An Evolutionary Approach to Discovering Execution Mode Boundaries for Adaptive Controllers

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Adaptability of Autonomous Robots

Internal Uncertainties

- degrading and complex (flexible) components
- changing objectives and control strategies

External Uncertainties

- dynamic environments
- significant damage

Adaptive Control

Model-based

- require a precise model
- perform parameter identification

Data-driven

- (or, model-free)
- input / output data
- “learns” how to adapt

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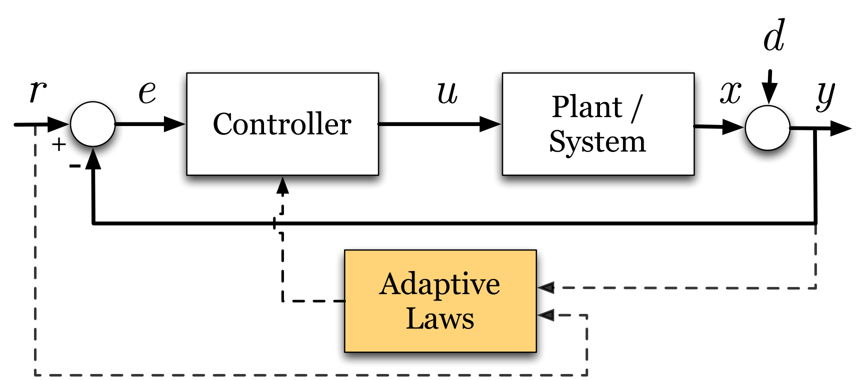

Limitations of Adaptive Control

- Adaptive controllers can continue to adapt as long as the system remains fundamentally unchanged
- That is, the system responds to inputs in roughly the same manner even after it changes

- For example, cut the tail fin of a robotic fish

Robotic Fish

Applications

- autonomous
  mobile sensors
- biological studies
  (elicit natural behaviors)

Robotic Fish

Research Platform

- benefit from flexible components
- operate in a nonlinear environment
- exhibit complex dynamics
- [Marchese 2014]

Robotic Fish

Research Platform

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- operate in a nonlinear environment
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This Study

1. Improve adaptive controllers, AND
2. Find the limits of these adaptive controllers.

- Using evolutionary computation

- From controller's perspective:
  - Reference signals are part of the environment
  - Fin morphology is part of the environment

Enhancing Adaptive Control

Exploit EC to Enhance an MFAC [Cheng 2000]

- differential evolution [Storn 1997]
- evolve MFAC parameters
- controlling a robotic fish
- adapt to:
  - changing fin flexibilities
  - changing fin length
  - changing control demands

Adaptive Neural Network

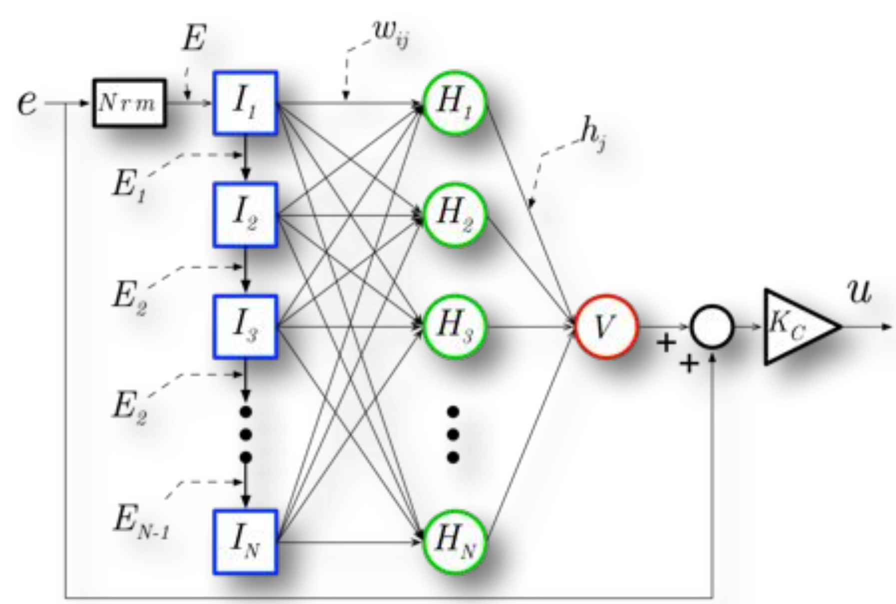
Network Activation

- feed-forward network
- propagated error
- sigmoid activation

Network Update

- minimize error

$$E_s(t) = \frac{1}{2}\, e(t)^2$$



Adaptive Neural Network

$$
\begin{aligned}
\Delta w_{ij}(n) &\propto \frac{\partial E_s}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial q}\frac{\partial q}{\partial w_{ij}}, \\
&= \frac{\partial E_s}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial o}\frac{\partial o}{\partial q}\frac{\partial q}{\partial p}\frac{\partial p}{\partial w_{ij}}. \\
&= \boxed{-\eta\, K_c\, S_f(n)\, e(n)\, q_j(n)\, (1 - q_j(n))\, E_i(n) \sum_{k=1}^{N} h_k(n),}
\end{aligned}
$$

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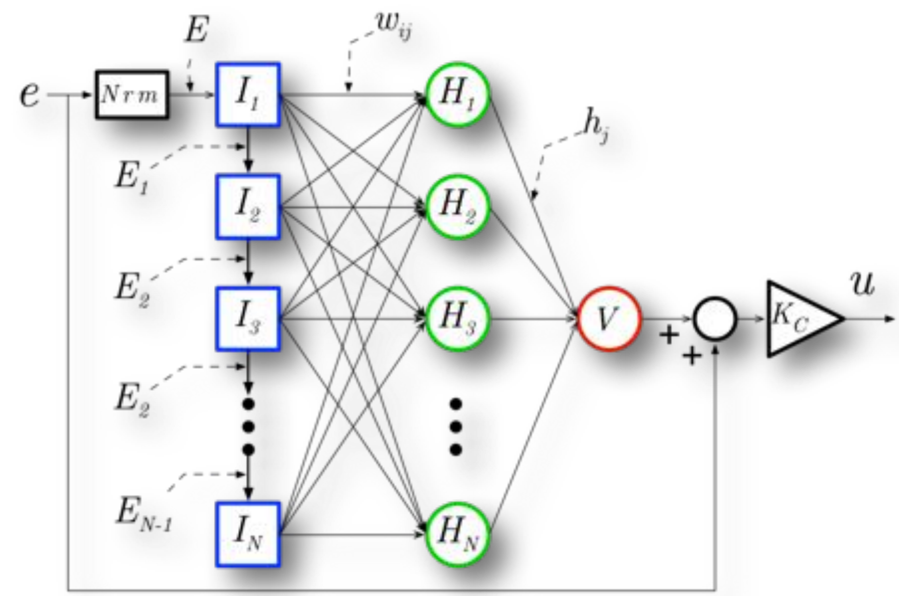
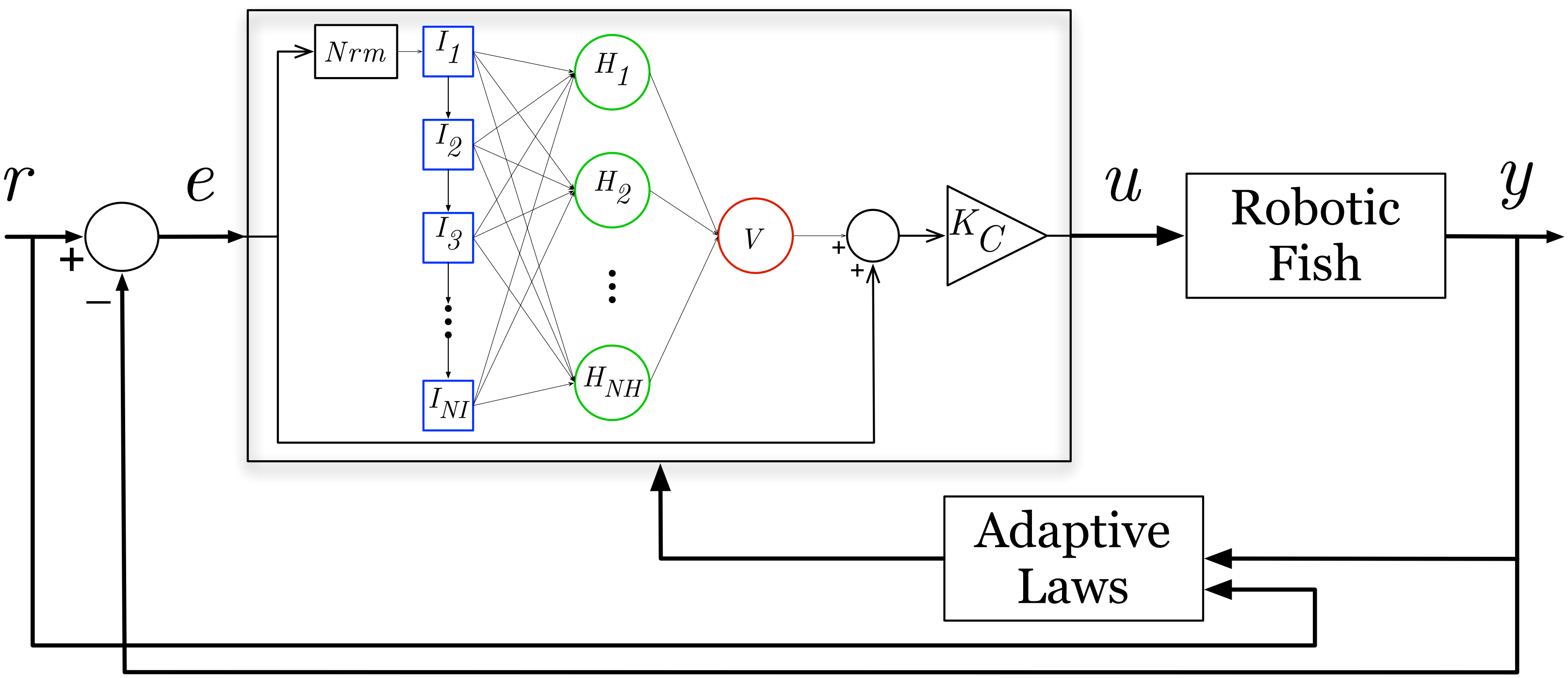
\end{aligned}
$$

Evolvable Parameters

Adaptive Neural Network

- neural network size/shape
- learning rate
- upper and lower error bounds
- controller gain
- controller update timing

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Robotic Fish
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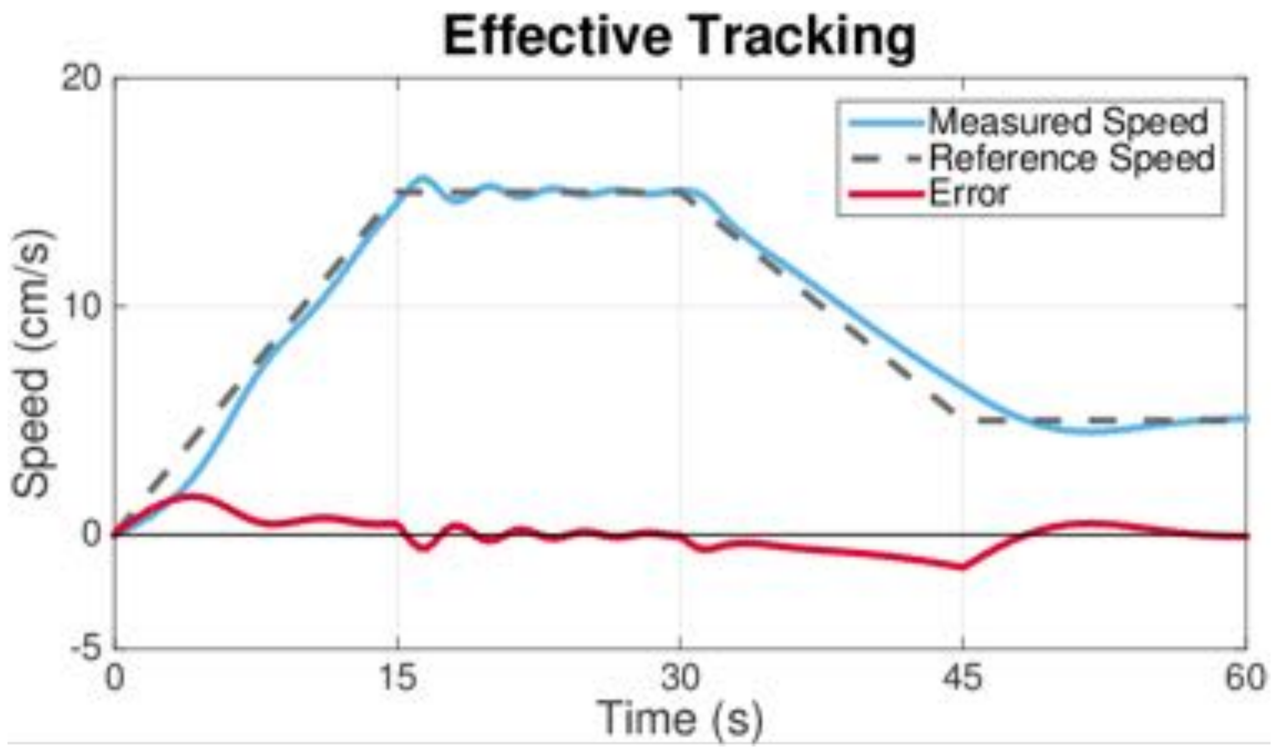
Adaptive Laws


Effective Tracking
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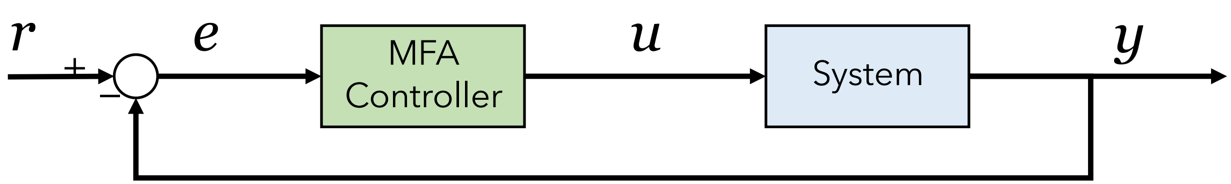
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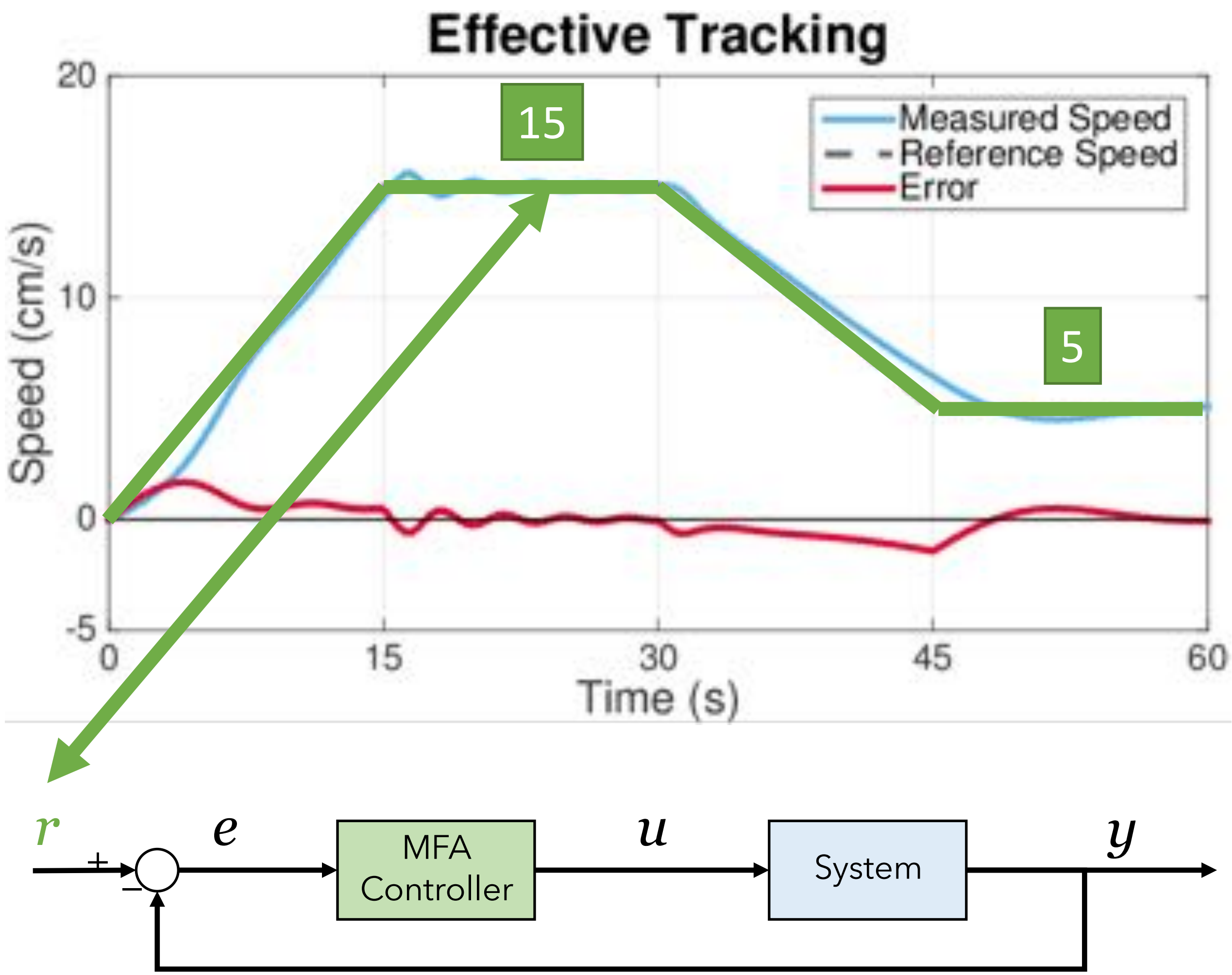
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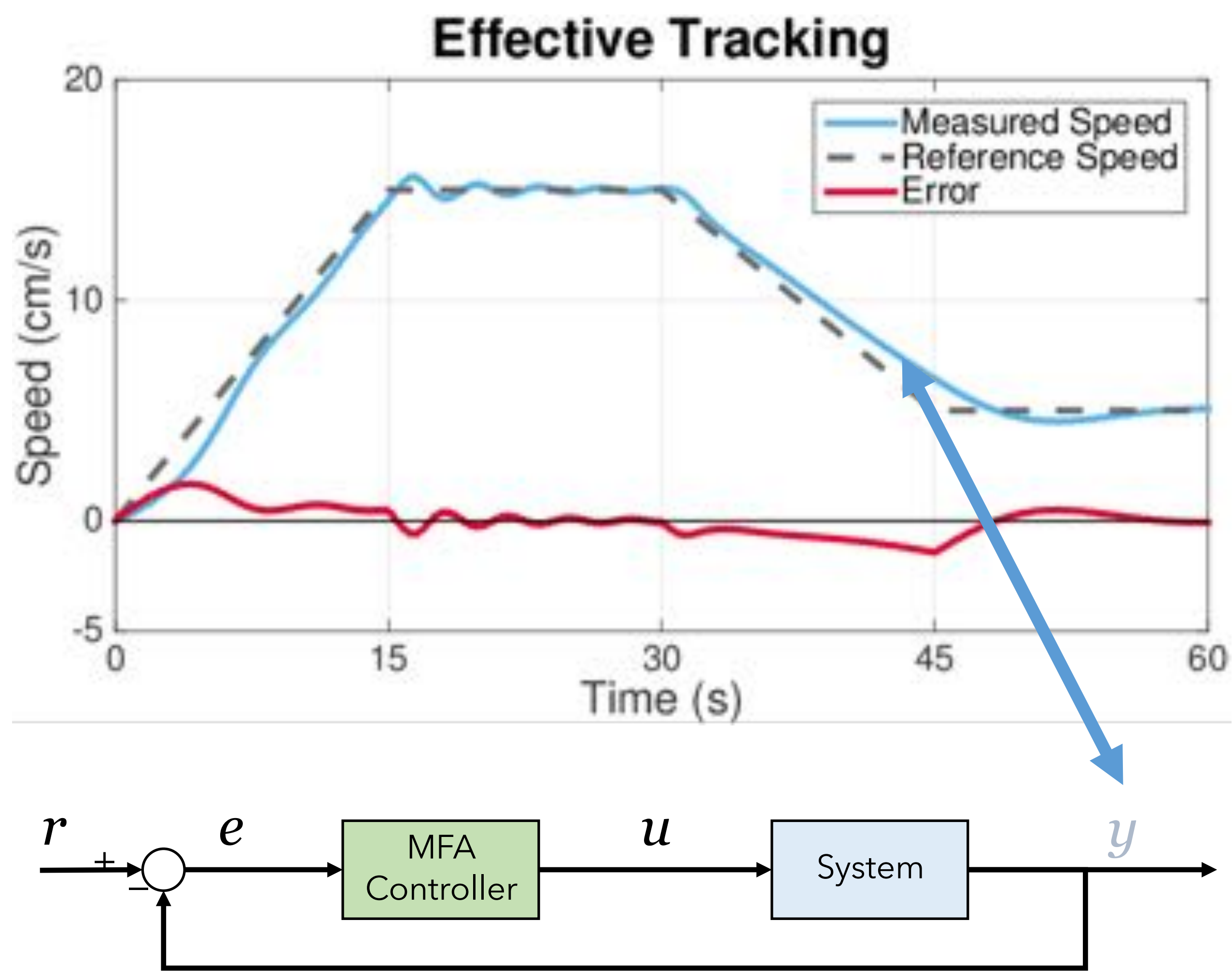
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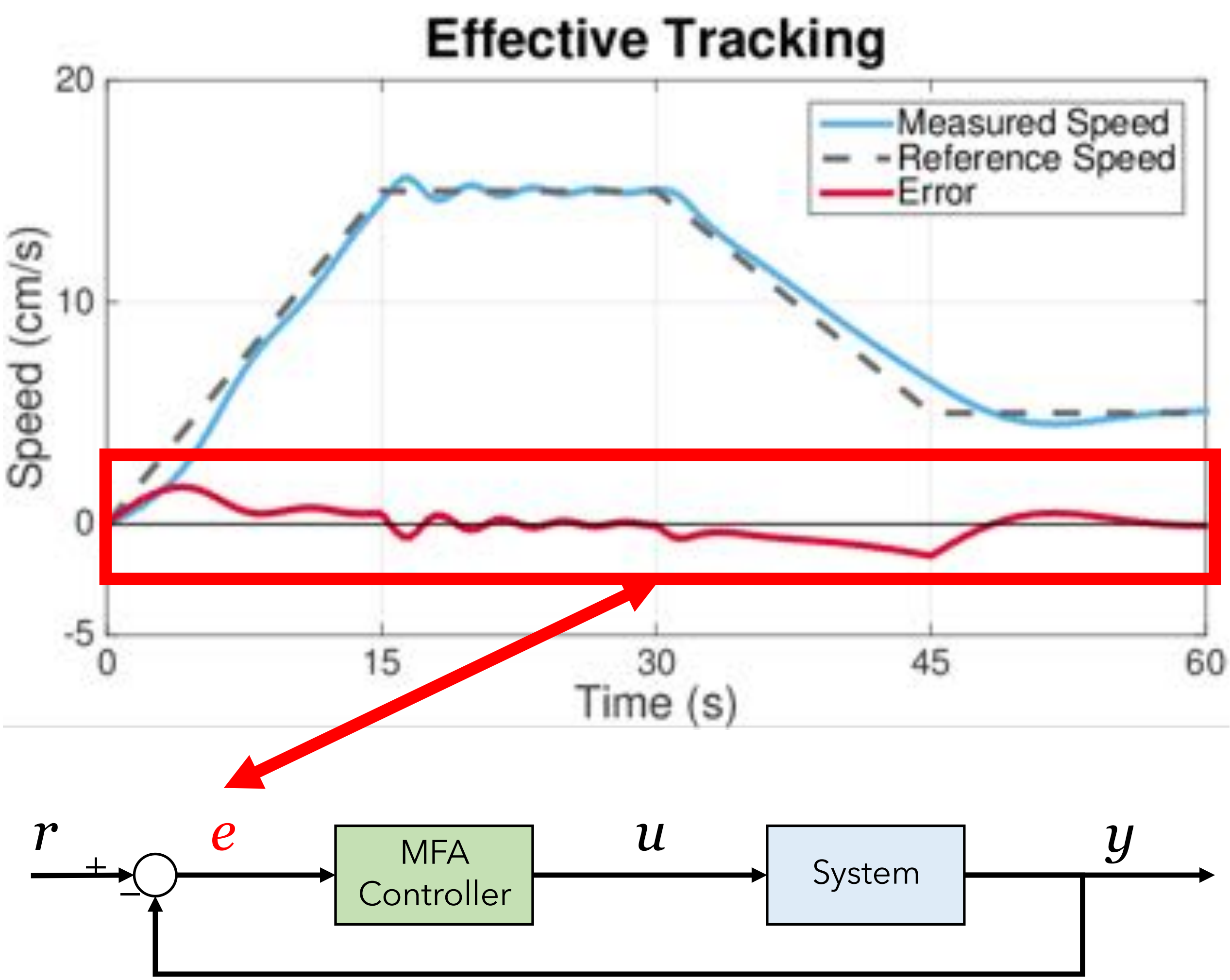
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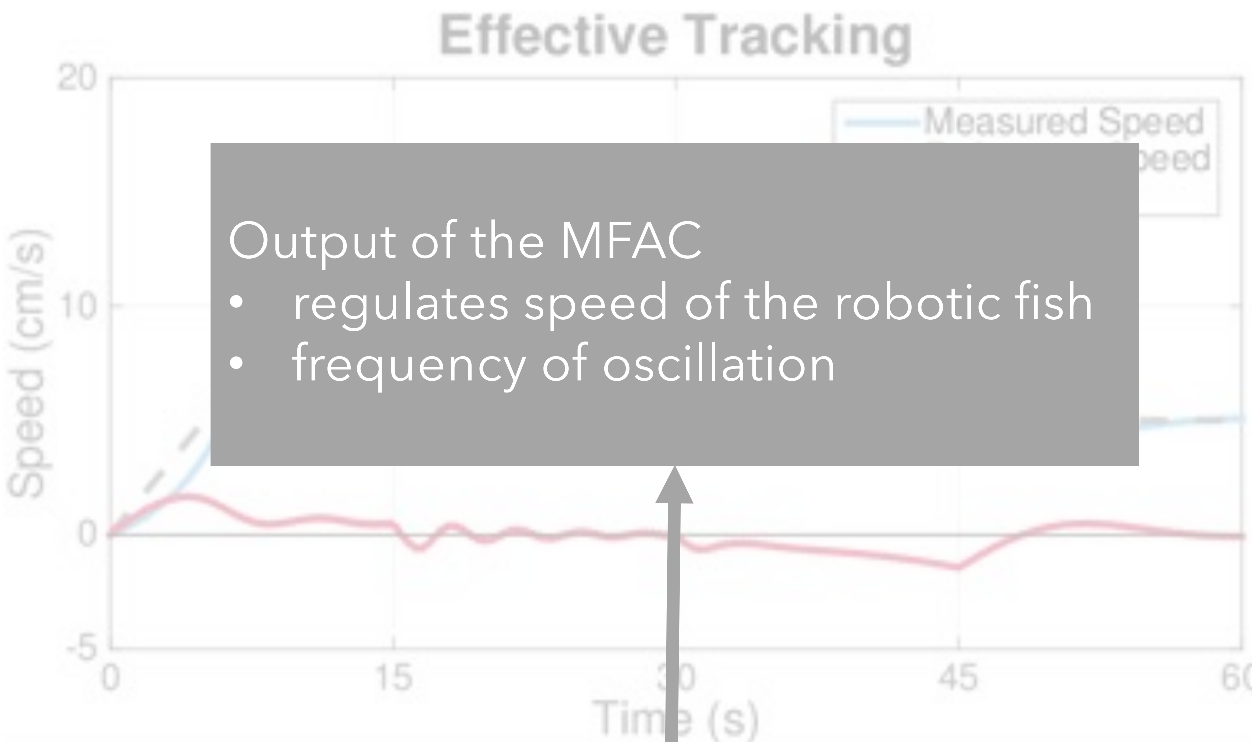
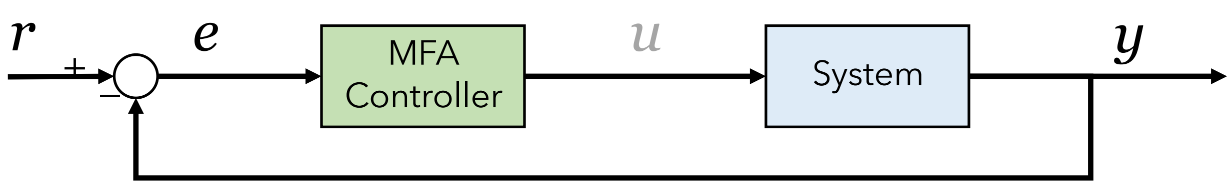


Output of the MFAC

- regulates speed of the robotic fish
- frequency of oscillation



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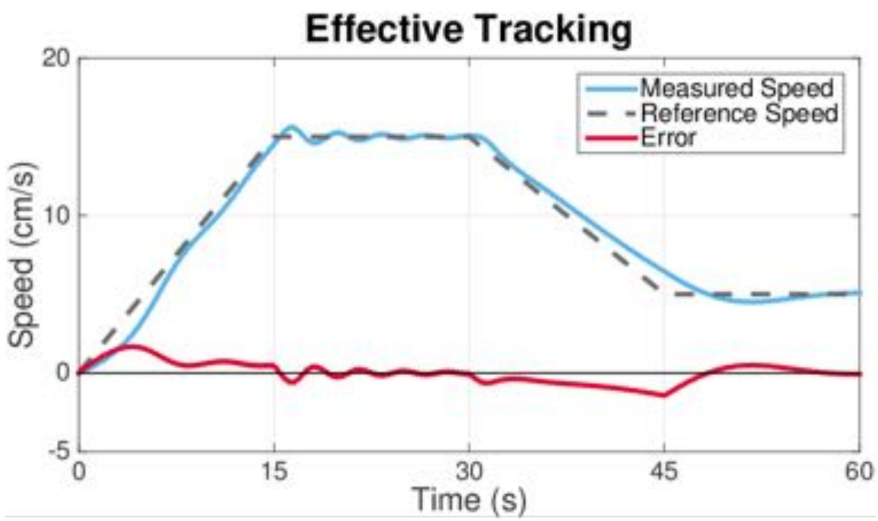
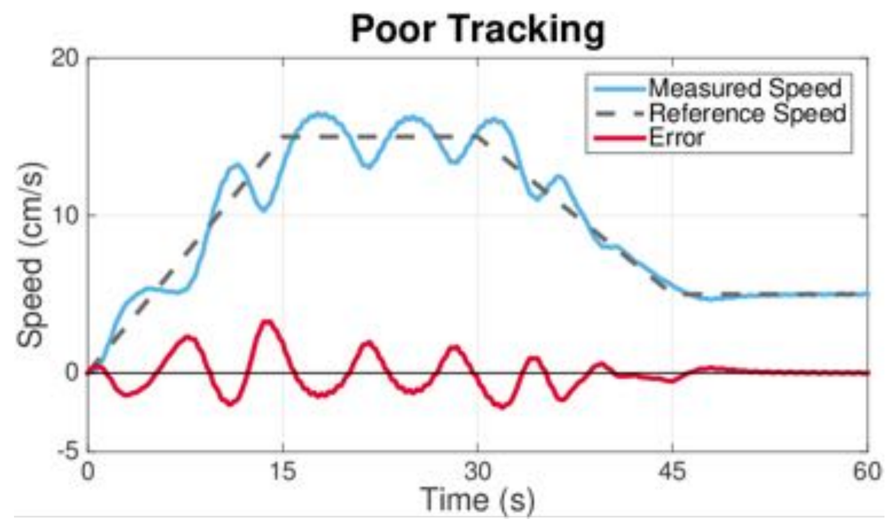
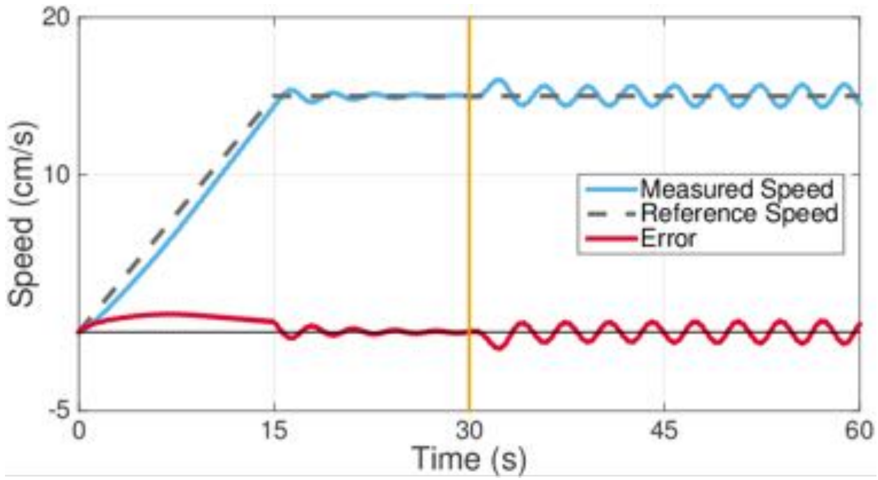
Tracking Behavior





Adaptation



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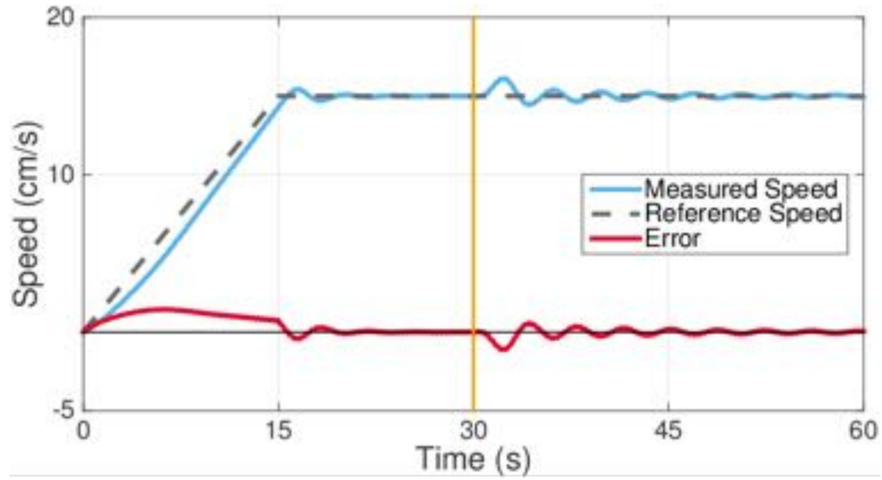

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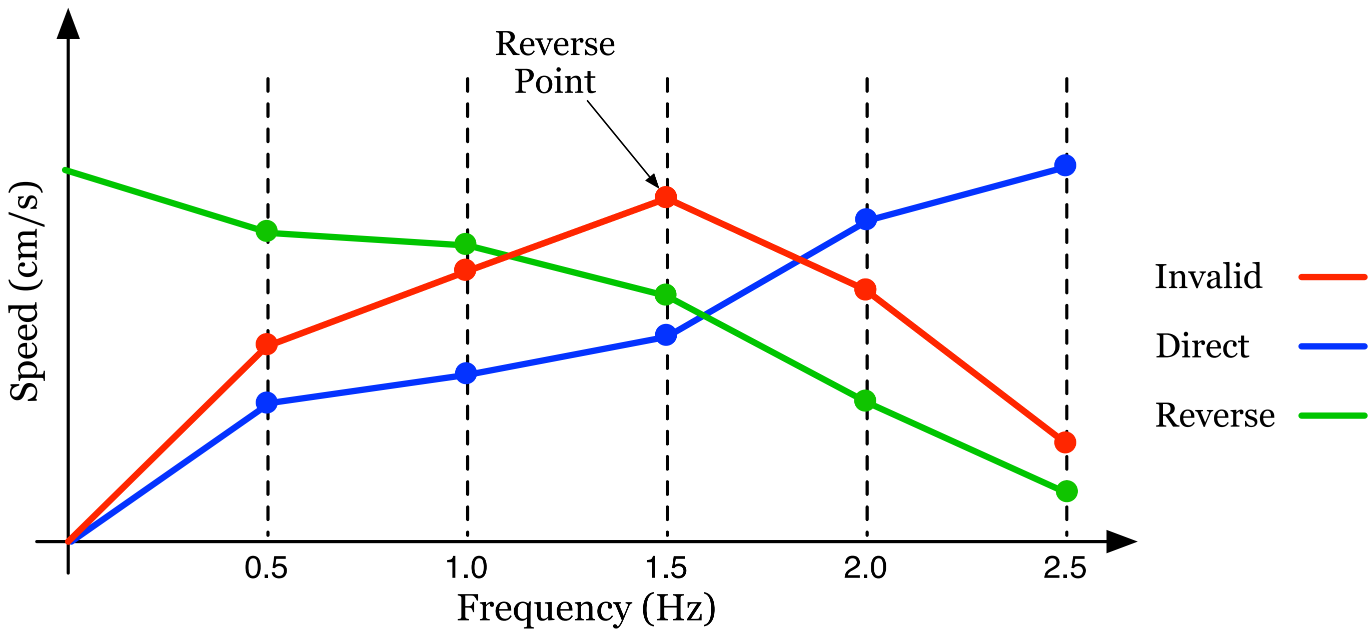
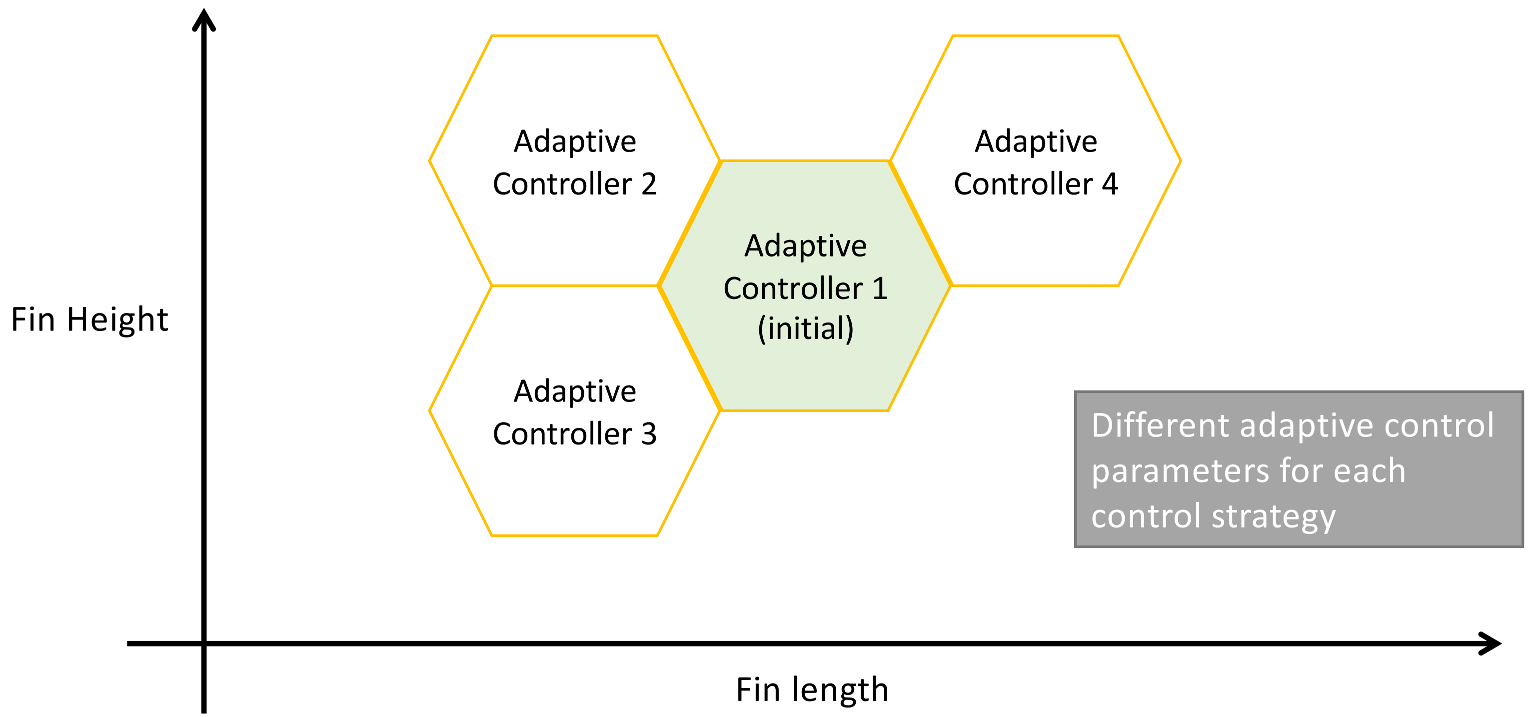
Limitations of Adaptation



Representation of Execution Modes



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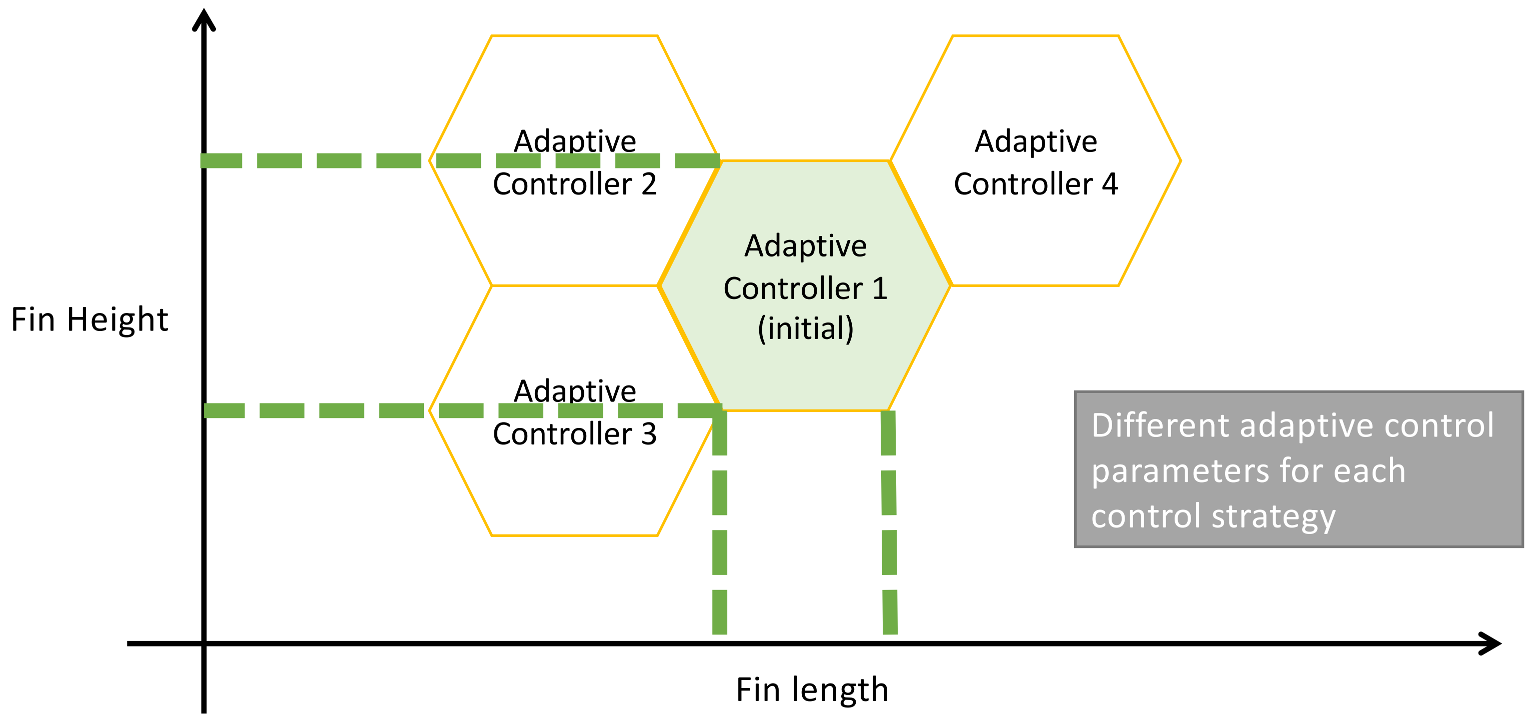
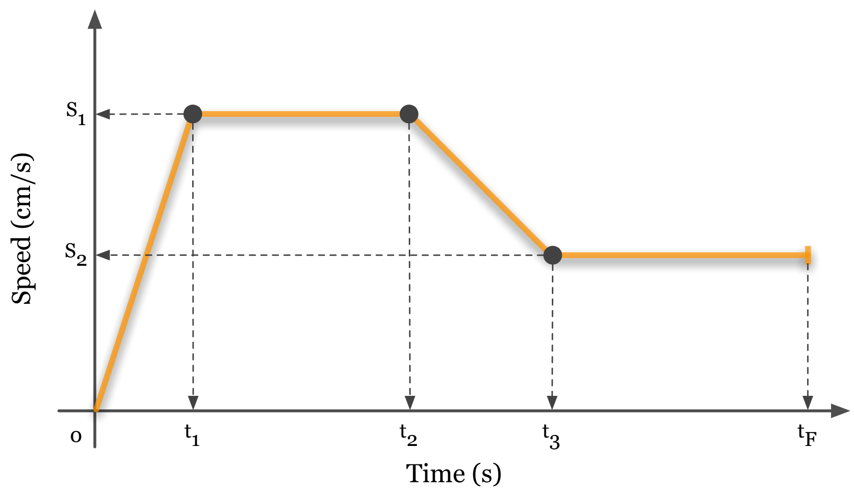
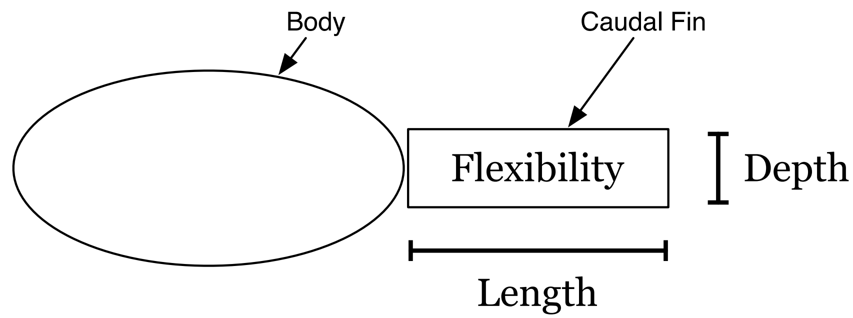


Scenarios

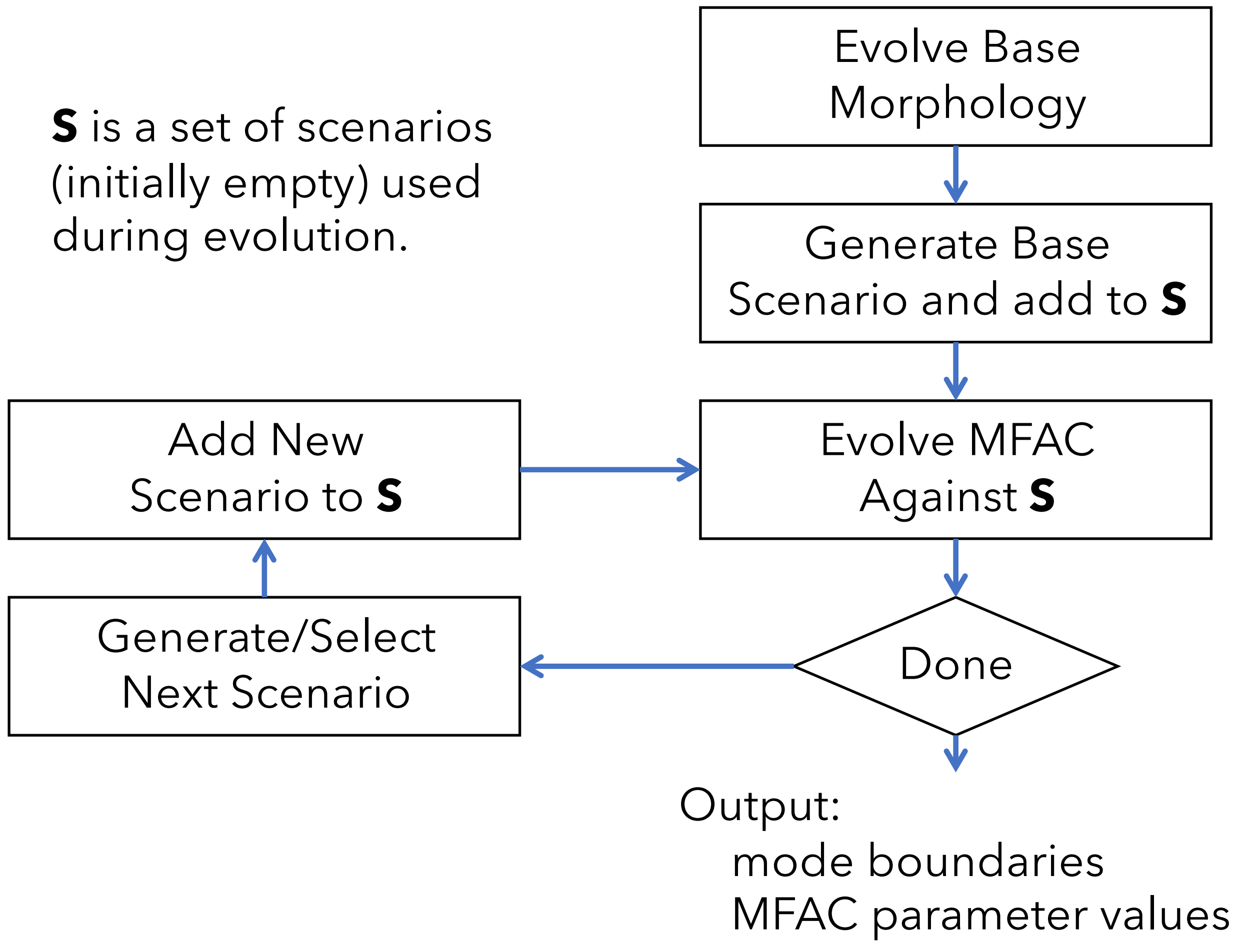


Input Reference Signal



Robotic Fish Diagram

S is a set of scenarios (initially empty) used during evolution.



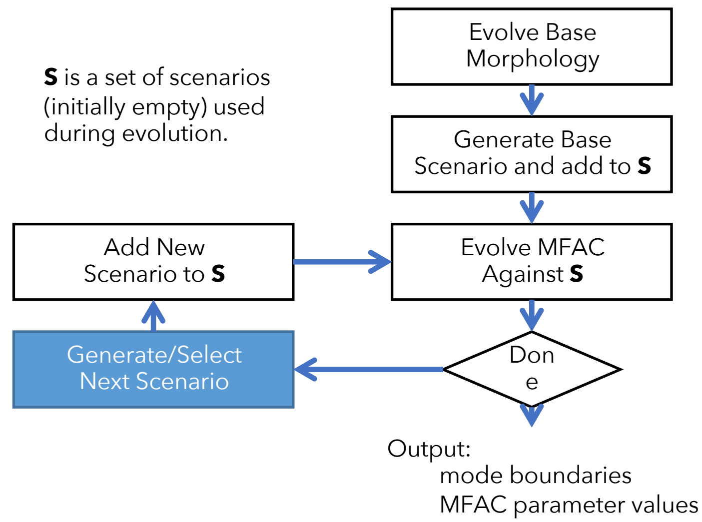
Boundary Selection Method

1. Select a scenario parameter
   i.e., fin length, height, flexibility

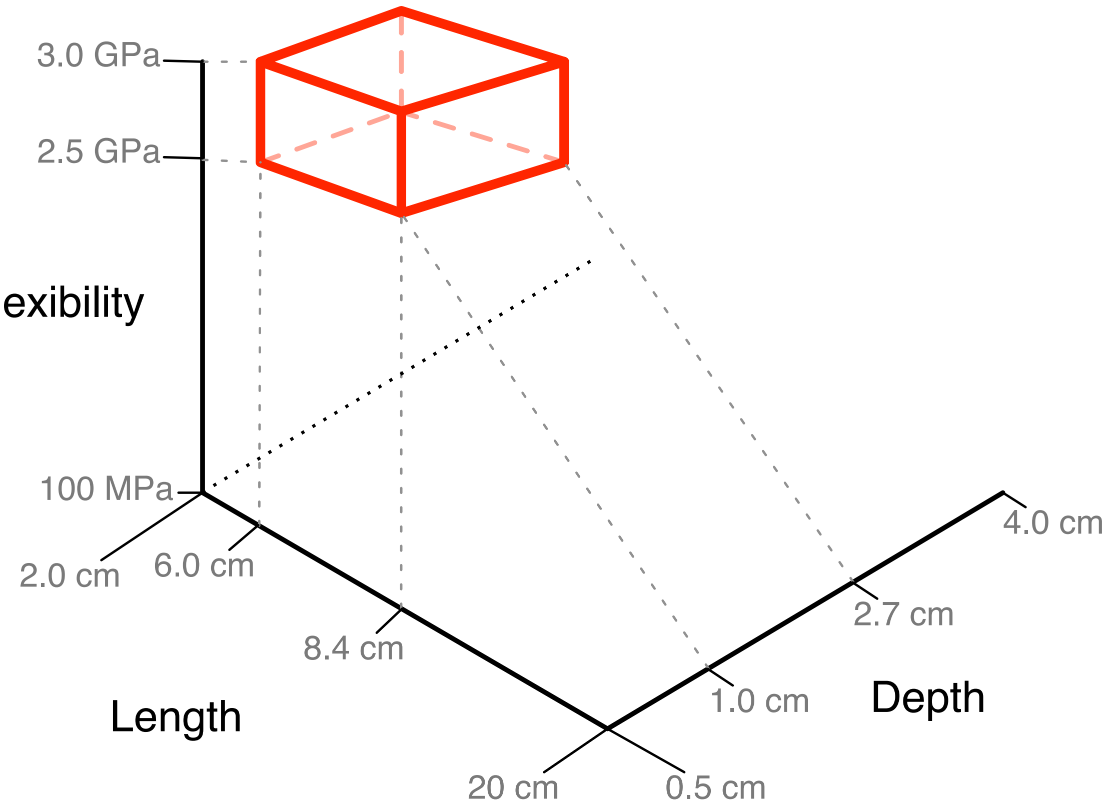
2. Select a direction
   (increase value or decrease value)

3. Increase/decrease parameter until the system becomes infeasible

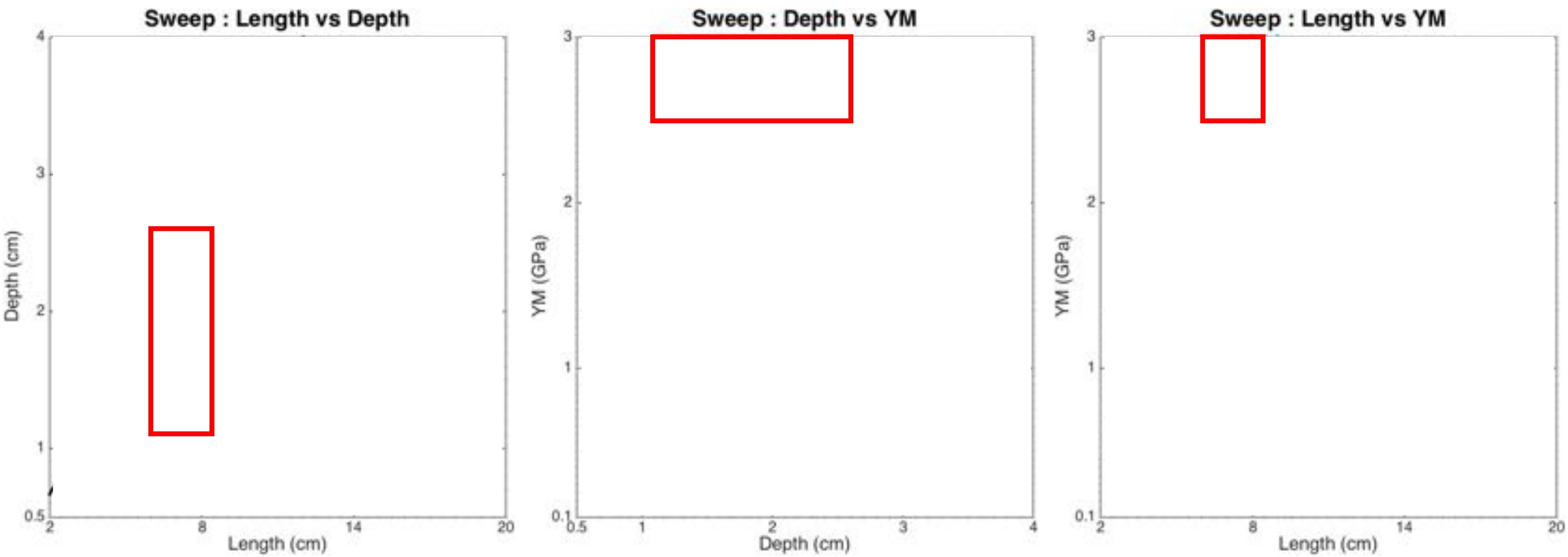
4. Add scenario to **S**



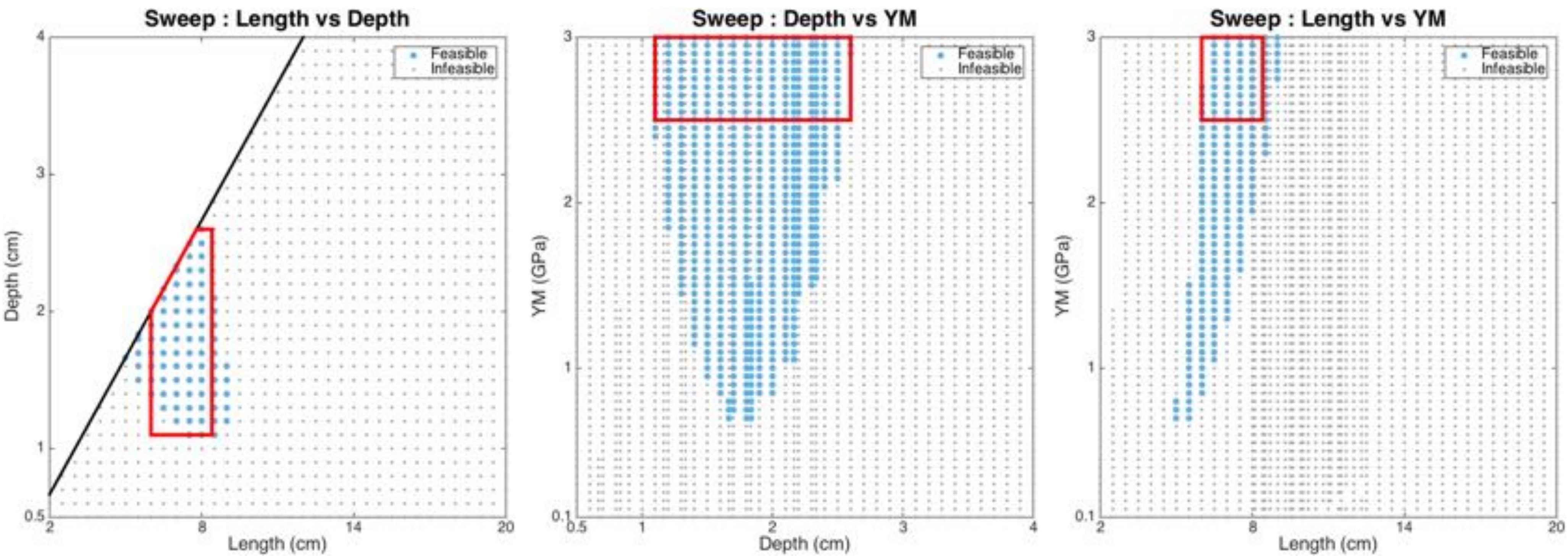
Boundary Scenarios



2D Views of Cuboid



“Ground-Truth”



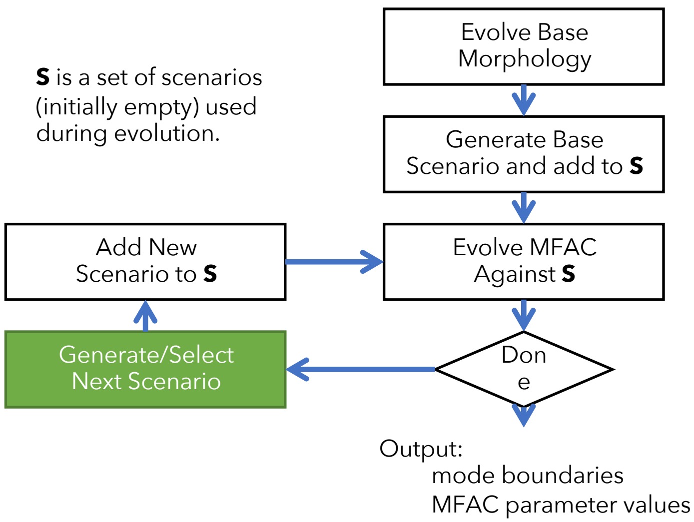
Volume Selection Method

1. Randomly generate 25 scenarios

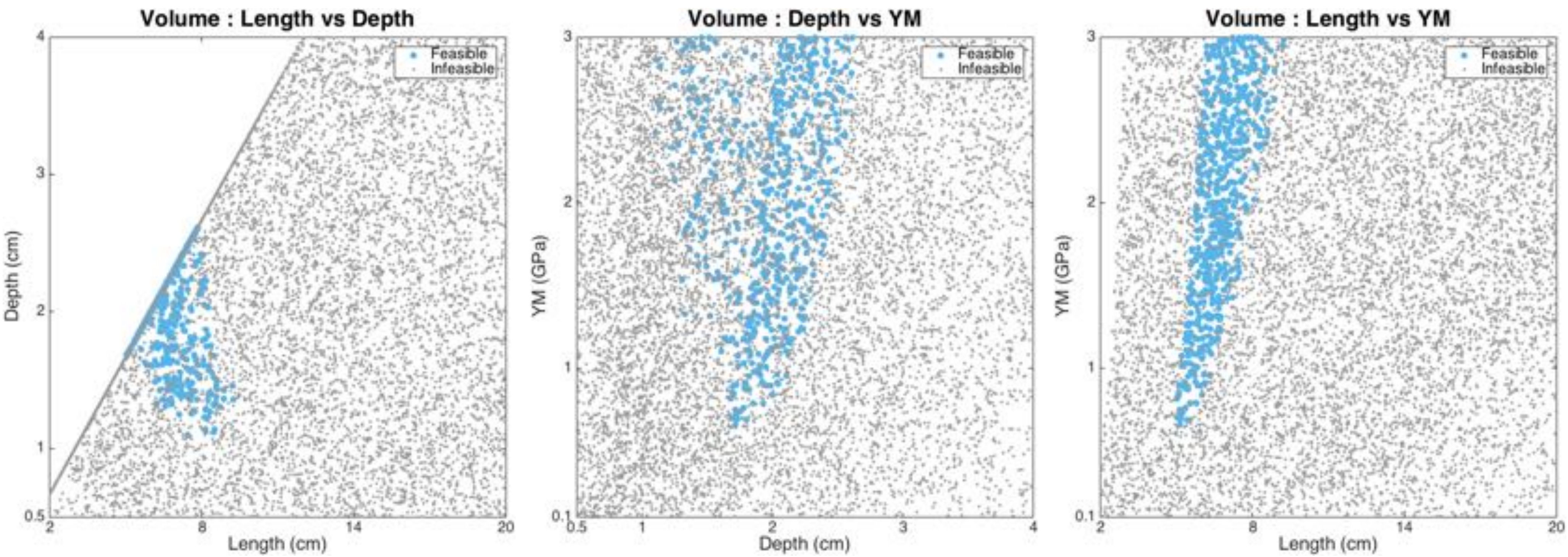
2. Evaluate all against the current best MFAC

3. Select the feasible scenario that produces the most error

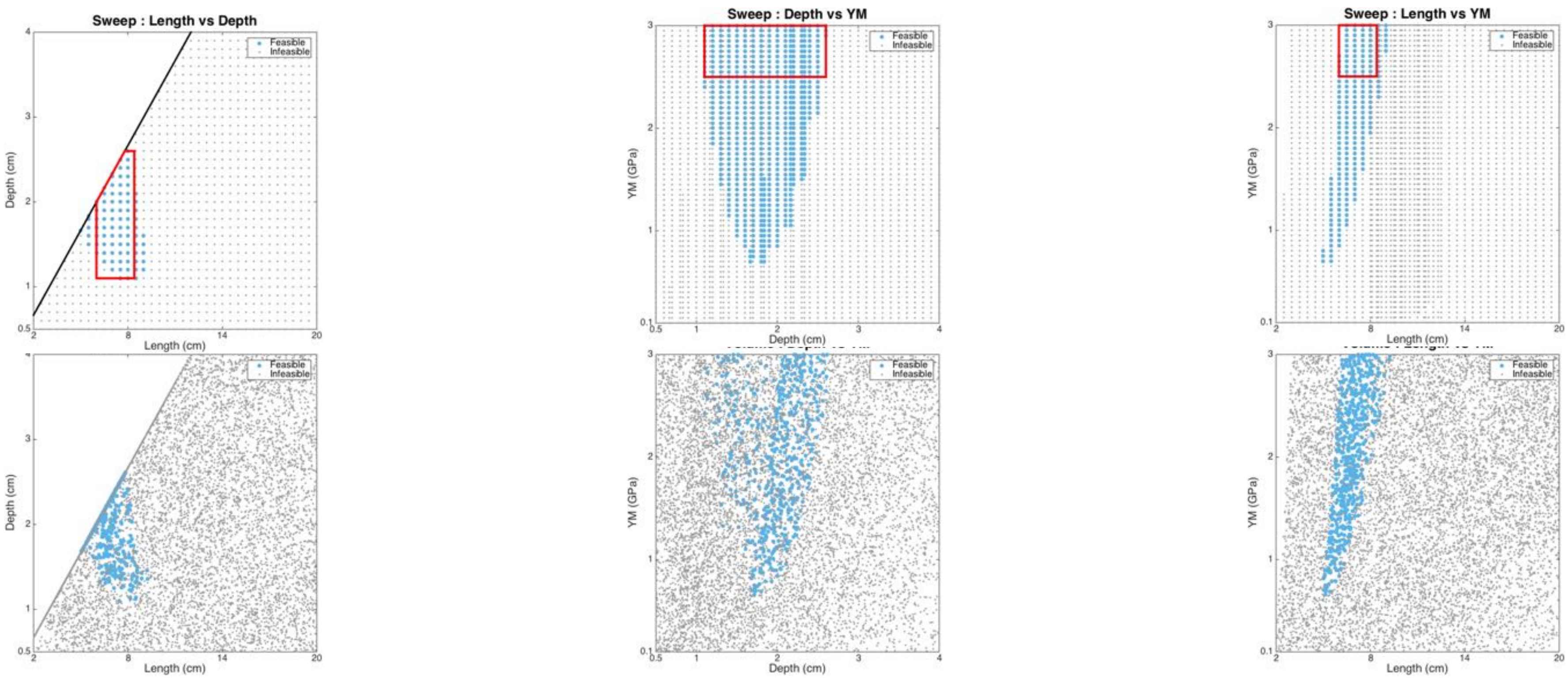
4. Add scenario to ***S***



Volume Scenarios



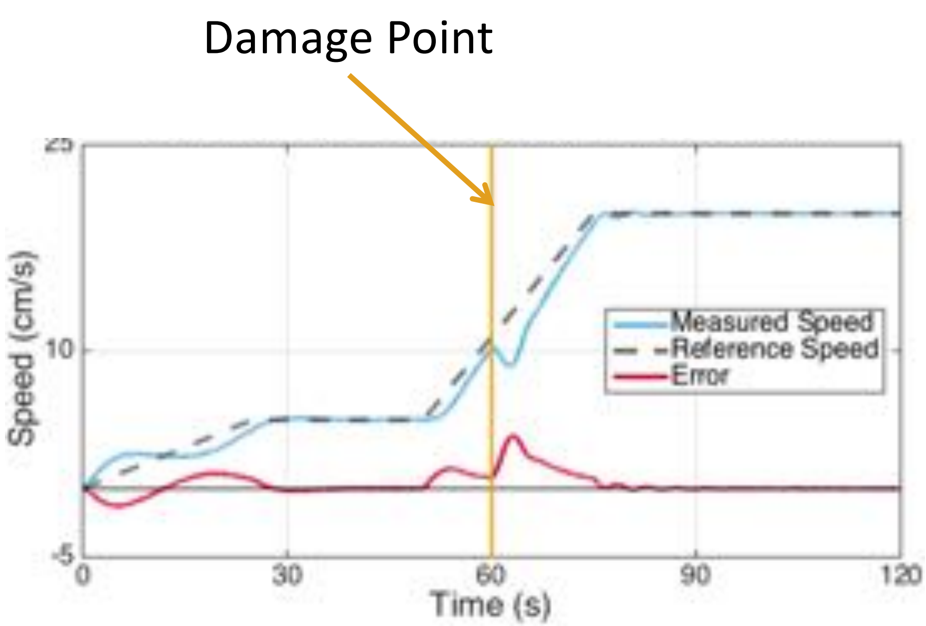
Volume Scenarios



Mean-Absolute-Error Comparison

Scenario Name	Boundary	Volume
Base	2.76 %	**2.60 %**
Min Length	9.30 %	**7.63 %**
Max Length	2.74 %	**2.73 %**
Min Depth	6.23 %	**4.87 %**
Max Depth	3.12 %	**2.92 %**
Random Boundary	4.70 %	**4.54 %**
Random Volume	3.19 %	**3.14 %**

Adapting to Damage



Fin length

- 8.0 → 6.4 cm

Fin Depth

- 2.6 → 2.1 cm

Fin Flex

- 3.0 → 2.1 GPa

Summary

- Automatically discover limits of an adaptive controller
- While at the same time optimizing the controller against "good" scenarios
- These limits define an execution mode
- Our future work involves combining this technique with self-modeling processes to account for automated switching between modes

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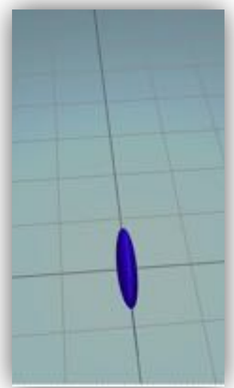
Thank You.
Questions?



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