

DEPARTMENT OF COMPUTER SCIENCE

IT3105 - AI PROGRAMMING

General Purpose JAX-based Controller

Author: Edvard Bjørnevik

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1 Plant Models

These are the shared configuration parameters for all runs:

Parameter	Value
plant	0
controller	0
epochs	100
timesteps	50
$timestep_duration$	1
kp	0.2
ki	0.1
kd	0.05
min_disturbance	-0.01
max_disturbance	0.01
learning_rate	0.1
weight_initial_min	-0.1
weight_initial_max	0.1
bias_initial_min	-0.1
bias_initial_max	0.1

Table 1: Configuration parameters

1.1 Bathtub Model

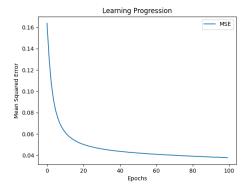
These bathtub parameters are shared for the run of the PID classic controller and neural-network-based controller:

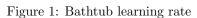
Parameter	Value
A	100
C	1
H_0	0.3
target	0.5
g	9.8

Table 2: Bathtub parameters

1.1.1 Run Summary PID Classic Controller

Figure 1 shows that the learning rate goes exponentially down. While Figure 2 shows how the k-parameters change over the epochs. This run gives an average error after 100 epochs of about 0.04.





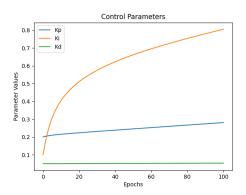


Figure 2: Bathtub control parameters

1.1.2 Run Summary PID Neural Network Controller

Figure 3 shows the learning progression using the AI controller. The MSE goes lineary down, but the result is worse than the classic PID controller: 0,186.

Parameter	Value
NN_layers	2
NN_neurons	5
activation_function	0
out_activation_func	0

Table 3: Neural Network Parameters

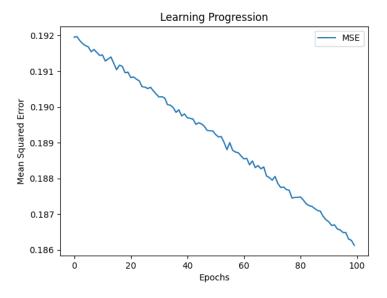


Figure 3: Bathtub AI learning rate

1.2 Cournot Competition Model

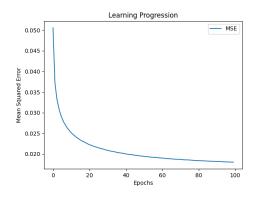
These Cournot Competition parameters are shared for the run of the PID classic controller and neural-network-based controller:

Parameter	Value
p_{max}	2
c_m	0.1
target	0.9
q_{1_0}	0
q_{2_0}	0

Table 4: Cournot competition parameters

1.2.1 Run Summary PID Classic Controller

Figure 4 shows that the learning rate goes exponentially down. While Figure 5 shows how the k-parameters change over the epochs. This run gives an average error after 100 epochs of about 0,02.



Control Parameters

Figure 4: Cournot competition learning rate

Figure 5: Cournot competition control parameters

1.2.2 Run Summary PID Neural Network Controller

Figure 6 shows the learning progression using the AI controller. The MSE goes down exponentially, but at a slower slope than the PID controller. The result is the same as the classic PID controller: 0,02.

Parameter	Value
NN_layers	2
NN_neurons	5
$activation_function$	0
out_activation_func	0

Table 5: Neural Network Parameters

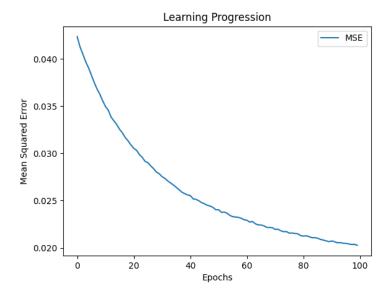


Figure 6: Cournot AI learning rate

1.3 Rabbit Population

Rabbits are known to breed rapidly and the population of the zoo rabbits is now exploding. As head of the Animal Control Team (ACT), it is your responsibility to control the rabbit population.

Your first task is to develop a growth model. Using a document found in your desk drawer you calculate that the rabbit population increases by r each month:

$$P_{t+1} - P_t = r * P_t \tag{1}$$

The ACT receives two inputs every timestep:

- U, the output of the controller.
- D, a random disturbance in the efficiency of the ACT team.

With this understanding, you develop a model to calculate ACT's intervention (I) in the population:

$$\frac{\varphi I}{\varphi t} = U * P_t + D * P_t \tag{2}$$

Then, on each timestep, the population is computed as follows:

$$P = P_t + I \tag{3}$$

In this model, the target value (T) denotes the goal population. Thus:

$$E = T - P \tag{4}$$

and the error (E) serves as input to the controller on each timestep.

The model is inspired by (Nykamp 2025).

1.3.1 Rabbit Population Parameters

These Rabbit Population parameters are shared for the run of the PID classic controller and neural-network-based controller:

Parameter	Value
Growth Rate	0.2
Initial Population	0.5
Target	1

Table 6: Parameters Rabbit Population

1.3.2 Run Summary PID Classic Controller

Figure 1 shows that the learning rate goes exponentially down. While Figure 2 shows how the k-parameters change over the epochs. This run gives an average error after 100 epochs of about 0,01.

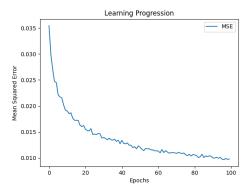


Figure 7: Rabbit population learning rate

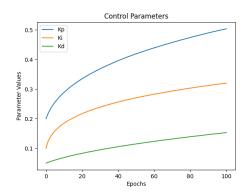


Figure 8: Rabbit population control parameters

1.3.3 Run Summary PID Neural Network Controller

Figure 9 shows the learning progression using the AI controller. The MSE goes down exponentially, at a steeper slope than the PID controller. The result is the same as the classic PID controller: 0,01.

Parameter	Value
NN_layers	0
NN_neurons	0
activation_function	1
out_activation_func	0

Table 7: Neural Network Parameters

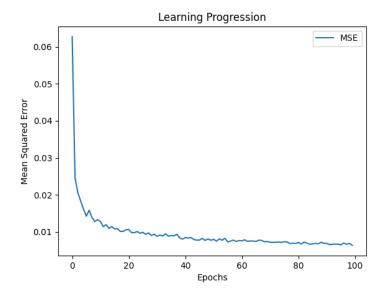


Figure 9: Rabbit Population AI learning rate

Bibliography