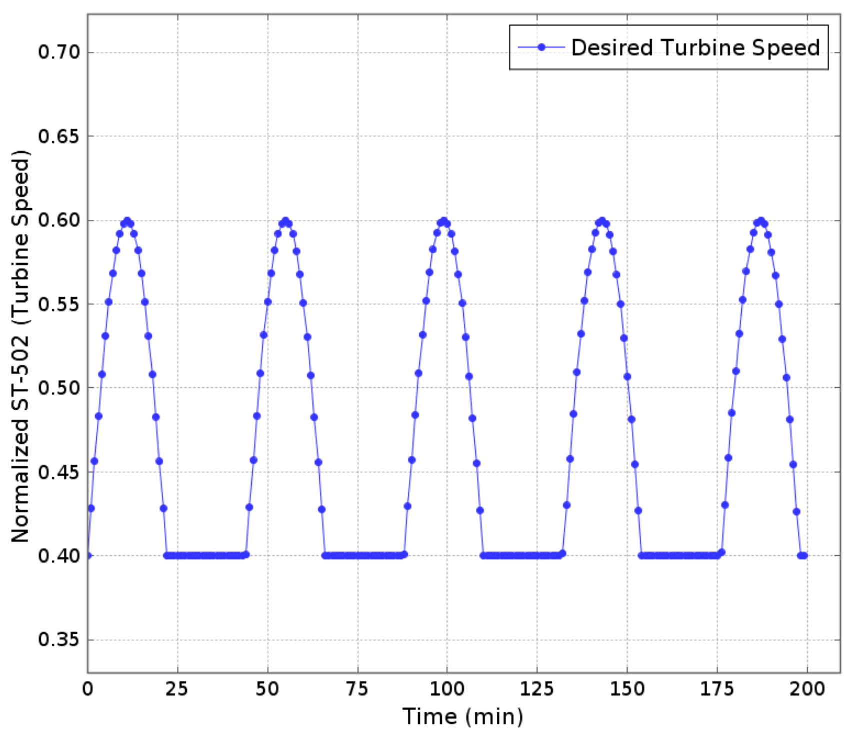
Close the Loop

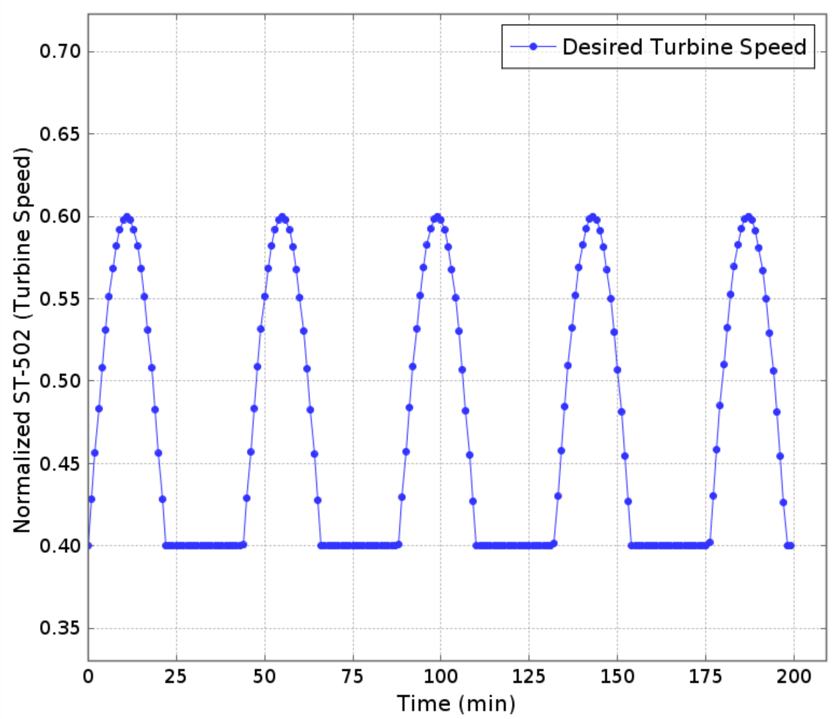


Desired Turbine profile



Controller trained with Perfect Information





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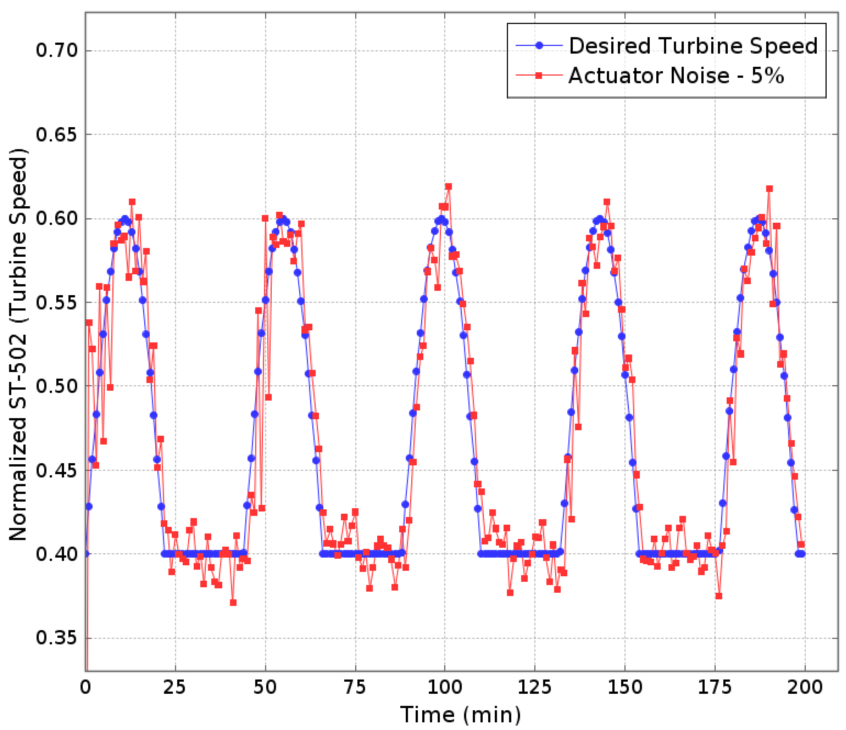

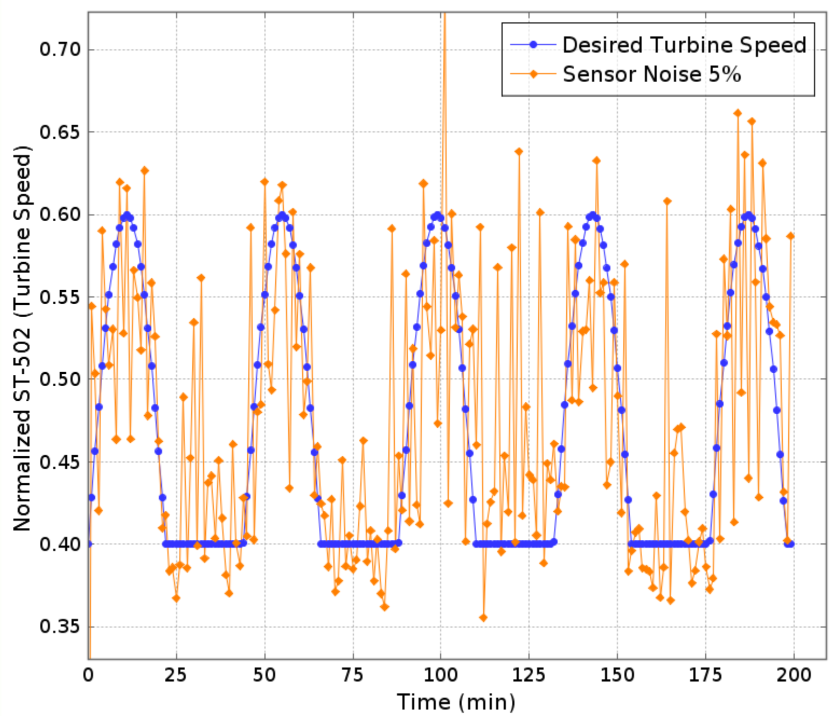

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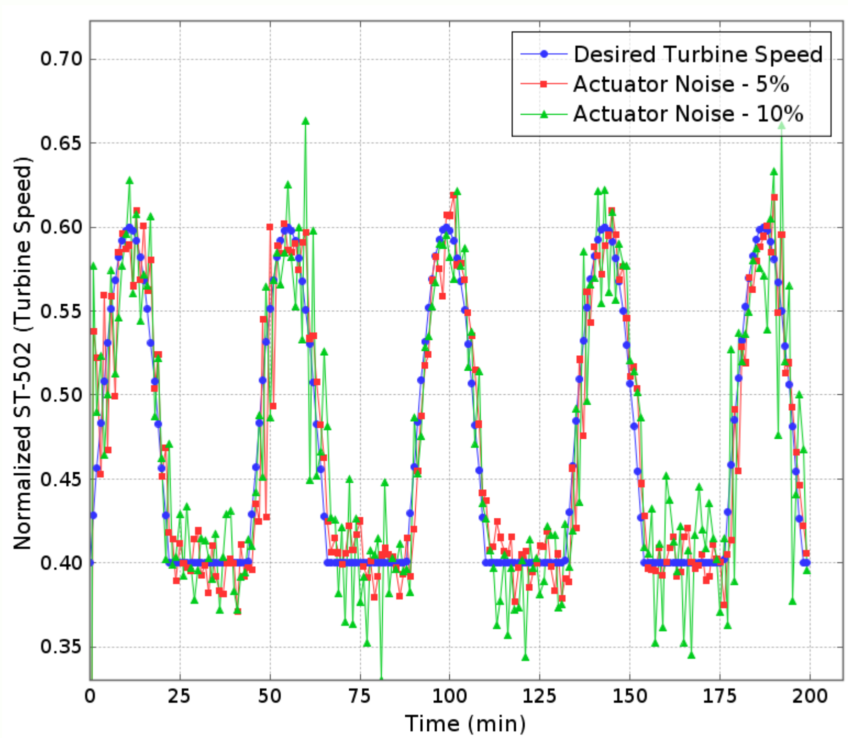

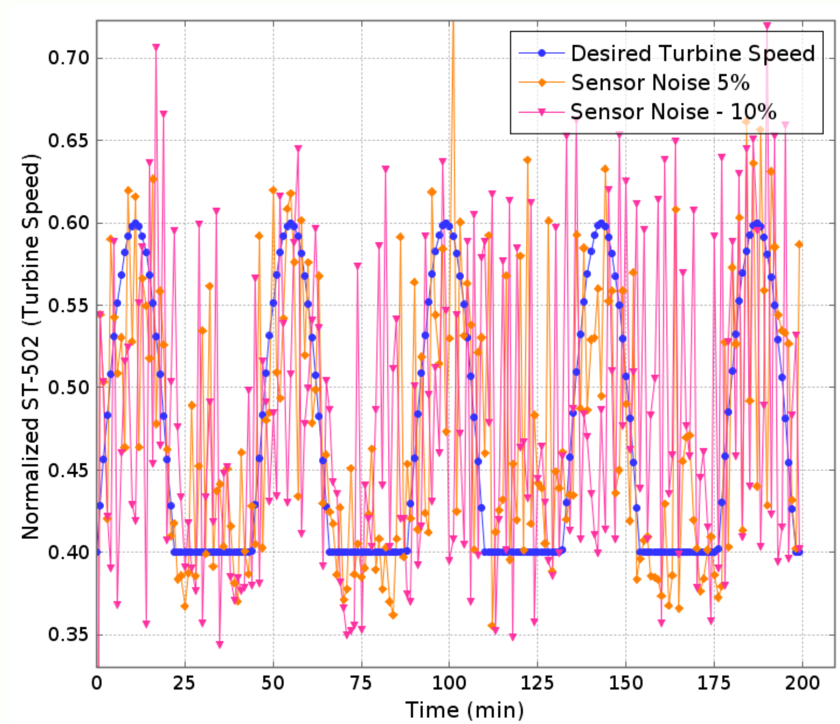

Training with Perfect Information Takeaways

- Not robust to noise
- Detrimentally rapid fluctuations in Turbine speed

Training with Perfect Information Takeaways

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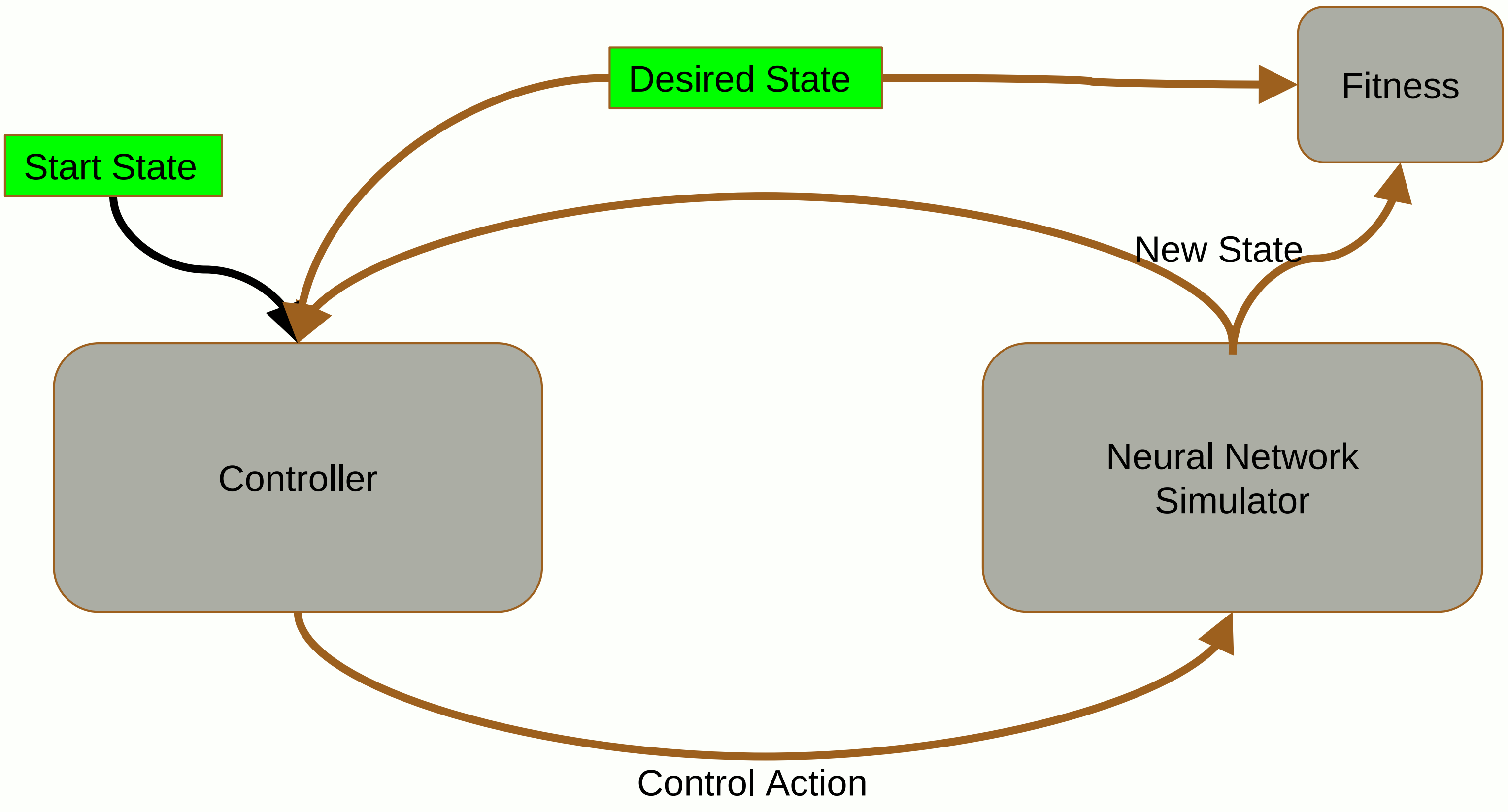
- Detrimentally rapid fluctuations in Turbine speed

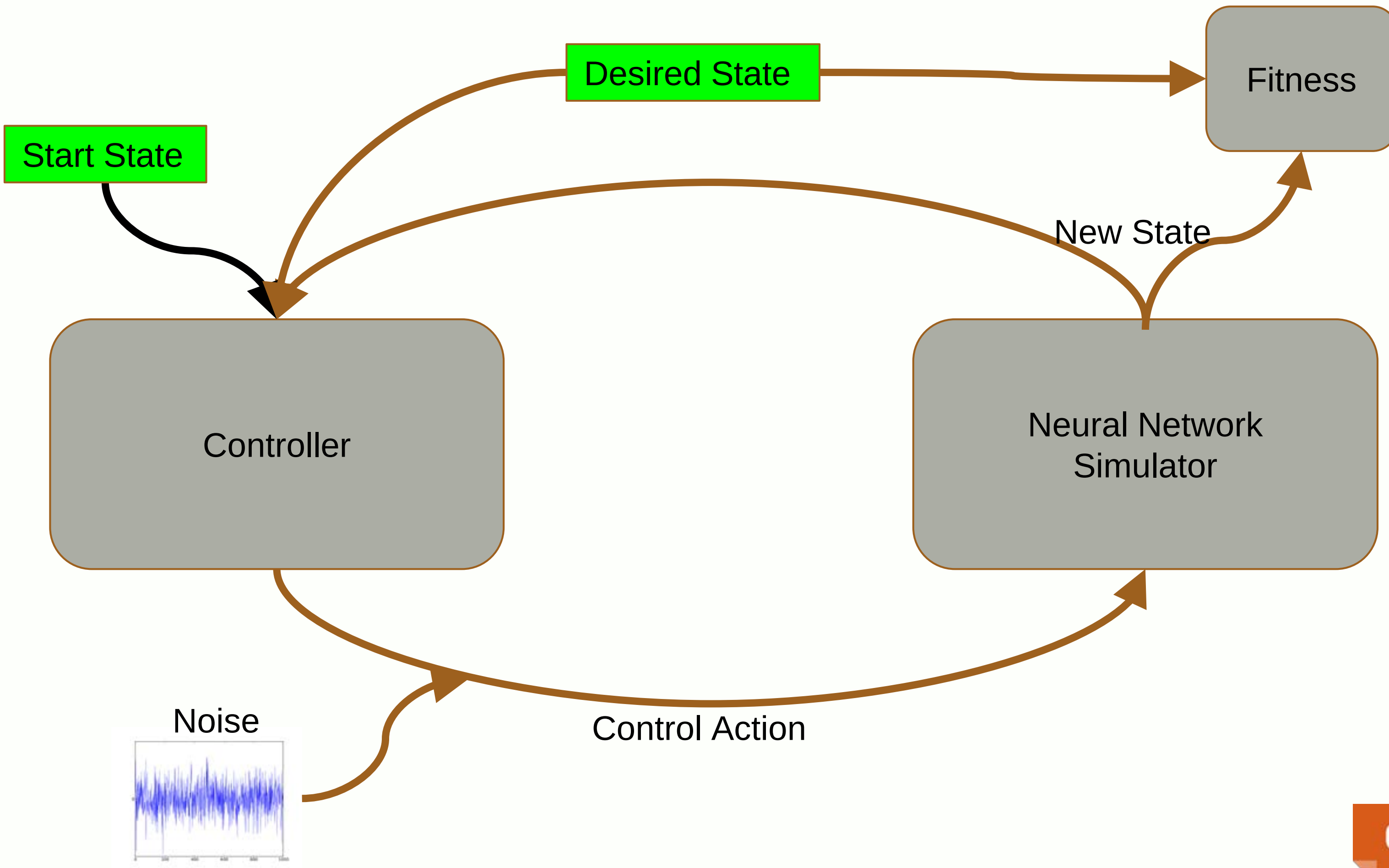
Solution:

- **Integrate noise in controller training scheme**
- **Gaussian noise**

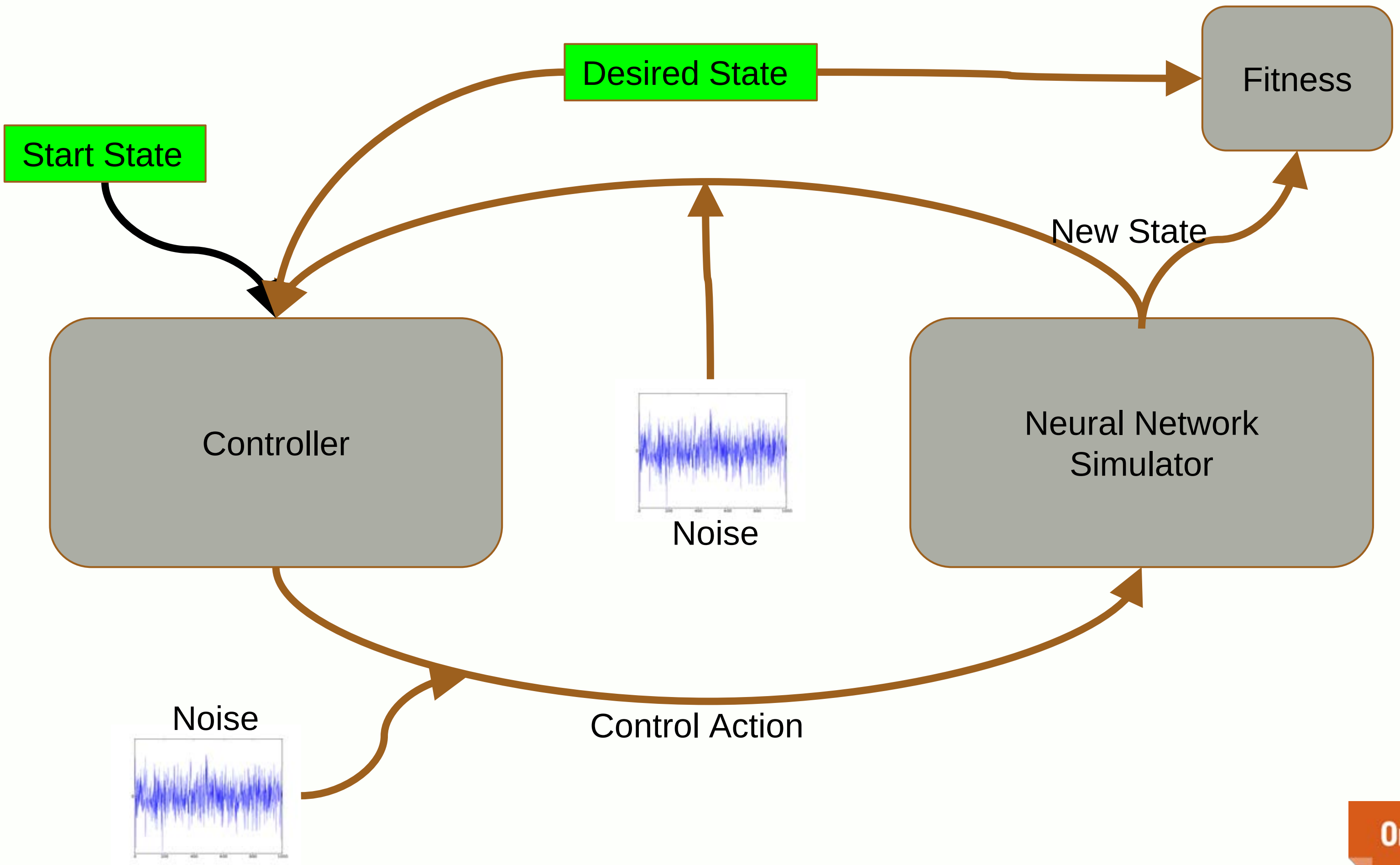
Controller Learning Setup with Perfect information



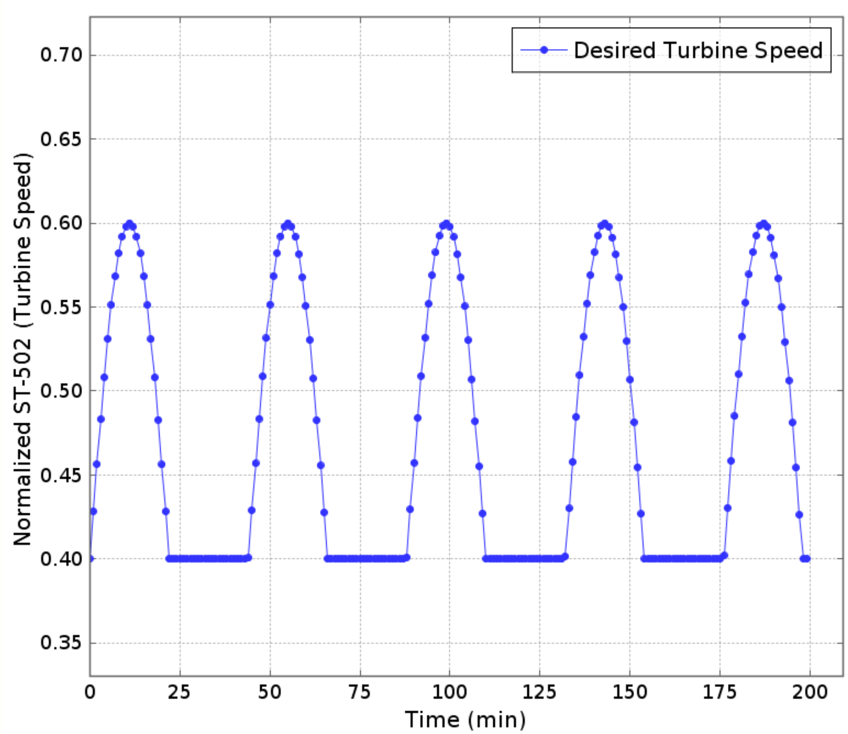
Ading Actuator Noise

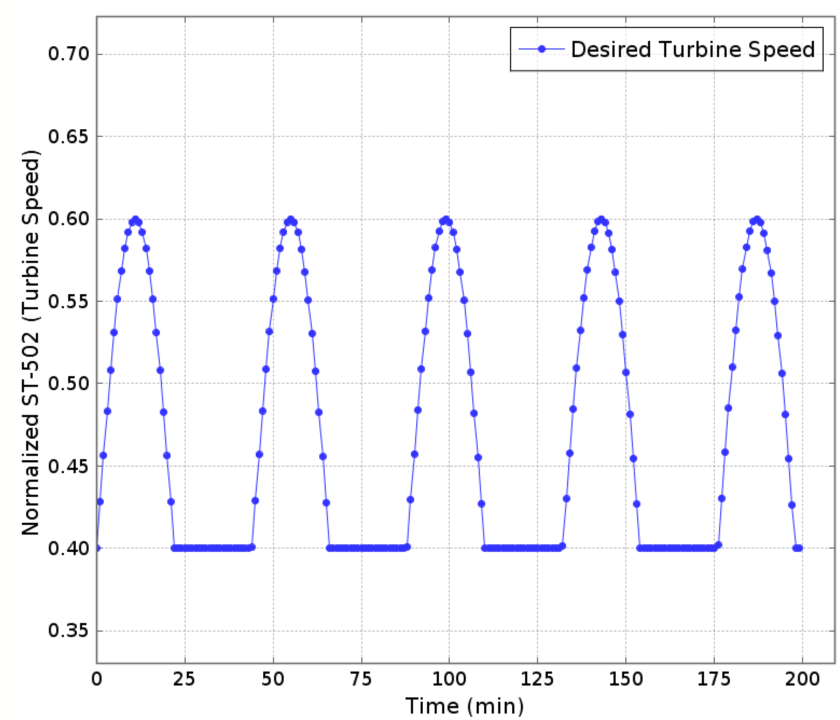


Adding Sensor Noise



Controller trained with 5% noise





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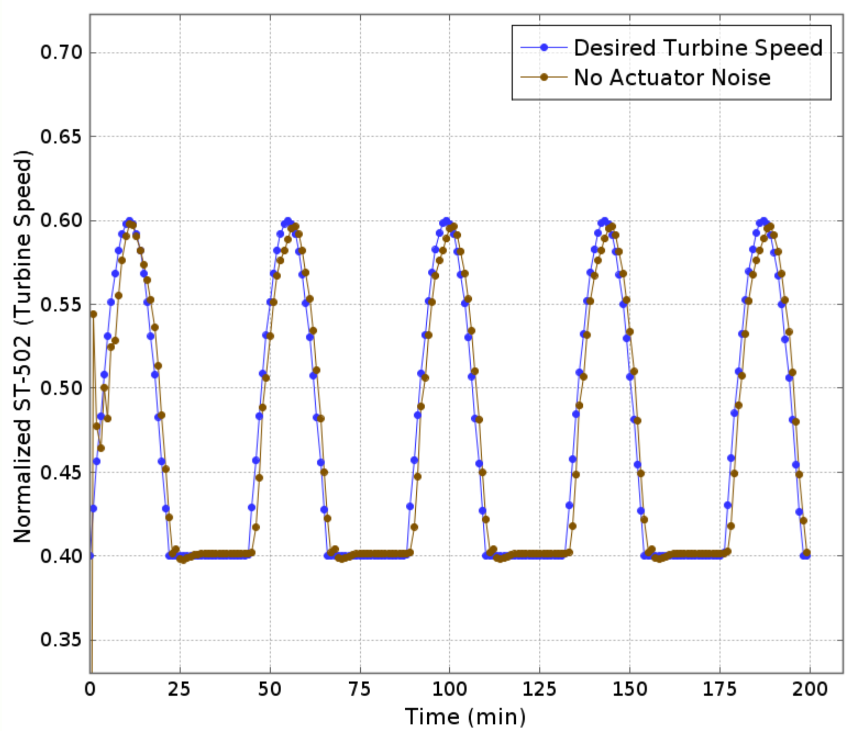

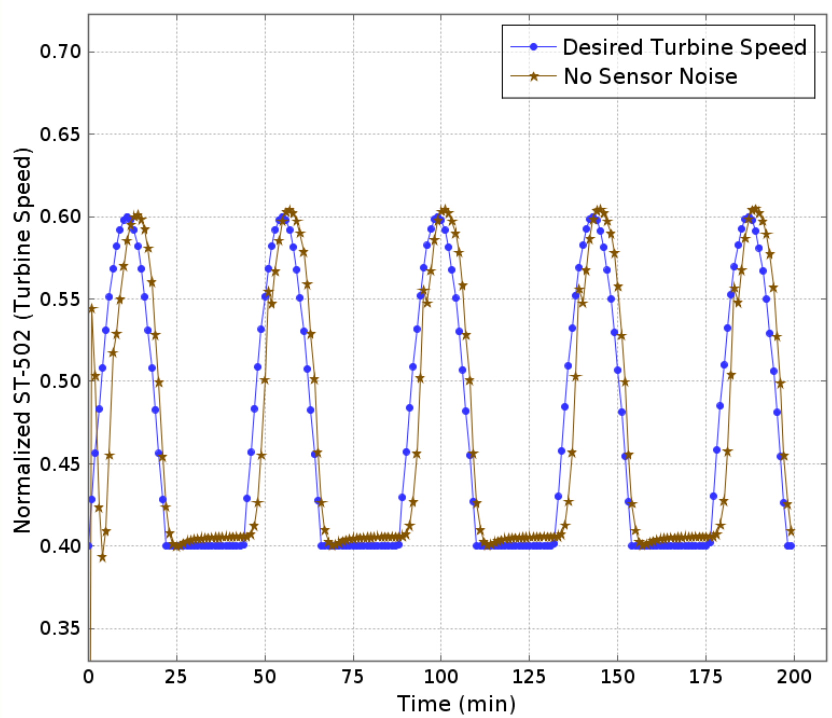

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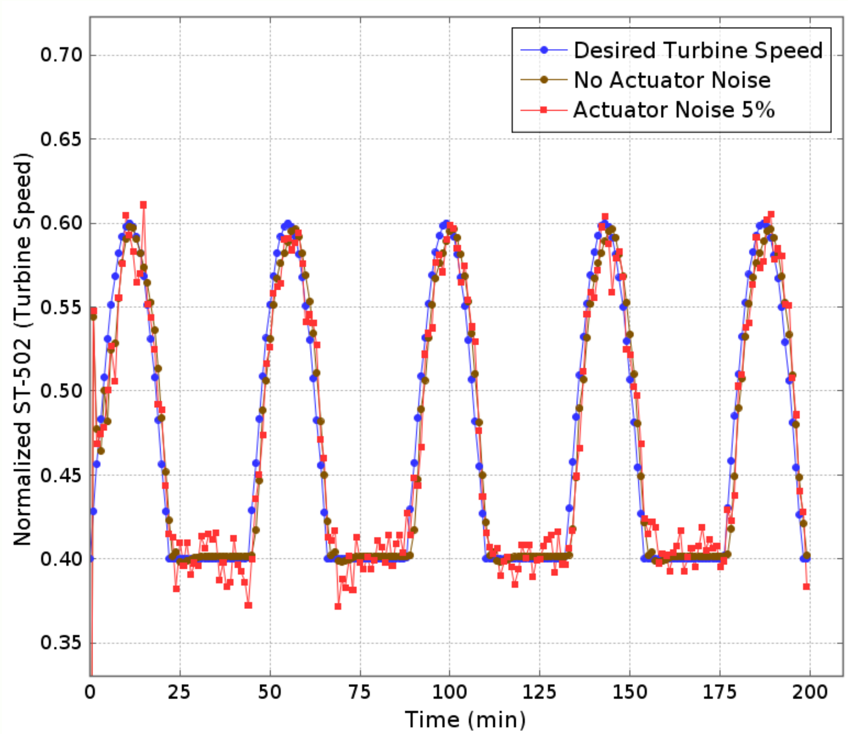

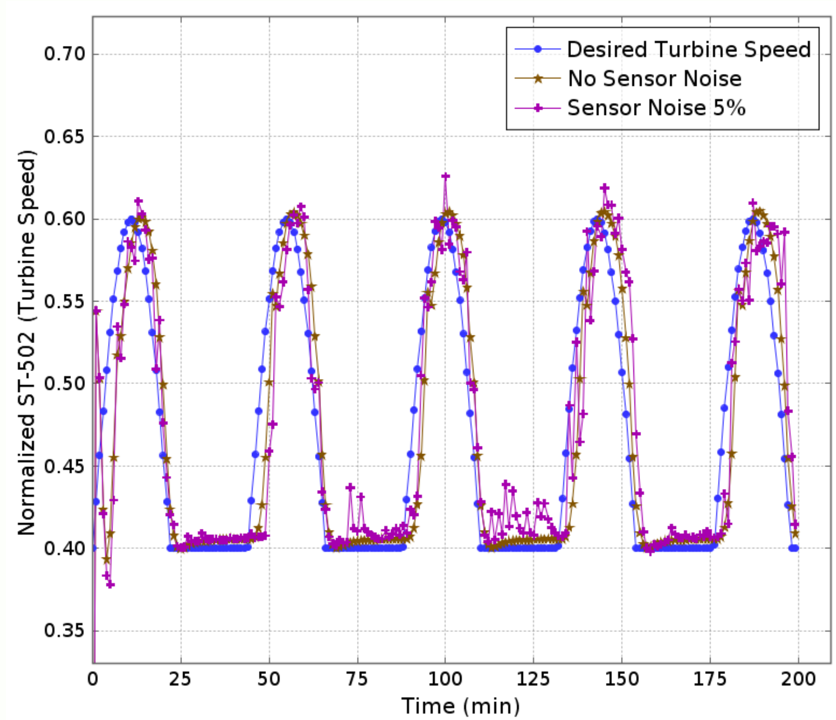

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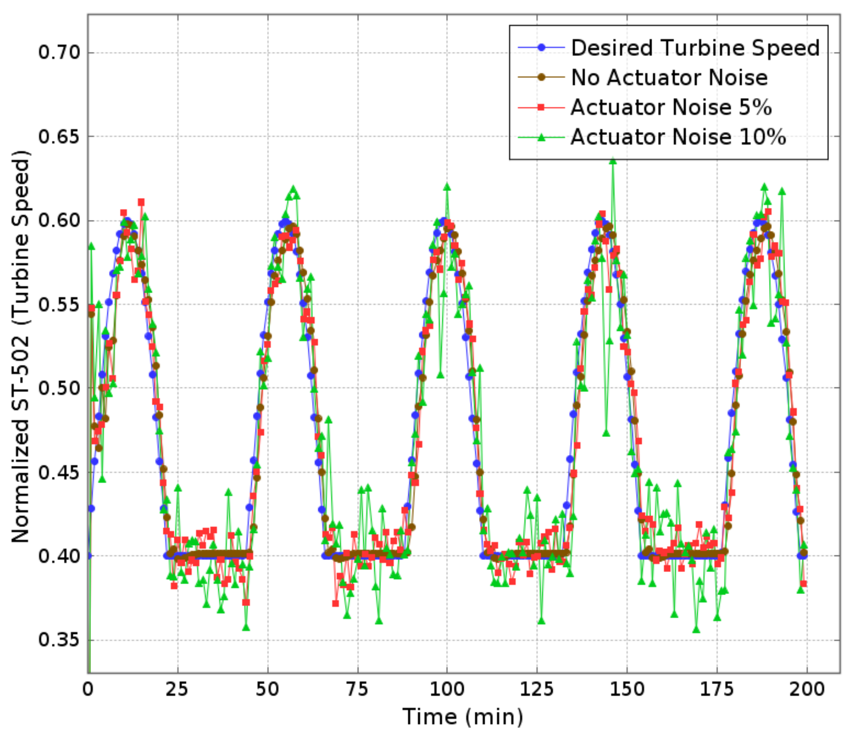

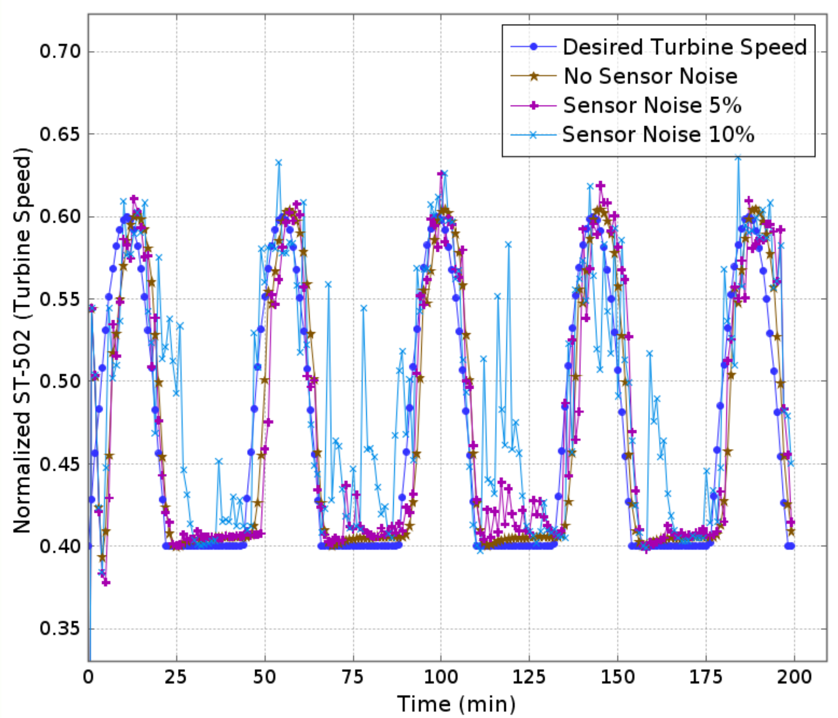

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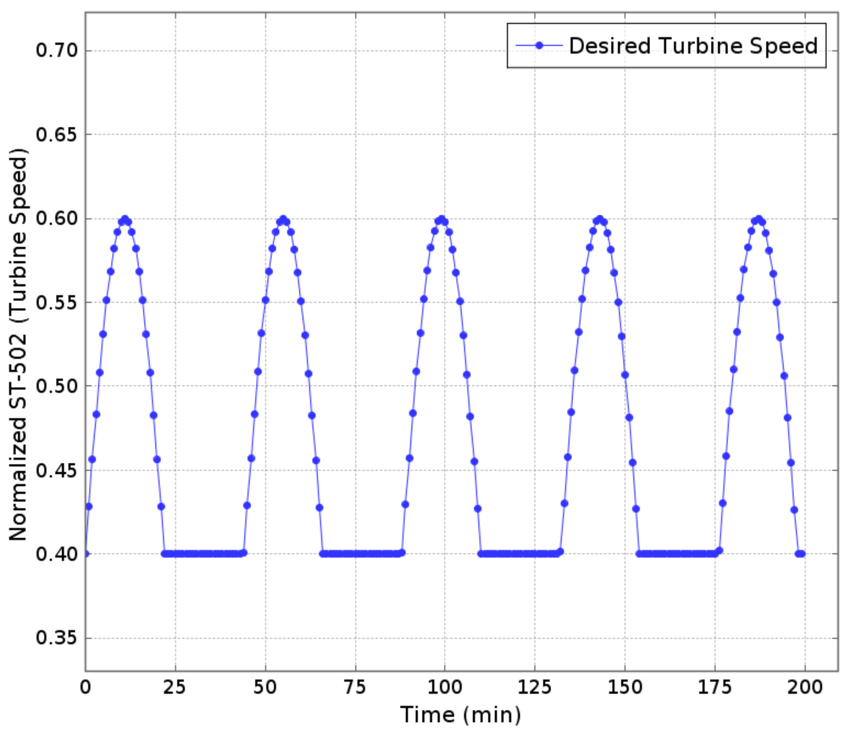
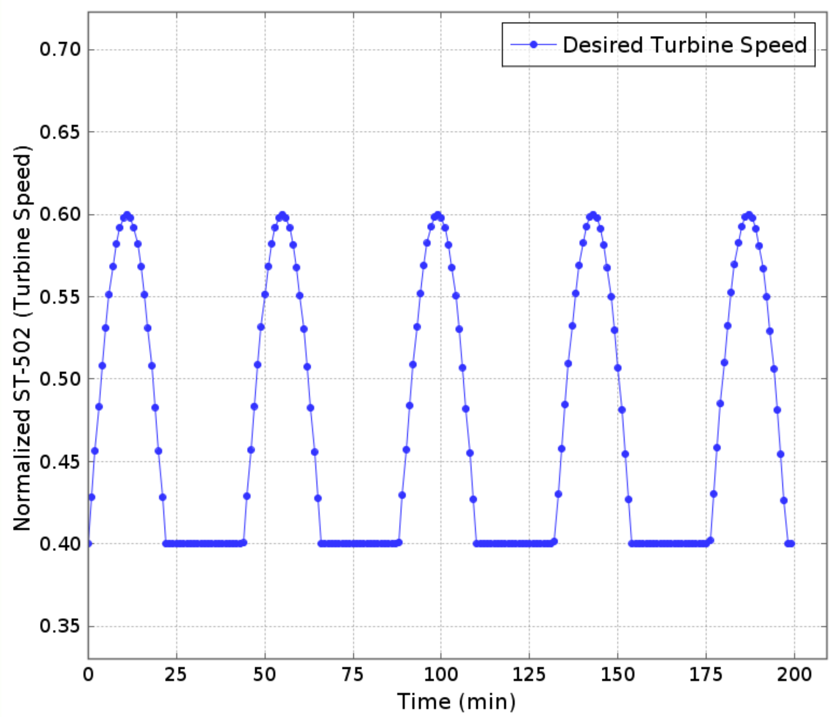
Controller trained with 10% noise





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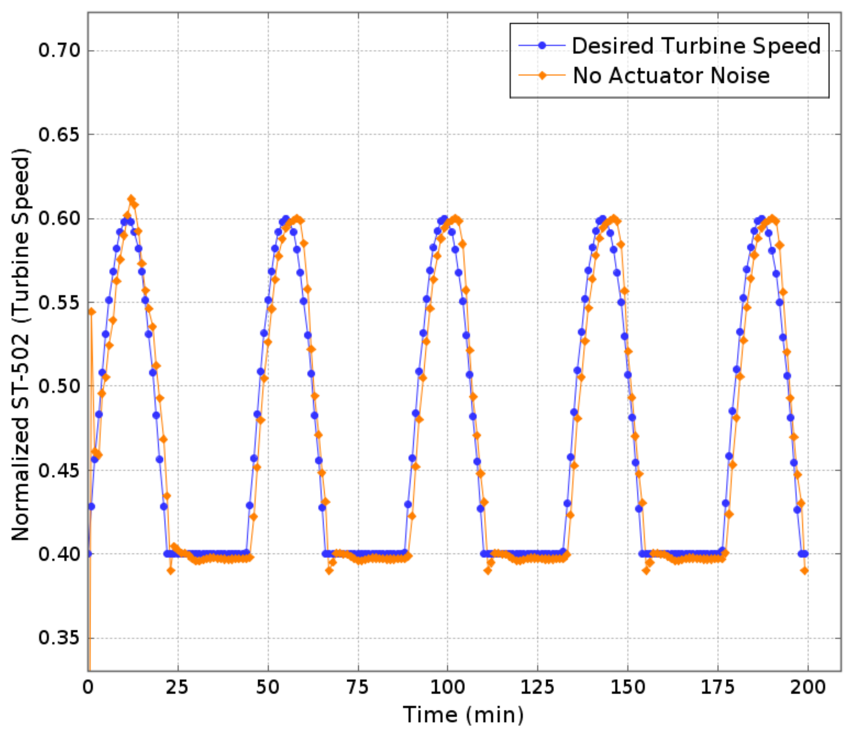

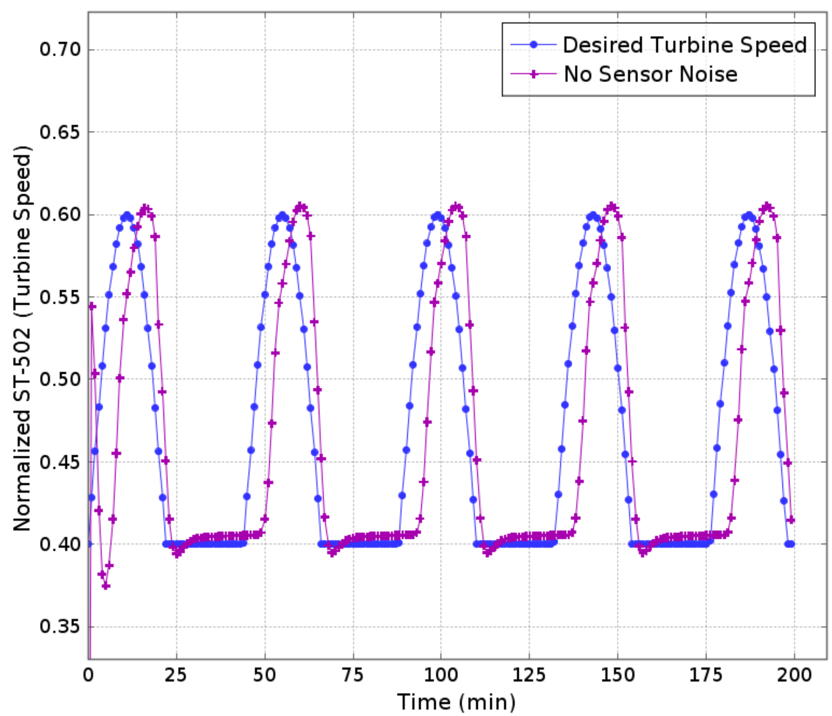

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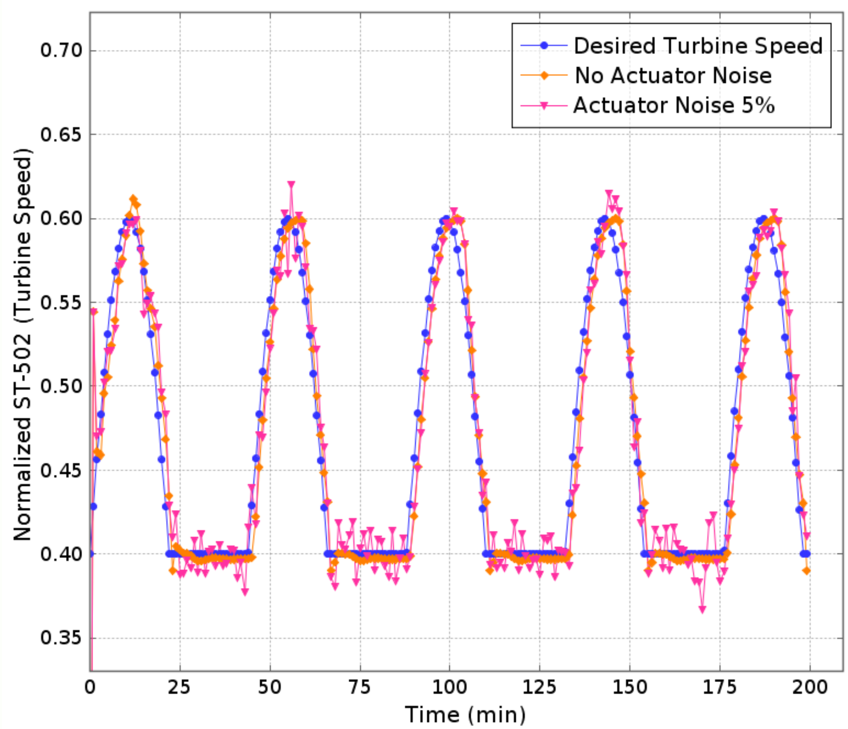

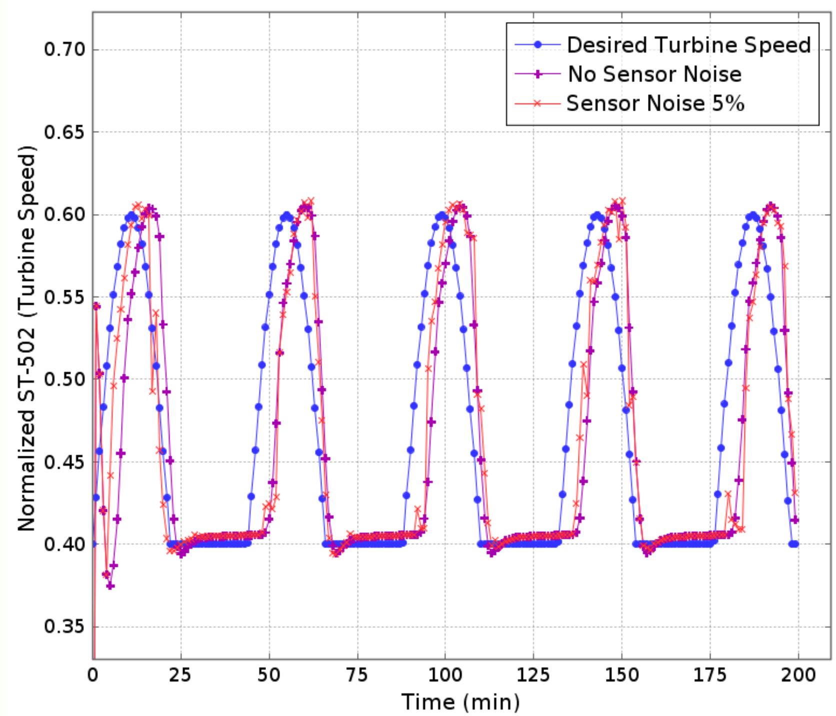

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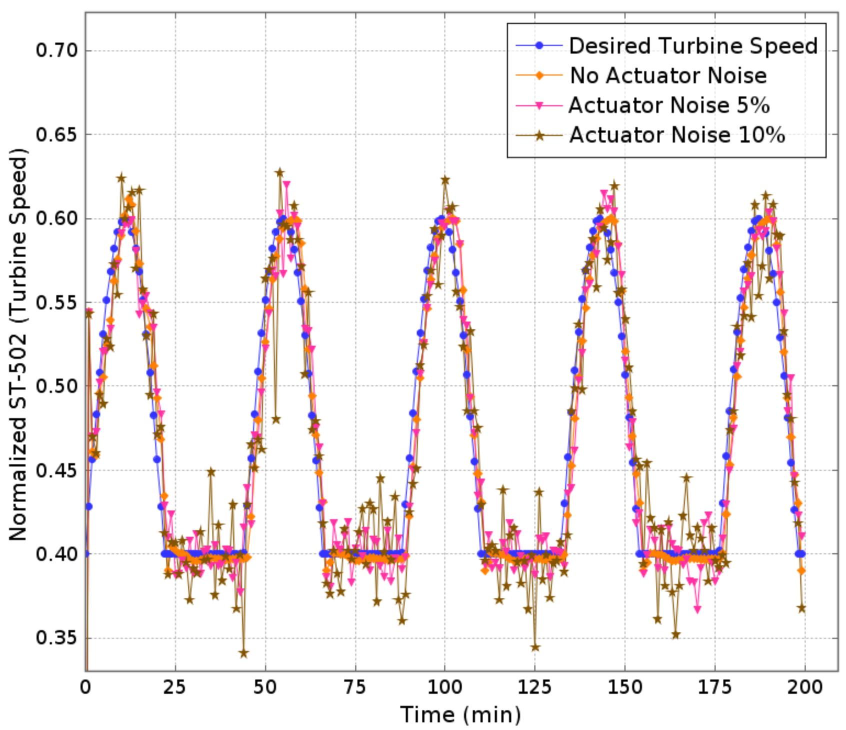

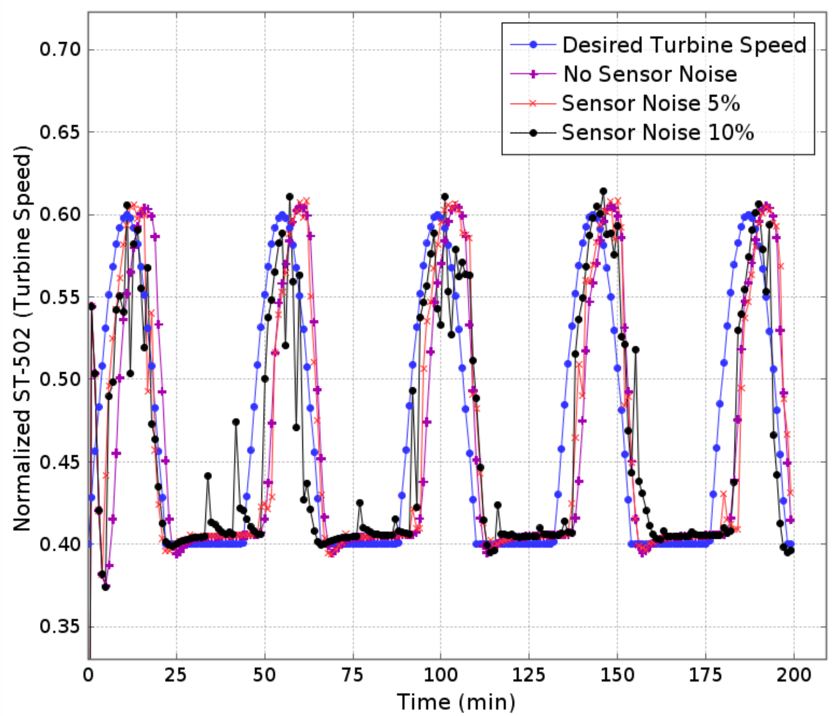

Training Neuro-Controllers With Noise

- Integrate Gaussian noise to controller and simulator output and train the controller in a loop
- Optimize for overall performance using an evolutionary algorithm

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Robust controller capable of handling noise for both sensors and actuators

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Milestone 6: Reconfigurable Controller

- Reconfigurable controller that can adapt to fluctuating demands
  - Demand profile normally periodic and stable
  - Not always!
  - Special circumstances can briskly alter demand profile

Need: **Need controller than can reconfigure to demand, on demand!**

Let’s look at reconfigurability

- Adapt behaviors to different performance profiles
- Rudimentary solution
  - Enumerate different performance profiles
  - Learn specific controller for them
  - Pick a controller, based on performance profile required

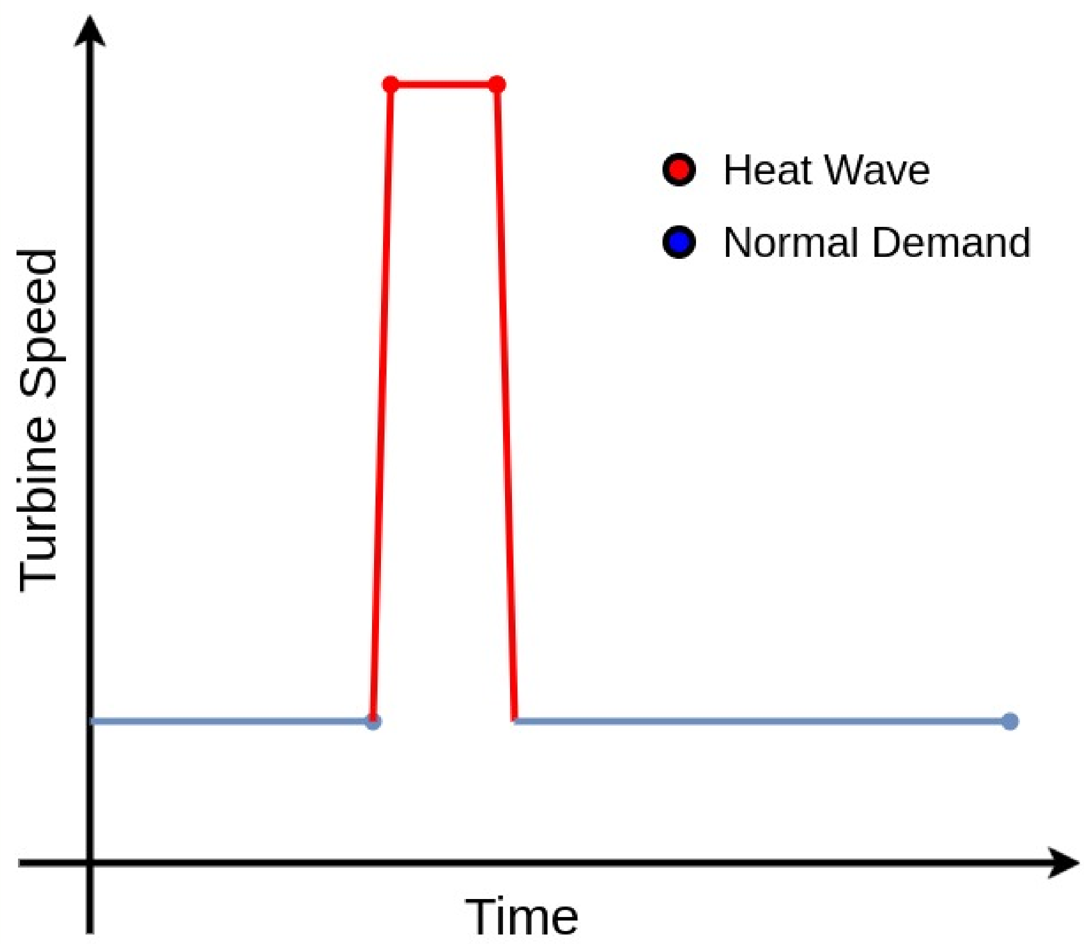
Let's look at reconfigurability

- Adapt behaviors to different performance profiles
- Naive solution
  - Enumerate different performance profiles
  - Learn specific controller for them
  - Pick a controller, based on performance profile required

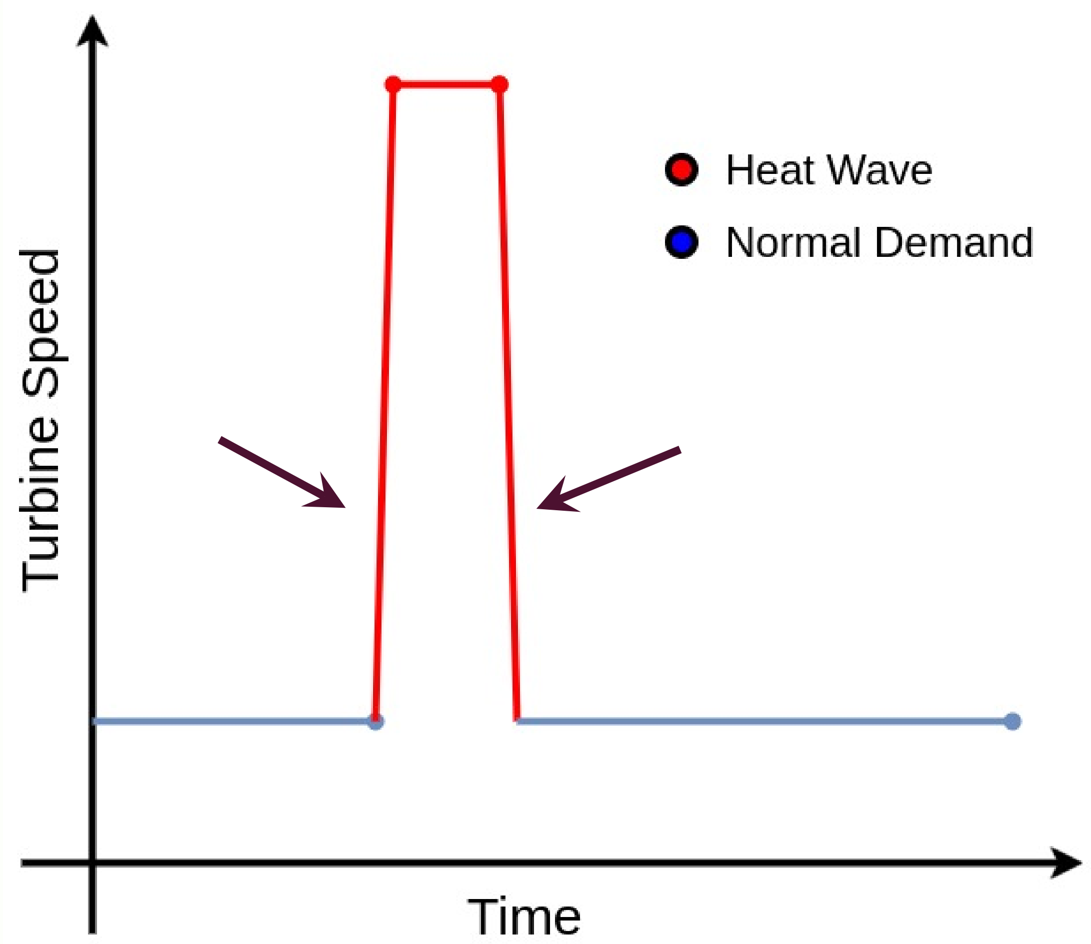
PROBLEM:

- Enumeration intractable
- Ignores dynamics

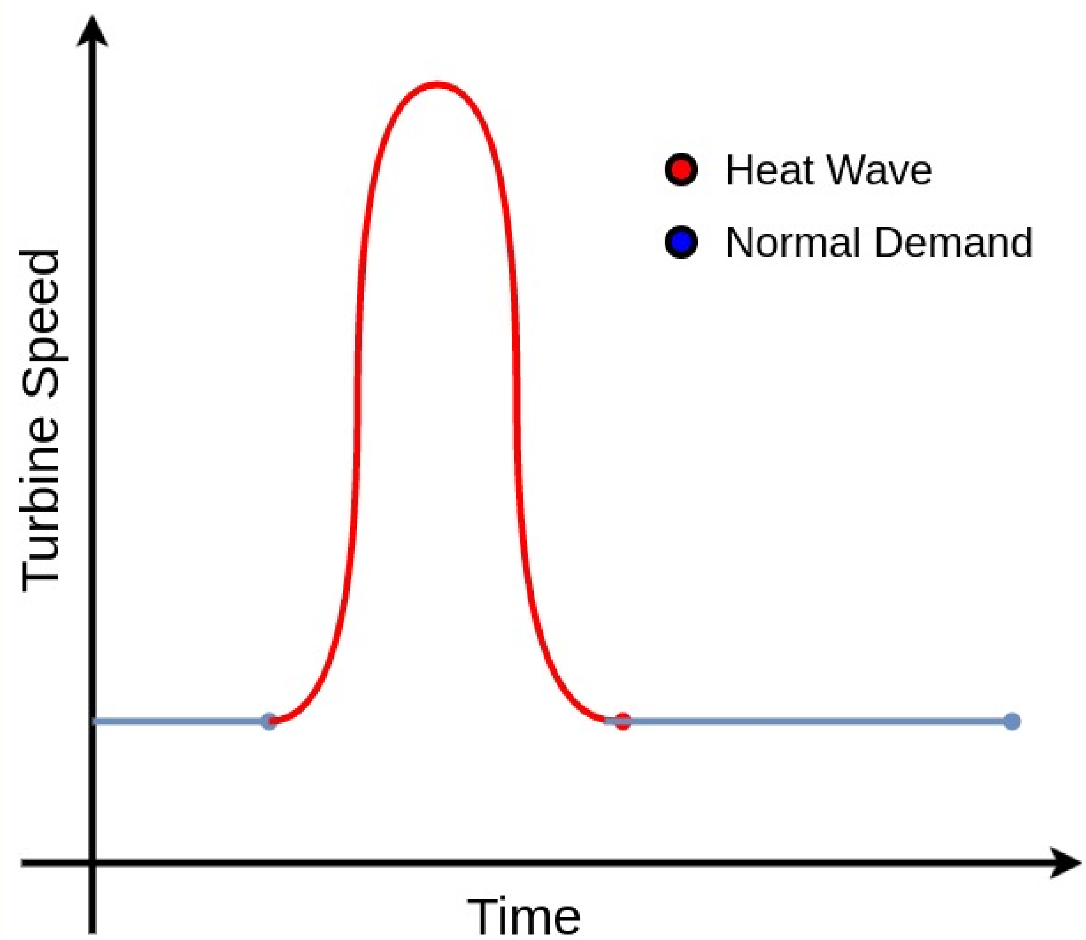
How may that look like?



Problematic transitions in dynamic space



A better transition



Need to account for dynamics

- Non-Markovian state
- Need to account for path taken to get there and where it's headed next

One possible solution is:

Need to account for dynamics

- Non-Markovian state
- Need to account for path taken to get there and where it’s headed next

One possible solution is:

- **MEMORY**
  - Consider path taken to get there and direction headed
  - Controller utilizes this information to reconfigure efficiently

Memory-Augmented Controller

- Use **Memory-Augmented Neural Networks (MANNs)**
    - Neural Networks augmented with memory
    - Deep Neural Network (perhaps the deepest kind)
    - “External” Memory
    - Capture long-term dependencies in the data
    - Capture variable term dependencies in the data

Two Major Types of MANNs

1. Small Memory tied with computation
    a. Long Short term Memory (LSTM)
    b. Gated Recurrent Unit (GRU)
2. Big external Memory Bank that is interacted with
    a. Neural Turing Machine (NTM)
    b. Differential Neural Network (DNC)

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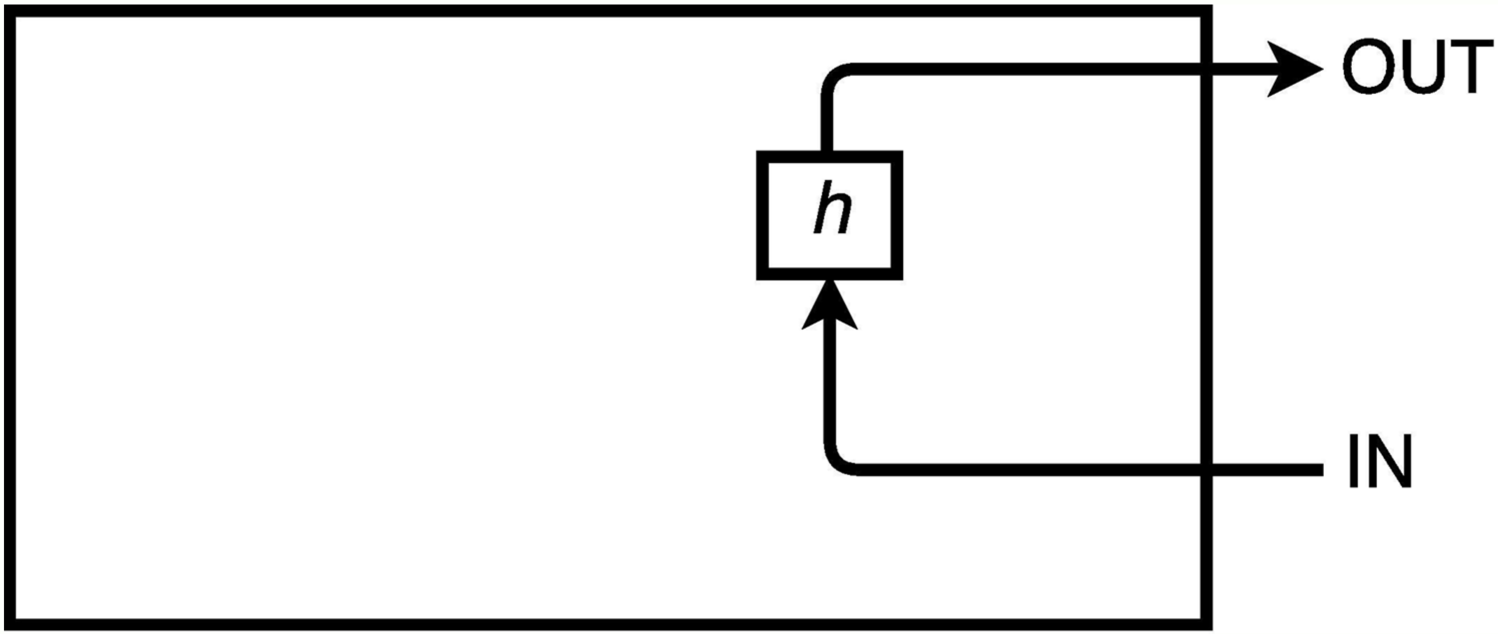
Solution:

- Combine the best of both worlds!

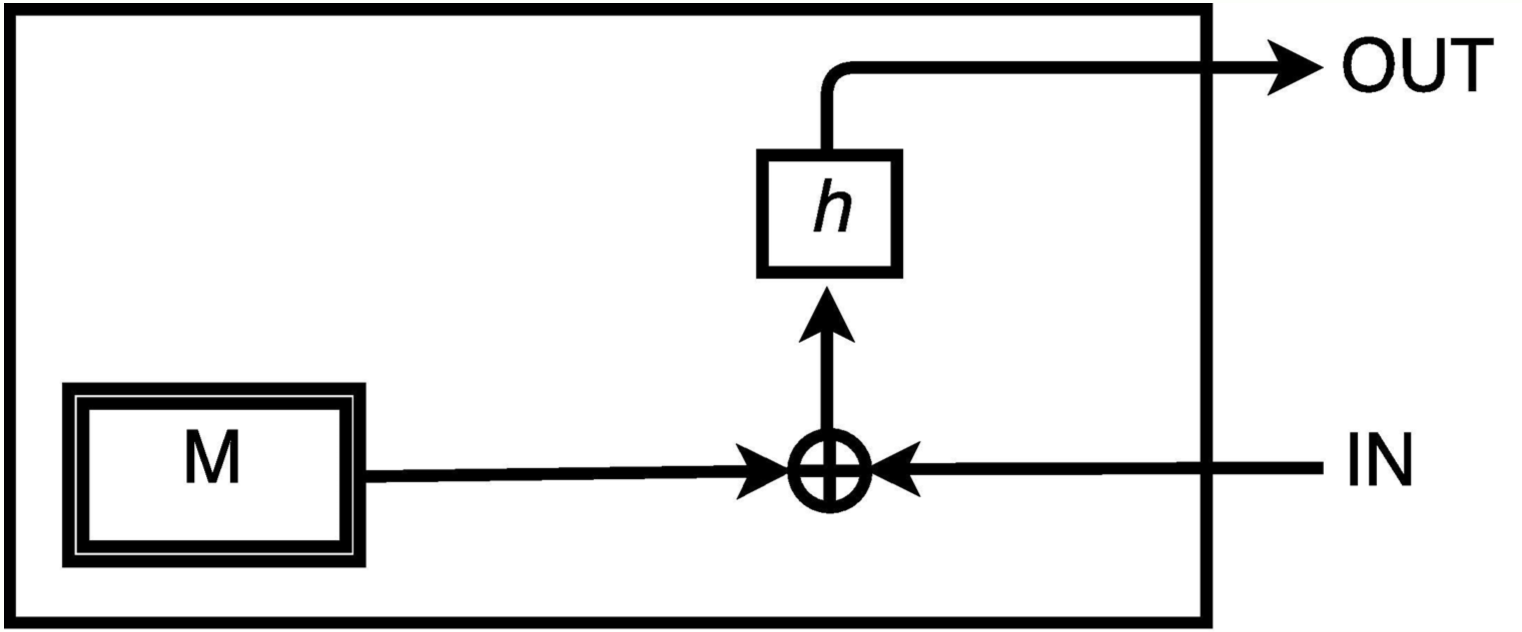
Gated Recurrent Unit with Memory Block (GRU-MB)

- Detached memory from computation
- Retained adjustable size tractable to train

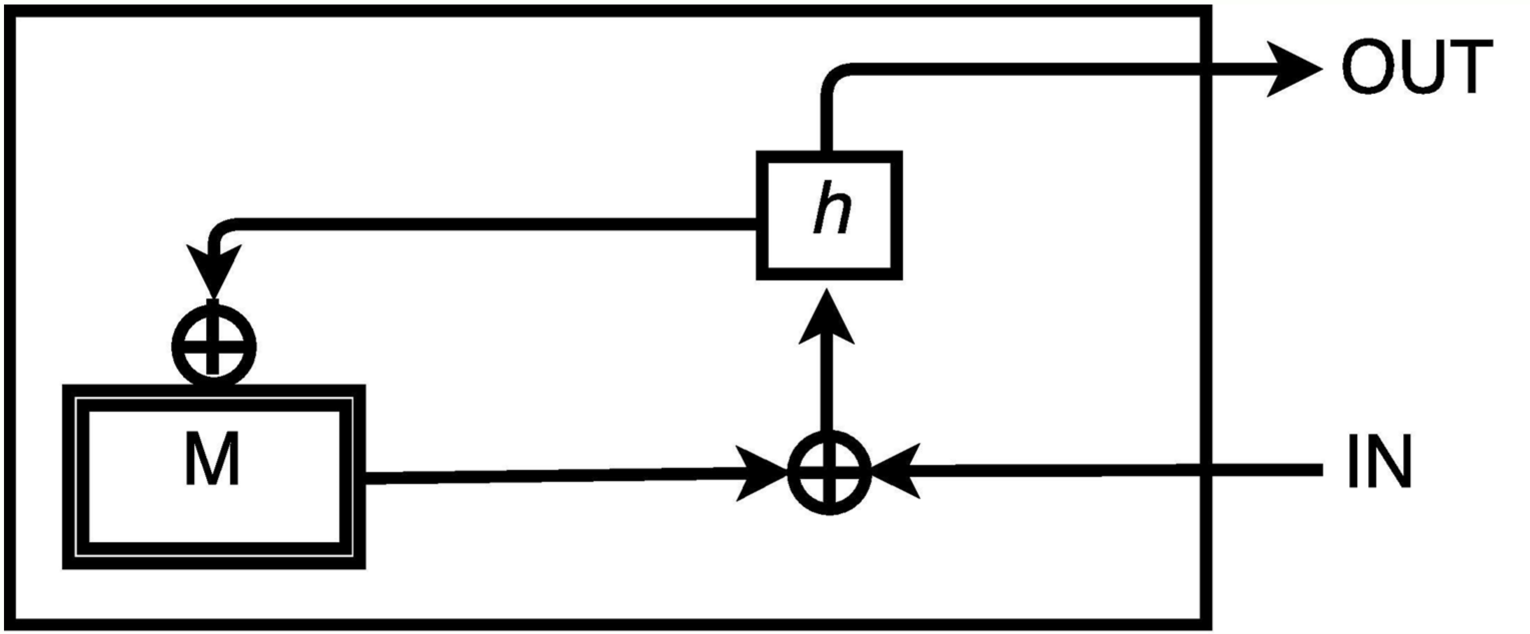
Feedforward Net



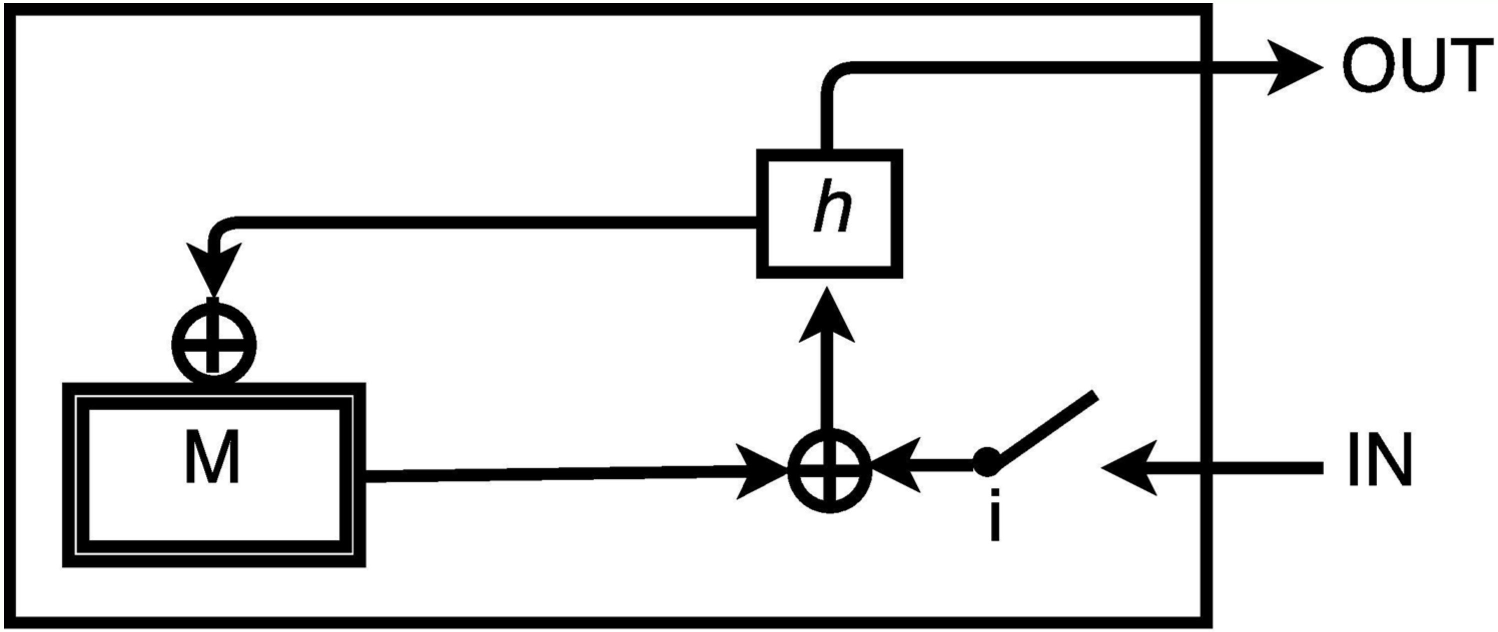
Read from external memory



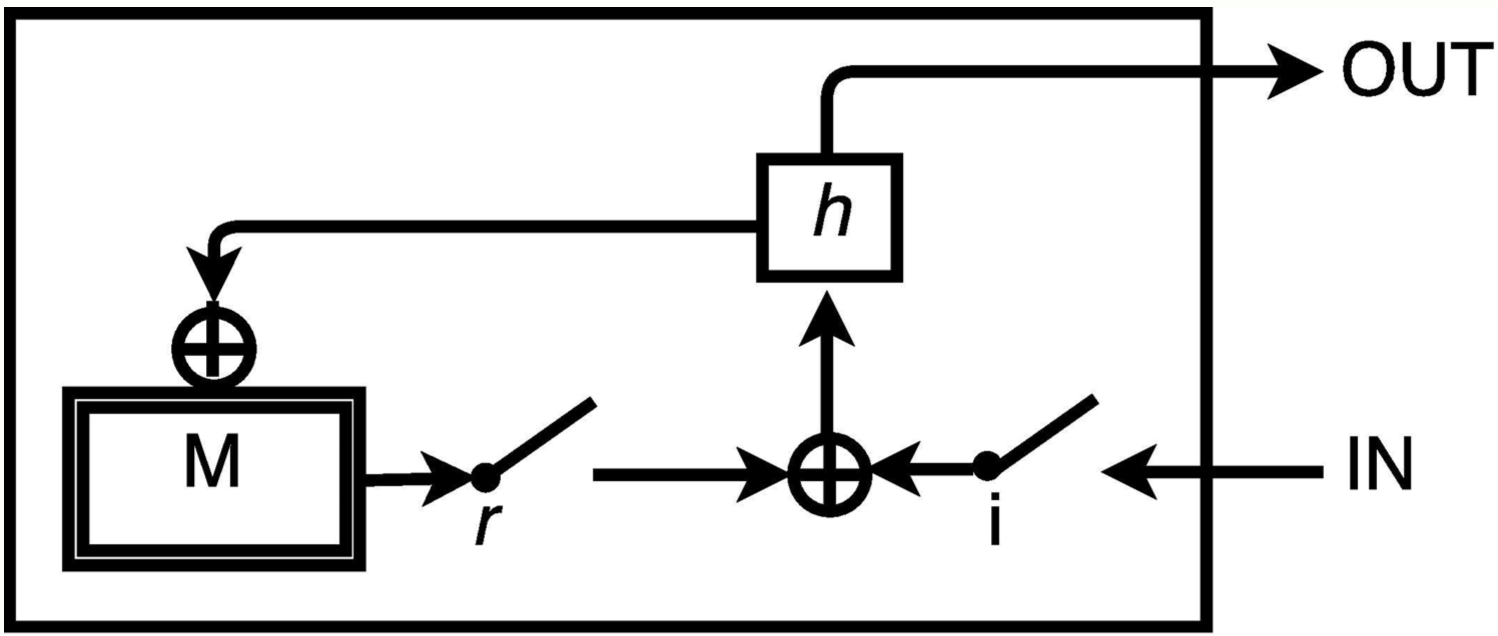
Write to memory



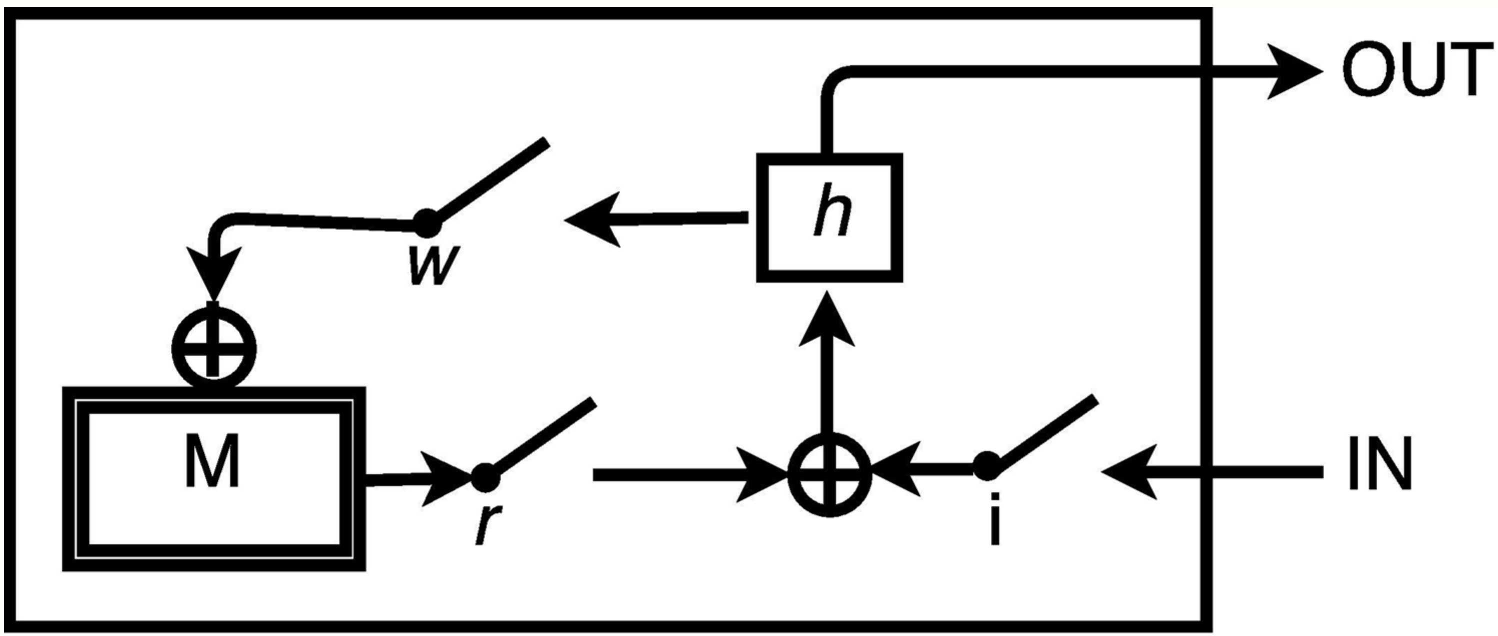
Gate Input



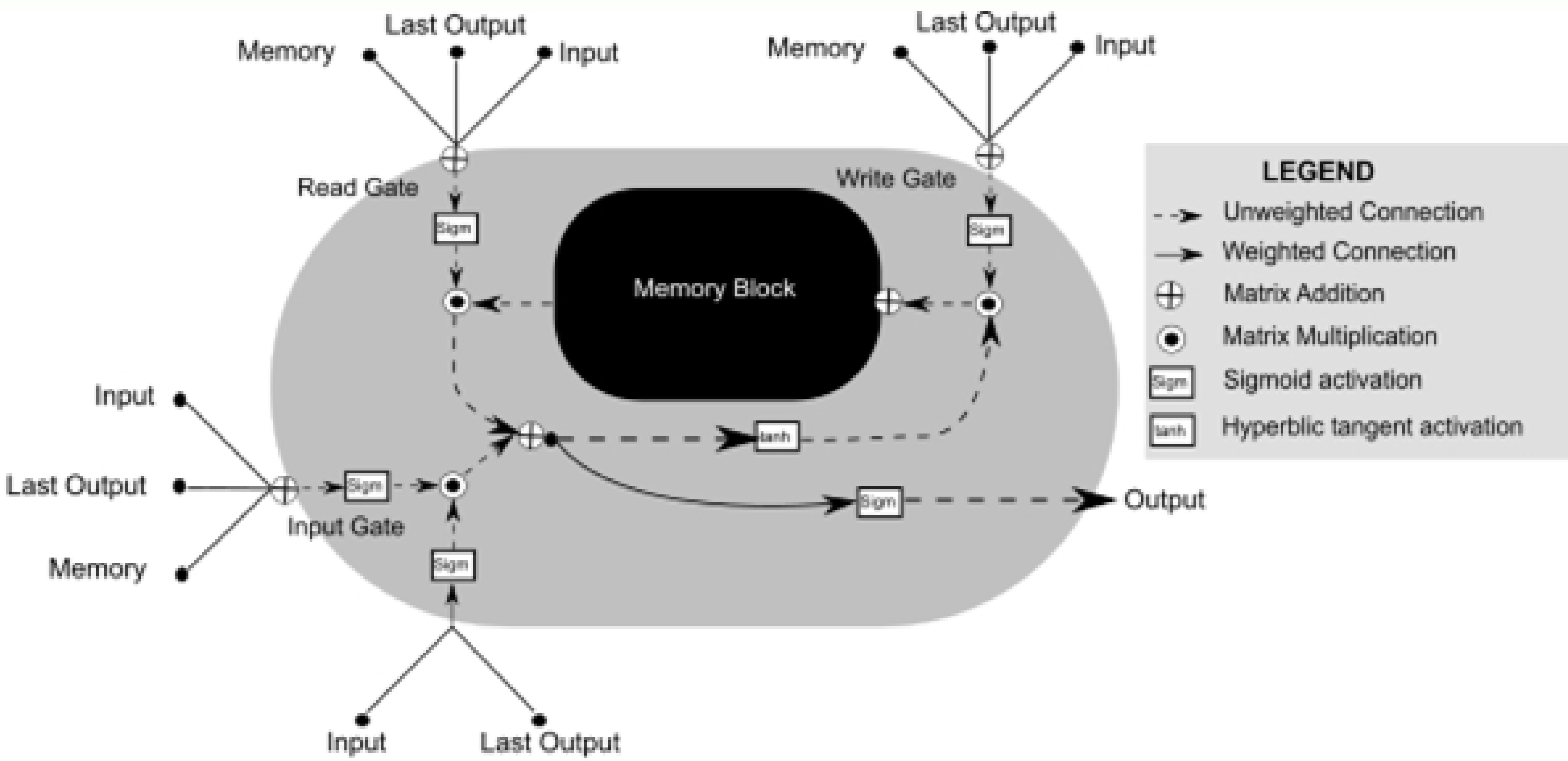
Gate what's read from memory



Gate what's written to memory



Gated Recurrent Unit with Memory Block (GRU-MB)

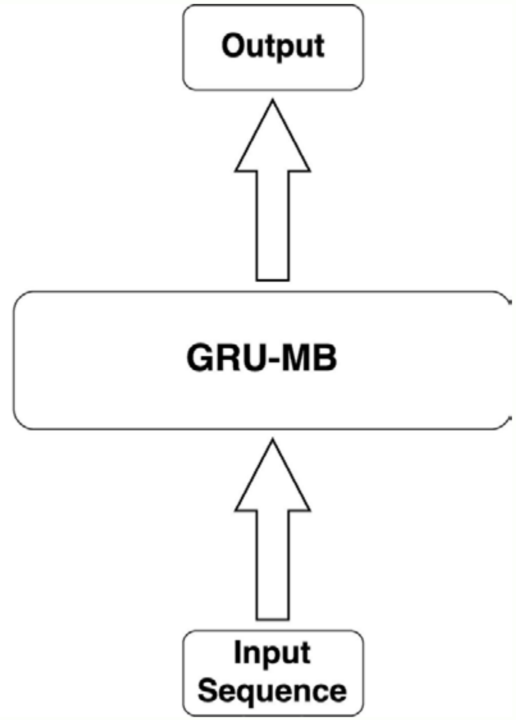


1. *Evolving Memory-Augmented Neural Architecture for Deep Memory Problems. S. Khadka, Jen. Chung, K. Tumer. In Proceedings of the Genetic and Evolutionary Computation Conference 2017, Berlin, Germany, July 15–19, 2017 (GECCO' 17)*

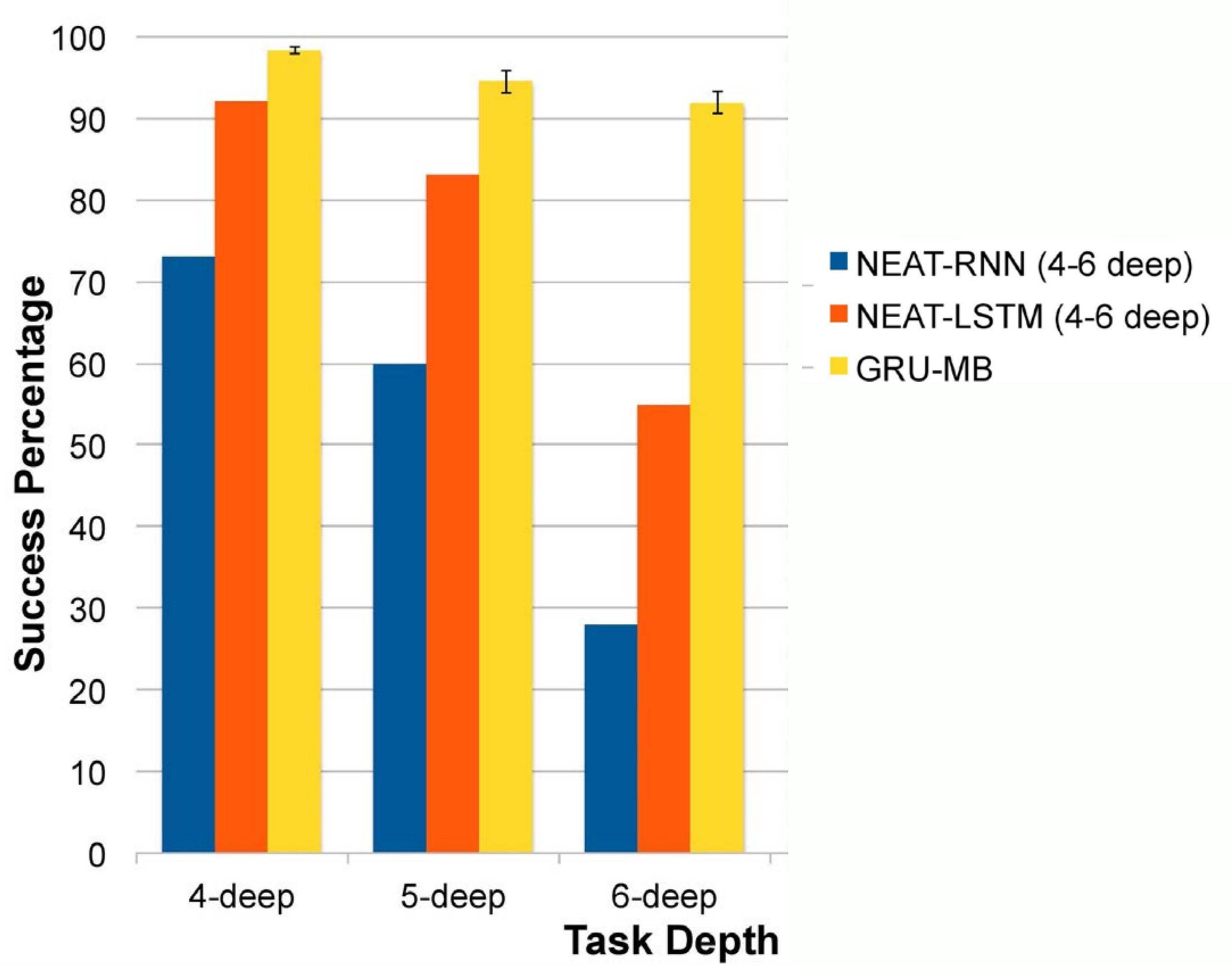
GRU-MB Results

- **Sequence Classification Task**

Input Sequence	Target Output
-1 0....0 1 0....0 -1	-1 .... 1 .... -1
-1 0....0 -1 0....0 1	-1 .... -1 .... -1
-1 0....0 1 0....0 1	-1 .... 1 1
1 0....0 1 0....0 -1	1 .... 1 1



Classification Accuracy



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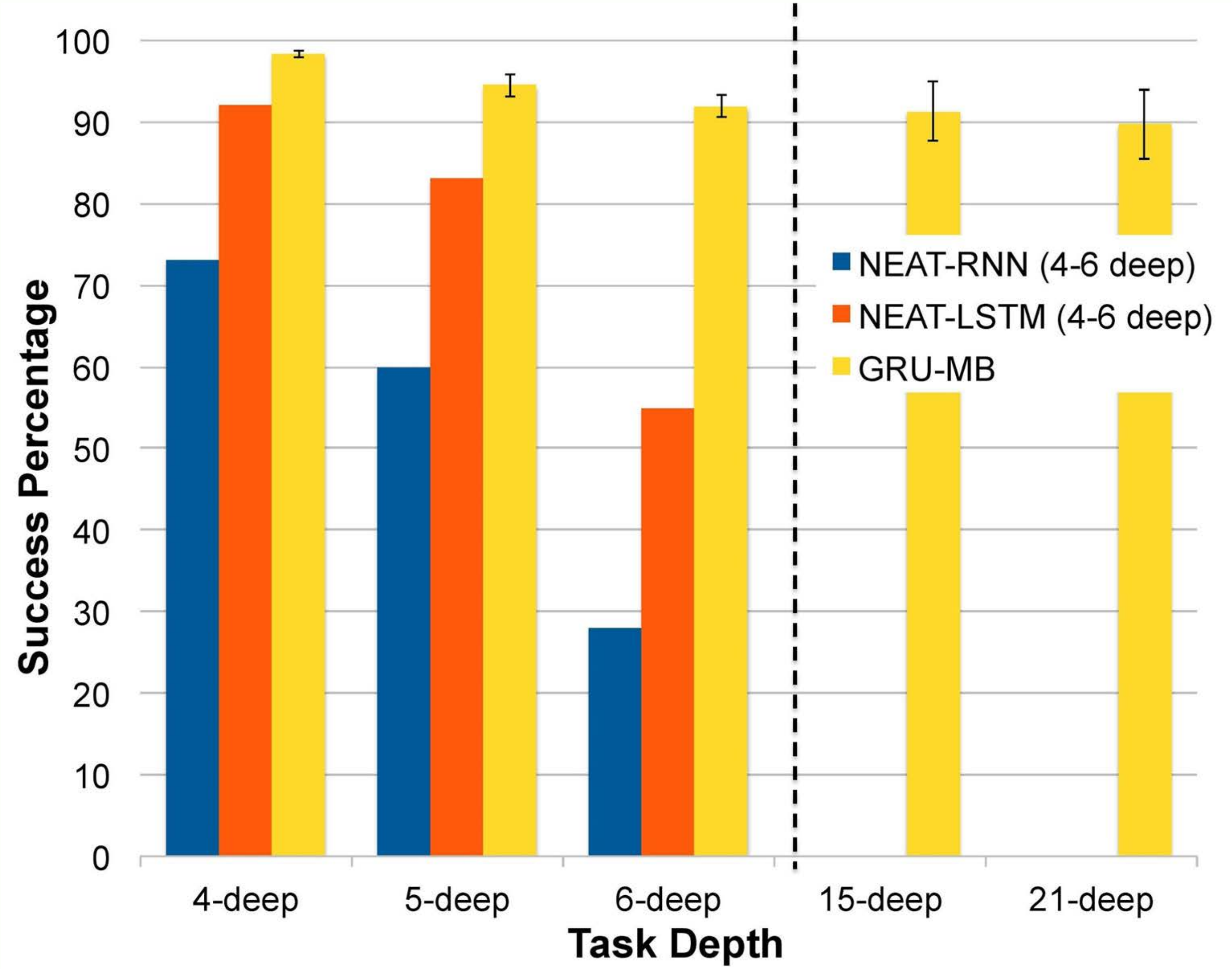
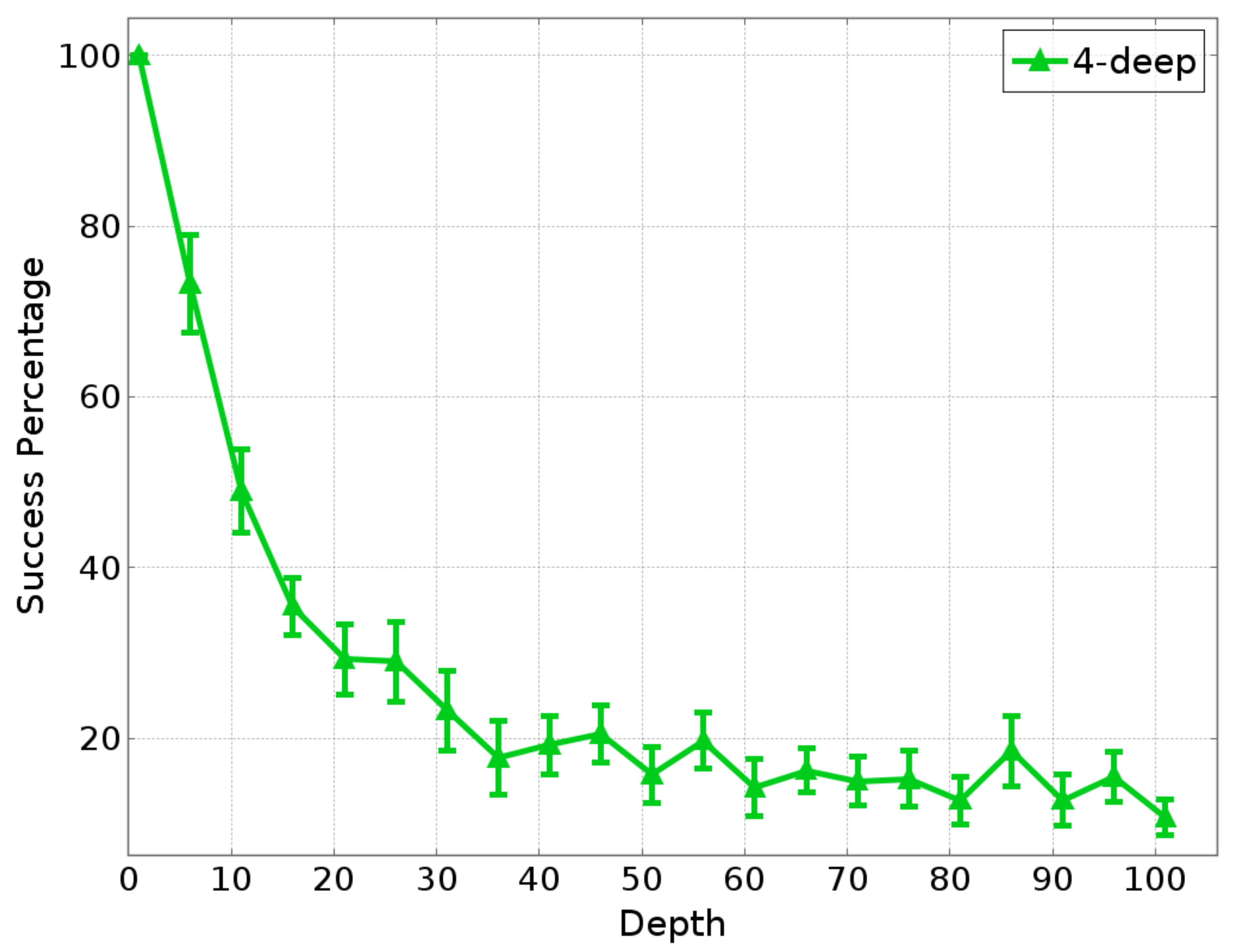
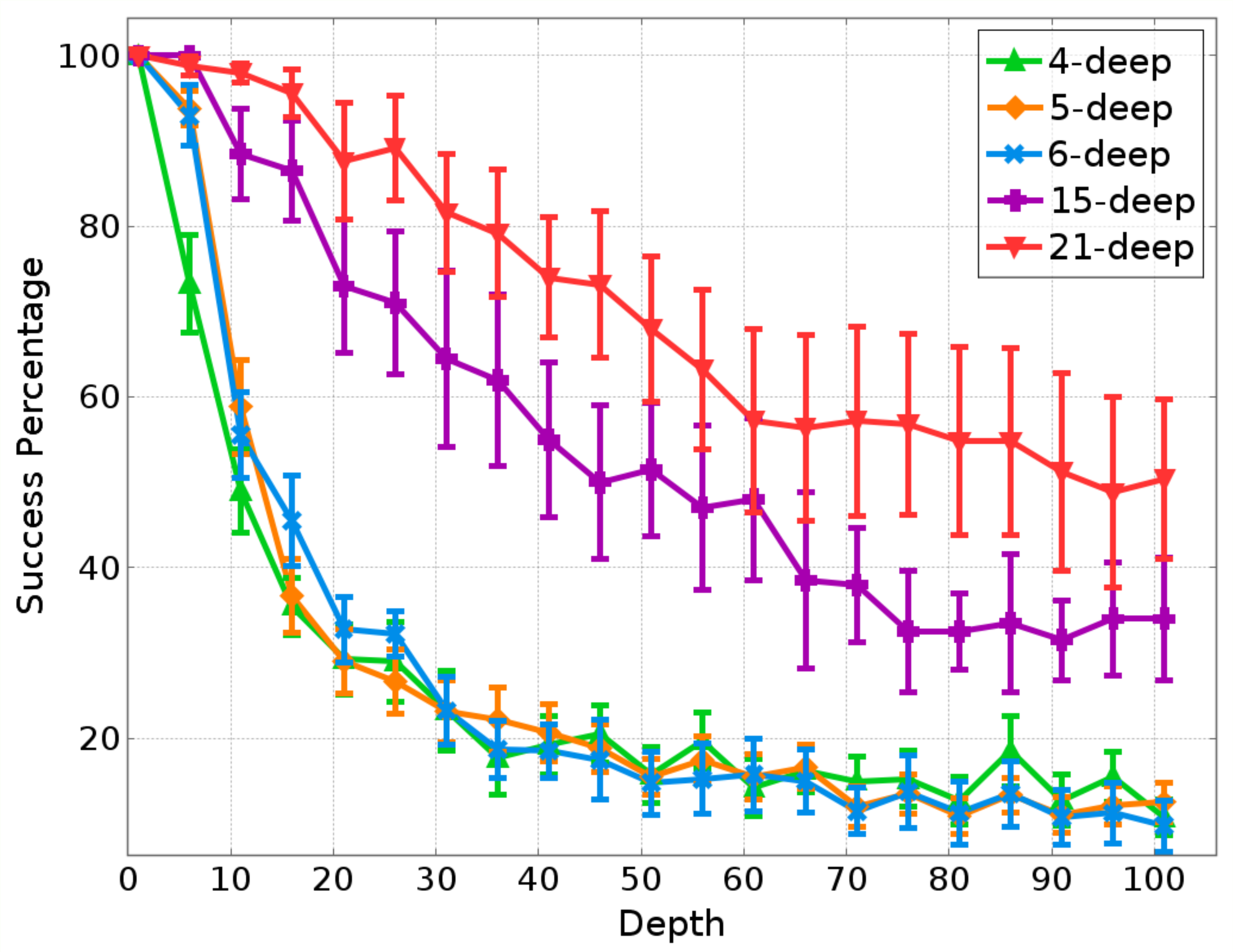


Depth generalization



Depth generalization



Next Steps

- GRU-MB tested and verified on benchmark sequence classification tasks
- Translate this onto an advanced power plant application
- Customize GRU-MB
- Train GRU-MB as reconfigurable power plant controllers

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
2	Develop bio-mimetic control algorithm for advanced power systems	Sept. 2014	Sept. 2014 ✓
3	Develop system metrics to measure tradeoffs of plant objectives	March 2015	March 2015 ✓
4	Develop multi-objective control algorithm for advanced power systems	Sept. 2015	Sept. 2015 ✓
5	Develop robust controller for advanced power system	June 2016	June 2017
6	Develop reconfigurable, multi-objective controller for advanced power system	Sept. 2016	September 2017

Publications

1. ***Evolving Memory-Augmented Neural Architecture for Deep Memory Problems. S. Khadka, Jen. Chung, K. Tumer. In Proceedings of the Genetic and Evolutionary Computation Conference 2017, Berlin, Germany, July 15–19, 2017 (GECCO' 17)***

2. *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.*

3. *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.*

4. *Learning Based Control of a Fuel Cell Turbine Hybrid Power System.* A. Gabler, M. Colby, and K. Tumer. In Proceedings of Genetic and Evolutionary Computation Conference (GECCO) 2015 (Extended Abstract). Madrid, Spain. July 2015.

5. *Approximating Difference Evaluations with Local Information*. M. Colby, W. Curran, and K. Tumer. In Proceedings of the Fourteenth International Joint Conference on Autonomous Agents and Multiagent Systems (Extended Abstract). Istanbul, Turkey, May 2015.

6. *A Replicator Dynamics Analysis of Difference Evaluation Functions*. M. Colby and K. Tumer. In Proceedings of the Fourteenth International Joint Conference on Autonomous Agents and Multiagent Systems (Extended Abstract). Istanbul, Turkey, May 2015.

Publications

7. *An Evolutionary Game Theoretic Analysis of Difference Evaluation Functions*. M. Colby and K. Tumer. In Proceedings of Genetic and Evolutionary Computation Conference (GECCO) 2015. Madrid, Spain. July 2015.
8. *Theoretical and Implementation Improvements for Difference Evaluation Functions*. M. Colby. Ph.D. Dissertation, Oregon State University.
9. *Approximating Difference Evaluations with Local Knowledge*. M. Colby, W. Curran, C. Rebhuhn, and K. Tumer. In Proceedings of the Thirteenth International Joint Conference on Autonomous Agents and Multiagent Systems (Extended Abstract). Paris, France, May 2014.
10. *PaCcET: An Objective Space Transformation to Iteratively Convexify the Pareto Front*. L. Yliniemi and K. Tumer. In *The Tenth International Conference on Simulated Evolution And Learning (SEAL 2014)*, Dunedin, New Zealand, December 2014.
11. *Multi-Objective Multiagent Credit Assignment Through Difference Rewards in Reinforcement Learning*. L. Yliniemi and K. Tumer. In *The Tenth International Conference on Simulated Evolution And Learning (SEAL 2014)*, Dunedin, New Zealand, December 2014

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  - **Shauharda (Shaw) Khadka, Drew Wilson**, Logan Yliniemi, Drew Gabler

Phd, 2015

MS, 2015

- Postdocs: Mitchell Colby, **Jen Jen Chung**

Phd, 2014

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

Questions?

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Distributed multi-objective Control?

Multiagent control   multi-objective control

Many agents, one objective

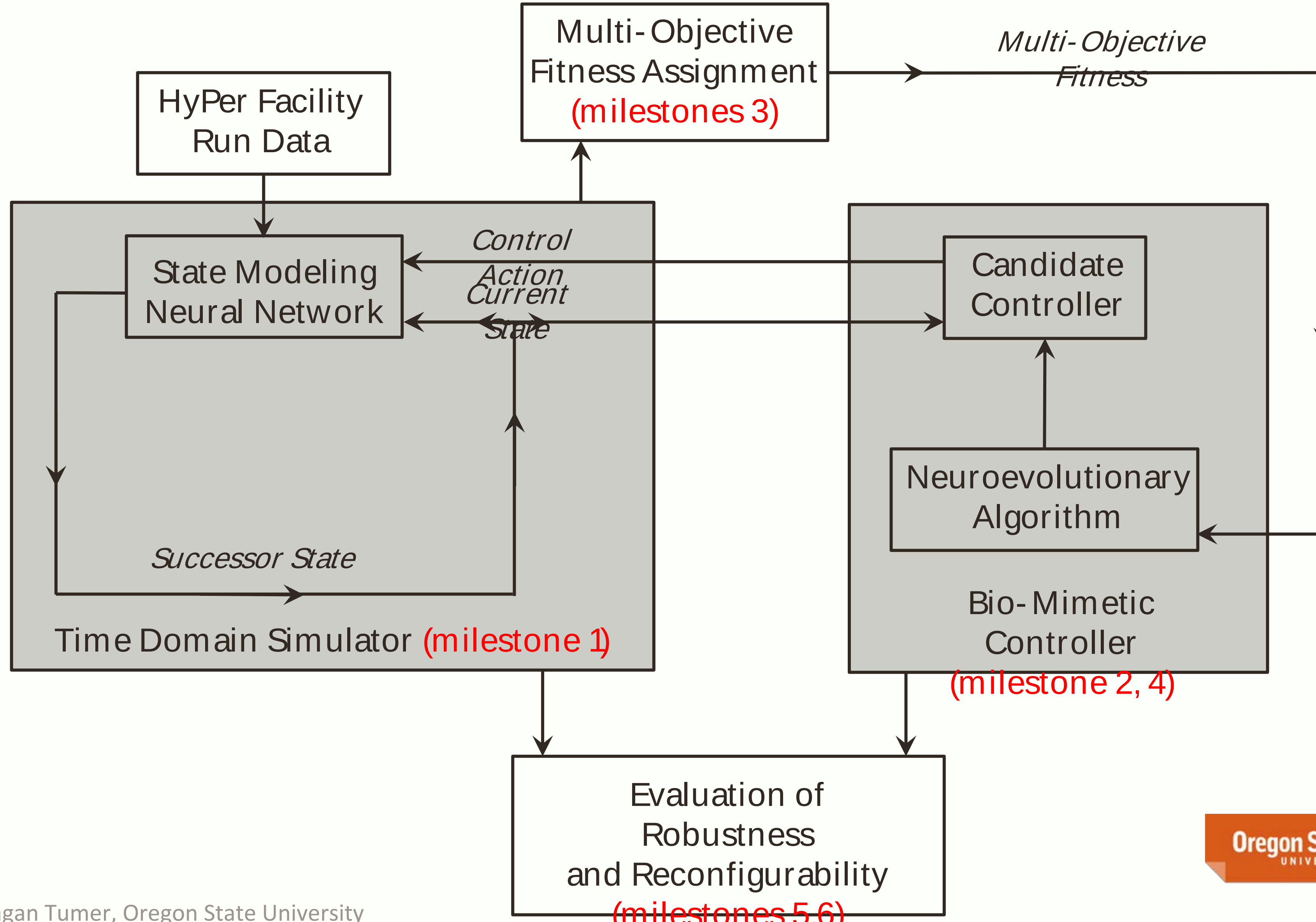
- Who does what ?

One agent, many objectives

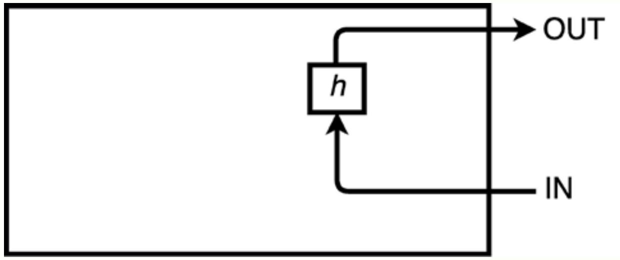
- trade-off objectives

Many agents , many objectives

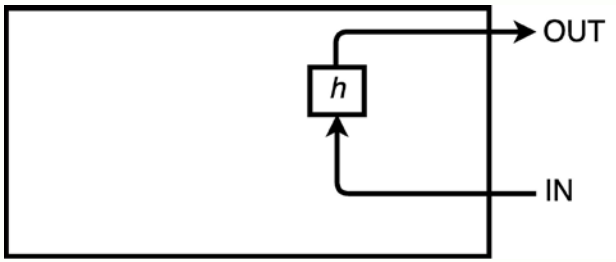
Project Overview

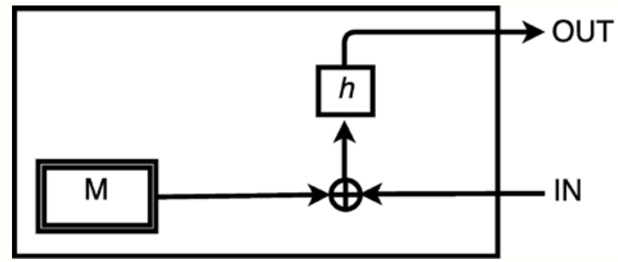


Feedforward Net

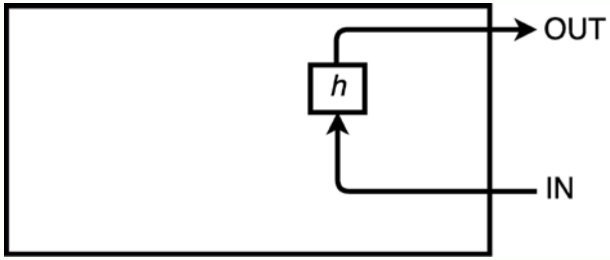


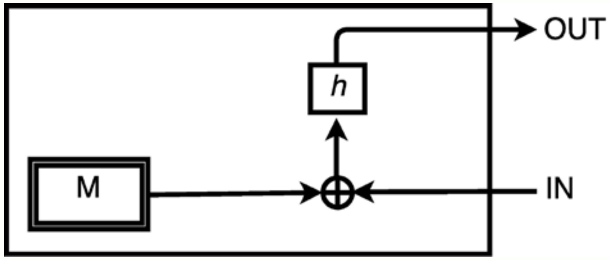
Read from an external memory

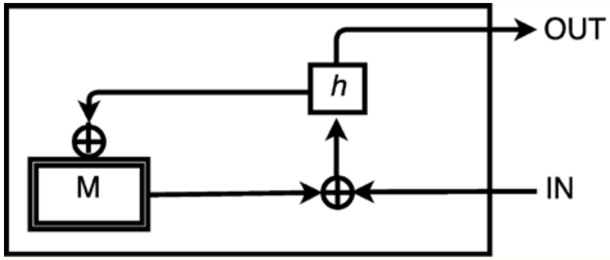




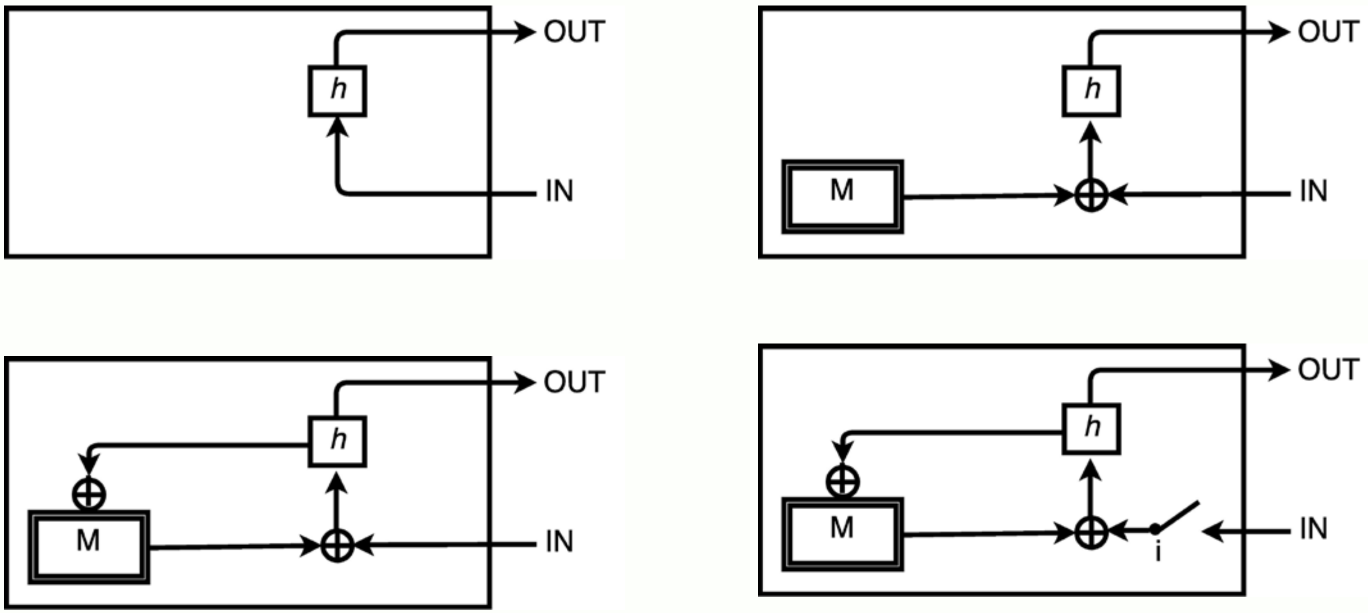
Write to memory



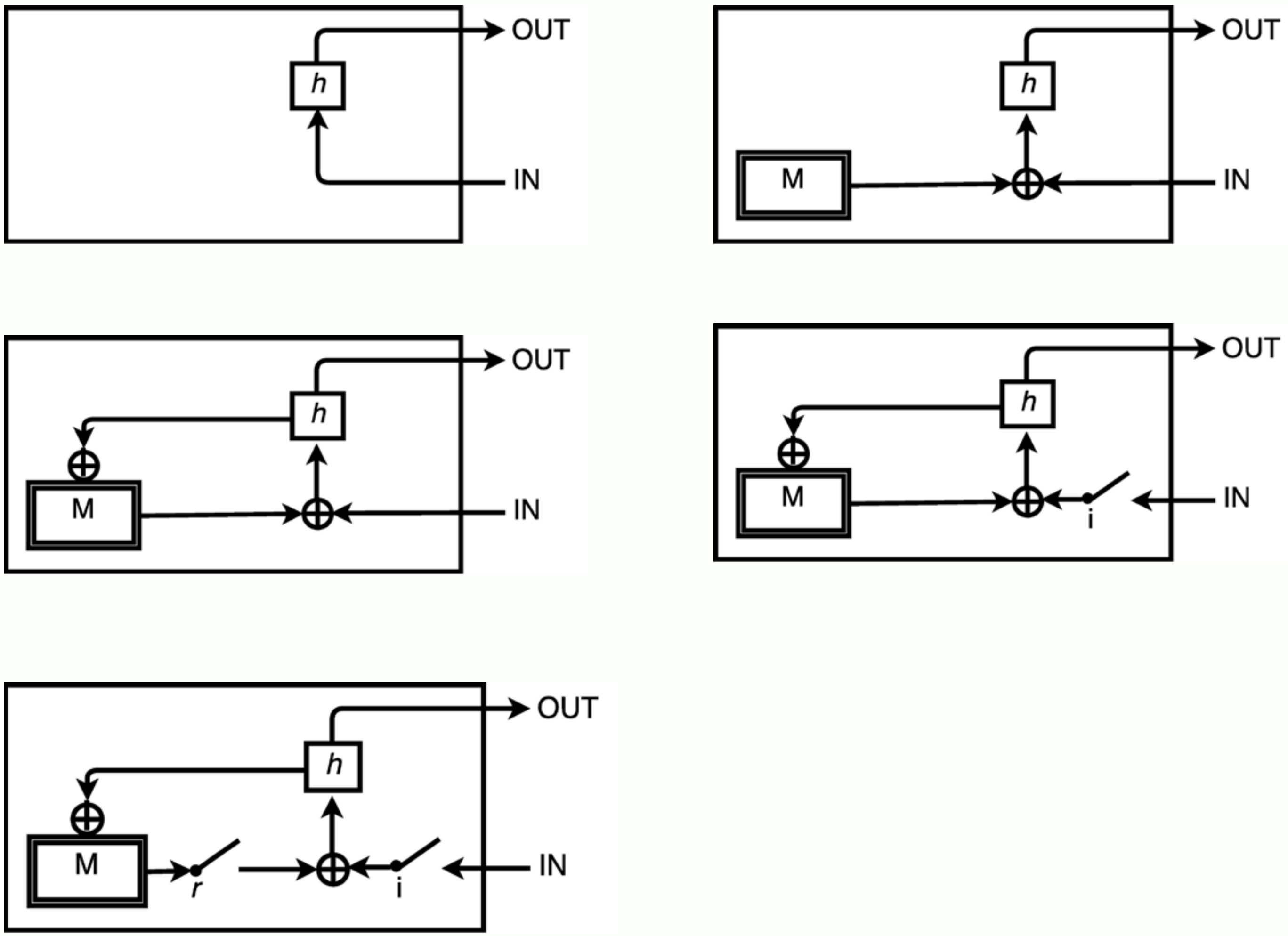




Gate input



Gate what’s read from memory



Gate what's written to memory