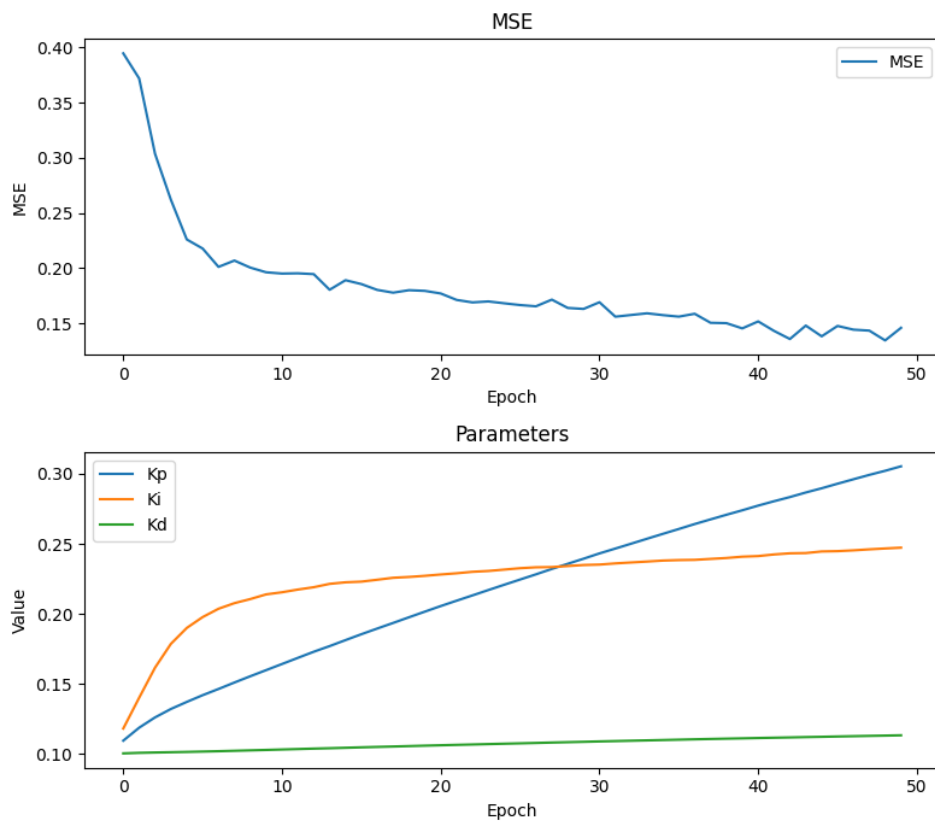


# Jax Controller Report

Group 128

## Bathtub Plant - Classic Controller

Parameter	Value
Epochs	50
Timesteps	50
Learning Rate	0.01
Disturbance Range	(-0.05, 0.05)
Initial $K_p$	0.1
Initial $K_i$	0.1
Initial $K_d$	0.1
A	10
C	0.1
Initial Height Water	5

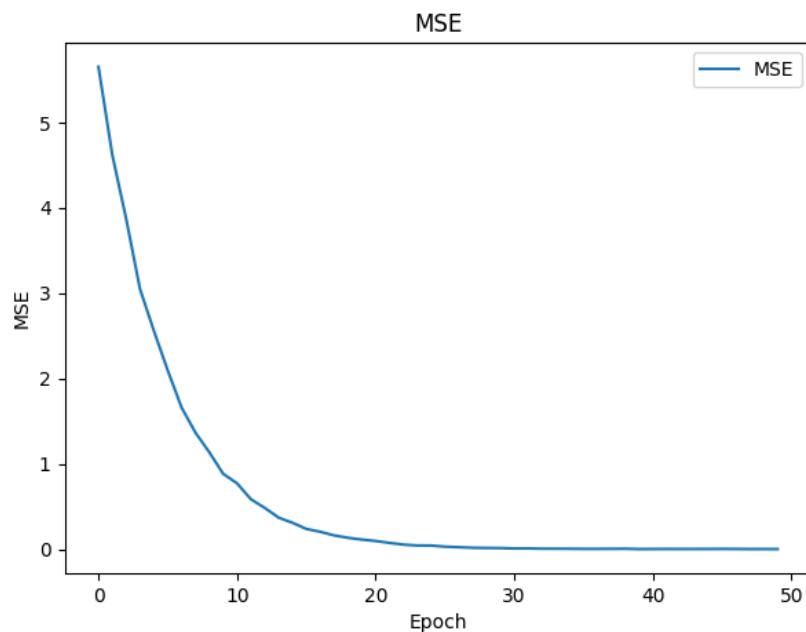


The initial error is not that high but it quickly goes down within the first 10 epochs. After

that it continues to go down, but at a lower rate. Given more epochs it might go down further. The MSE varies but this might be a response to the relatively high disturbance range. The parameters change more in the earlier epochs, especially the  $K_i$ . After about 10 epochs the  $K_i$  parameter changes at a lower rate. This is probably reflected in the MSE plot after 10 epochs, as we can see that the rate of change is lower after that point.

## Bathtub Plant - AI Controller

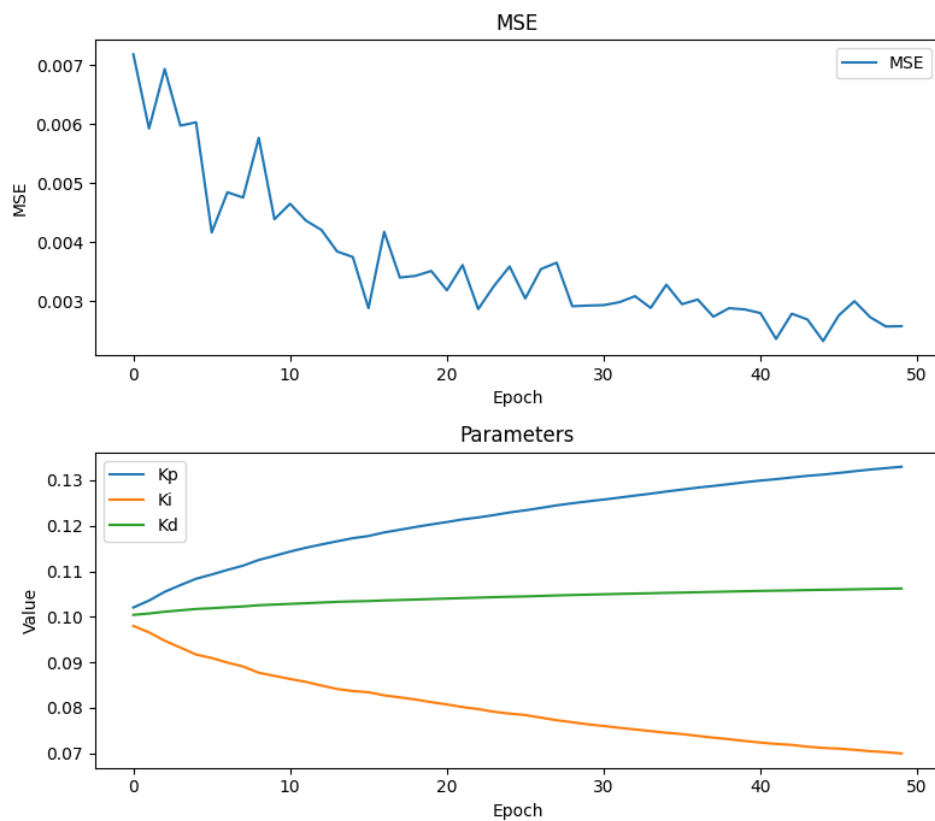
Parameter	Value
Epochs	50
Timesteps	50
Learning Rate	0.001
Disturbance Range	(-0.05, 0.05)
Number of Hidden Layers	2
Neurons per Layer	[64, 32]
Initial Weight/Bias Range	(-0.001, 0.001)
Activation Function	sigmoid
A	10
C	0.1
Initial Height Water	5



In this run the initial error is higher. This might be because of the random initializing of weights and biases. We can see that it goes steadily down, but the curve is not that steep. This is because the learning rate in this run is set to 0.001 instead of 0.01 as in the run with the classic controller above. In particular we observed that the gradients for the output layer could be high, indicating that these values were far off after initializing them. The controller still manages to learn, and displays a considerate change in MSE.

## Cournot Plant - Classic Controller

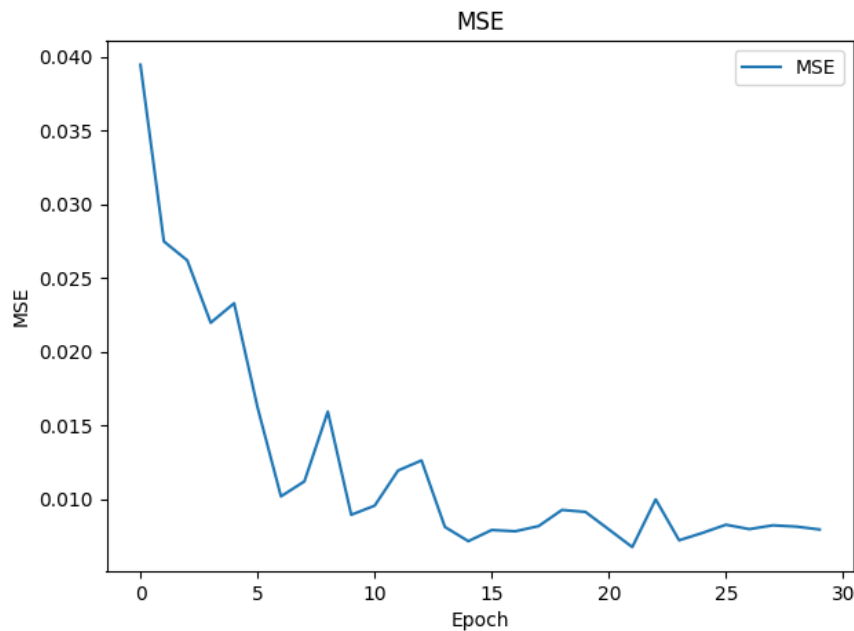
Parameter	Value
Epochs	50
Timesteps	50
Learning Rate	0.01
Disturbance Range	(-0.02, 0.02)
Initial $K_p$	0.1
Initial $K_i$	0.1
Initial $K_d$	0.1
Maximum Price	3
Marginal Cost	0.1
Target Profit	0.55
Initial $q_1$	0.4
Initial $q_2$	0.7



For this run we are using a slightly lower disturbance range. This is because the plant was more sensitive, caused by the lower numbers as input and used as state variables in the plant. The MSE plot indicates a lot of disturbance since it is not monotonous. The parameter tuning indicates that the  $K_i$  is initially too high, and it seems like in this plant it is more important to consider current error and the differentiation of error instead of the past error history.

## Cournot Plant - AI Controller

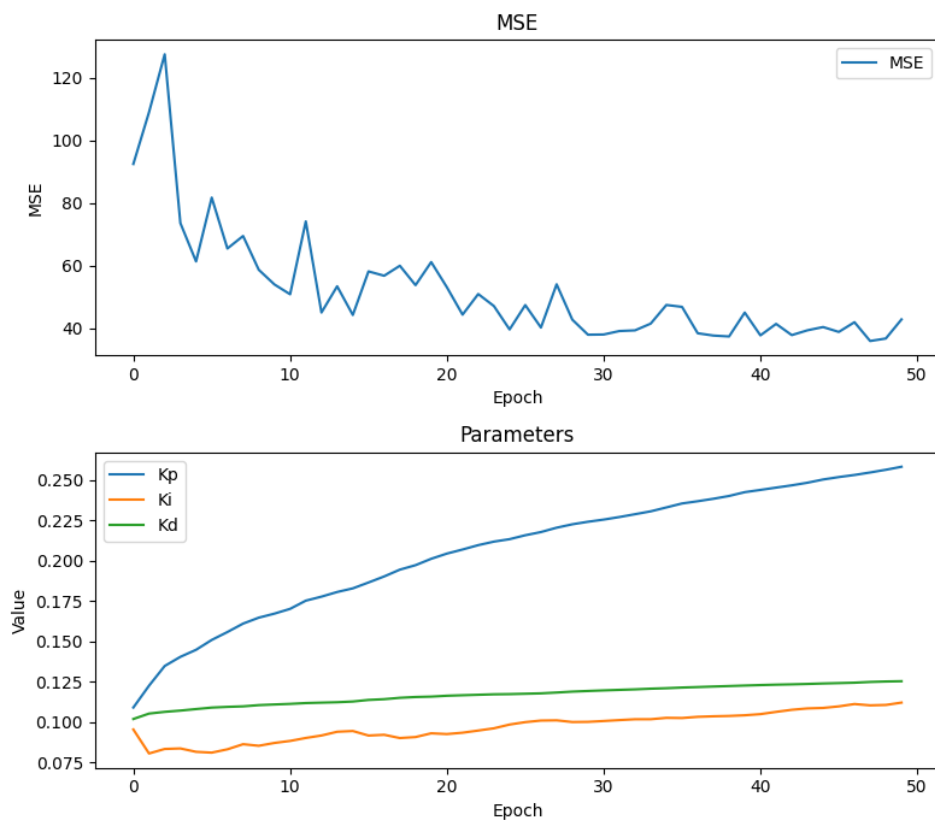
Parameter	Value
Epochs	30
Timesteps	30
Learning Rate	0.0001
Disturbance Range	$(-0.02, 0.02)$
Number of Hidden Layers	3
Neurons per Layer	[64, 64, 32]
Initial Weight/Bias Range	$(-0.001, 0.001)$
Activation Function	relu
Maximum Price	3
Marginal Cost	0.1
Target Profit	0.55
Initial $q_1$	0.4
Initial $q_2$	0.7



The error for this run starts at 0.04. This is a lot higher than 0.007 which is the starting error for the classic controller when controlling this plant. However, it quickly declines the first 5 epochs, and there is a tendency for declining further, but at a slower rate with more disturbances. It performs slightly worse than the classic controller, but it also has 30 epochs instead of 50.

## Population Plant - Classic Controller

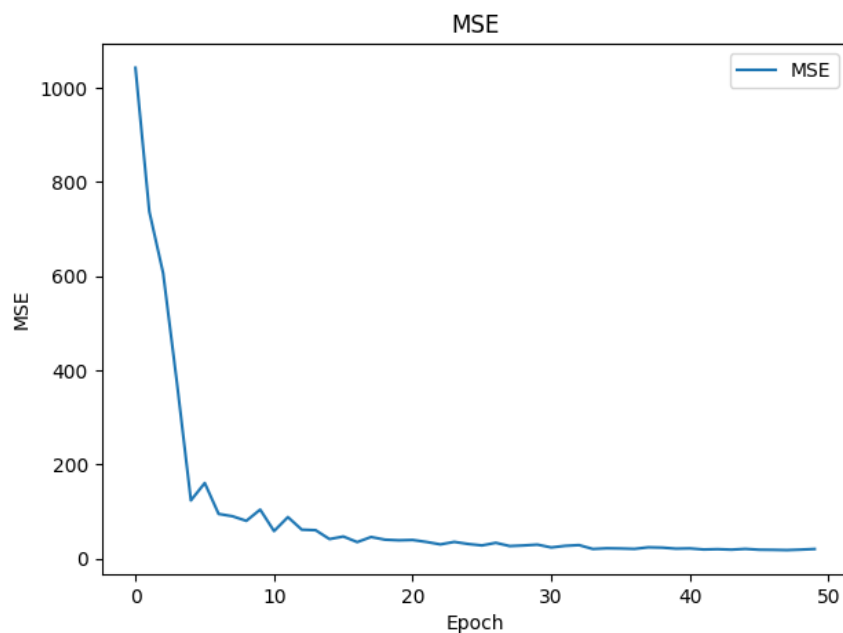
Parameter	Value
Epochs	50
Timesteps	50
Learning Rate	0.00001
Disturbance Range	(-1, 1)
Initial $K_p$	0.1
Initial $K_i$	0.1
Initial $K_d$	0.1
Initial Prey Population	90
Target Prey Population	100
Initial Predator Population	30
Prey Growth Rate	0.2
Predation Rate	0.01
Predator Growth Rate	0.002
Predator Mortality Rate	0.2



After the first epoch we can see that the error increases. After that it stabilizes again and decrease. There is a lot of disturbance, and that makes sense given that the mathematical model in this plant is oscilating. The first  $K_i$  value seems to be decreasing too much, and after that it increases.  $K_p$  is initially too low.

## Population Plant - AI Controller

Parameter	Value
Epochs	50
Timesteps	50
Learning Rate	0.0001
Disturbance Range	(-1, 1)
Number of Hidden Layers	3
Neurons per Layer	[64, 64, 32]
Initial Weight/Bias Range	(-0.1, 0.1)
Activation Function	relu
Initial Prey Population	90
Target Prey Population	100
Initial Predator Population	30
Prey Growth Rate	0.2
Predation Rate	0.01
Predator Growth Rate	0.002
Predator Mortality Rate	0.2



The error is very high after the first epoch. This might be because of the randomly initialized parameters in the neural network. Error rapidly decreases for the first few epochs. And continue to decrease after that. Better initializing of weights and biases could lead to a better result. Also when inspecting the gradients it seems like some of the weights are not changed much.

## Population Plant Description

This plant is based on Lotka-Volterra equations, which are used to model population oscillations in ecological systems. The basic idea is that the population of prey and predator will follow each other. When prey population increases, the predator population will also increase after some time, and vice versa.

The equations are a pair of first order non linear differential equations.

$$\frac{dx}{dt} = \alpha x - \beta xy \quad (1)$$

$$\frac{dy}{dt} = \delta xy - \gamma y \quad (2)$$

Equation 1 is the change in prey population and equation 2 is the change in predator population.  $\alpha$  represents the growth rate of prey.  $\beta$  represents the predation rate, which says something about the effect of predators on prey population.

$\delta$  is the predator growth rate and  $\gamma$  is the predator mortality rate.

The solution to these differential equations is the trivial solution when  $x$  and  $y$  is both 0, and the solutions

$$\left\{y = \frac{\alpha}{\beta}, x = \frac{\gamma}{\delta}\right\} \quad (3)$$

This is the equilibrium state, which means that if  $x$  and  $y$  is initially set to these values, they will not change.

In our plant we want to control the prey population, so we introduce the control signal  $U$  to the change in  $x$ .

We also introduce noise to the predator population. Thus the new equations for change in populations become

$$\frac{dx}{dt} = \alpha x - \beta xy + U \quad (4)$$

$$\frac{dy}{dt} = \delta xy - \gamma y + D \quad (5)$$