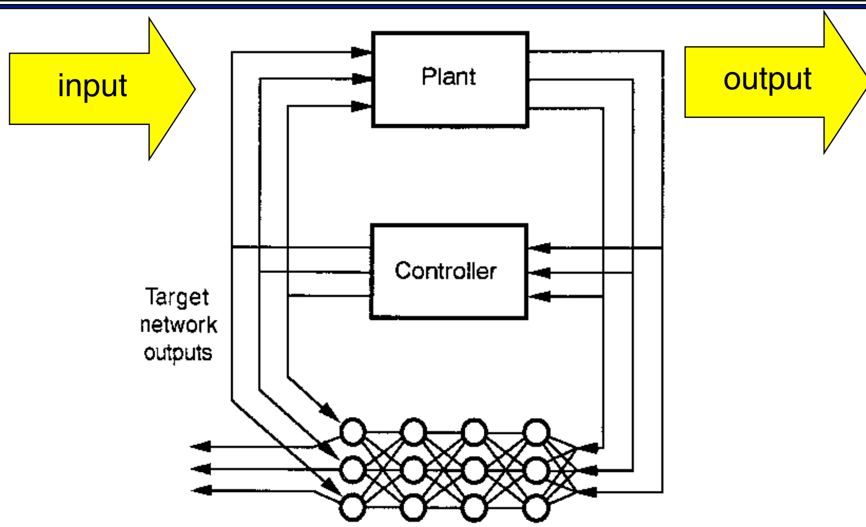
Control Applications of Neural Nets

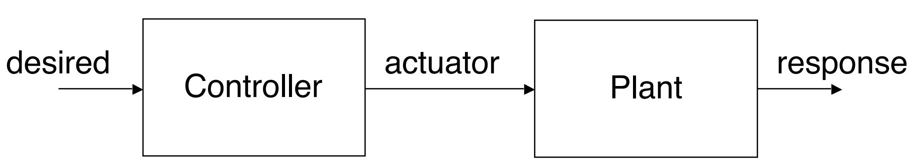
Control Systems in General

- Vocabulary:
  - “Plant” or “Process”: The thing being controlled
  - “Controller”: The thing doing the controlling
  - Generally both are functions responding to time-varying input.

“Copying” an Existing Controller with a Neural Net



Open-Loop Control

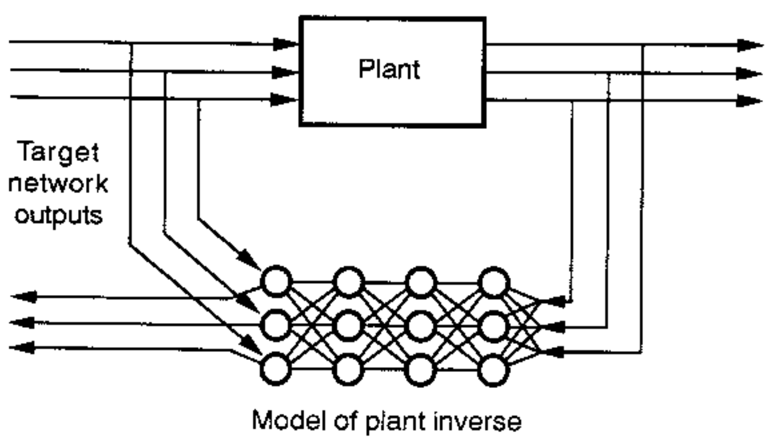


Open-Loop Control

- Description of plant (for all time t):
  response(t) = plant(actuator(t))
- Description of controller:
  actuator(t) = control(desired(t))
- Thus
  response(t) = plant(control(desired(t)))
- To make response(t) = □ desired(t), make

  control = plant^{-1} (the inverse function)

Training a neural net to compute plant^{-1}



Issues with "inverse" form of control

- plant function might not be known analytically (could be learned by an NN though)
- plant function might not be invertible
- plant function could be time-varying (which would require a time-varying net)

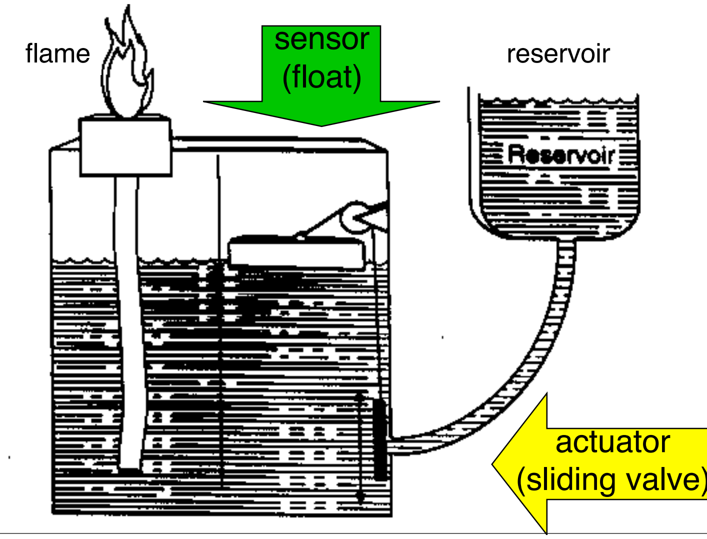
- The open-loop approach might be unstable.

- "Feedback control" can help with issue of stability.

Feedback Control

- Earliest known example?
  - How to keep the oil in a reservoir (such as a lamp) at a specific level?
  - Answer: Monitor the level; when it drops below the desired level, add more oil, until it reaches the desired level.
  - Philon's lamp regulator (220 b.c.)

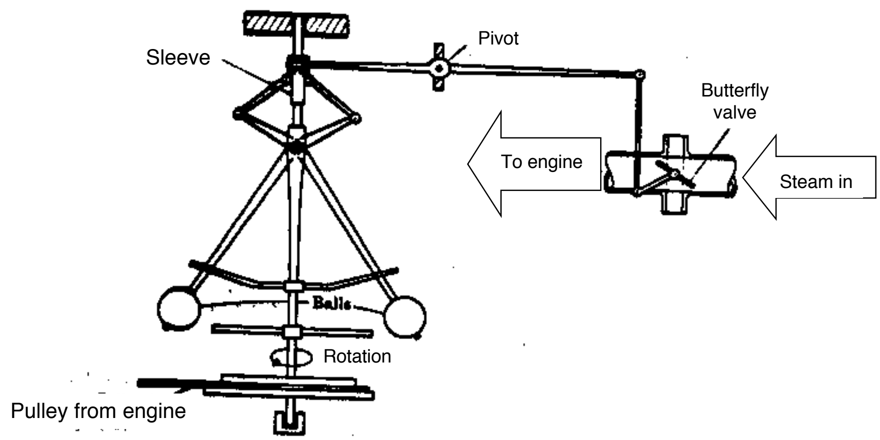
Philon’s Lamp Regulator



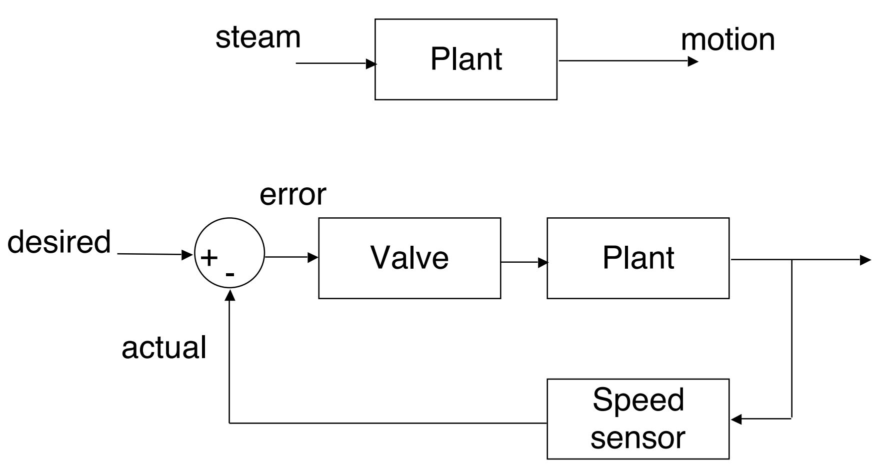
Steam-Engine Governor

James Watt, 1748

Flyball Governor
(James Watt, 1748)

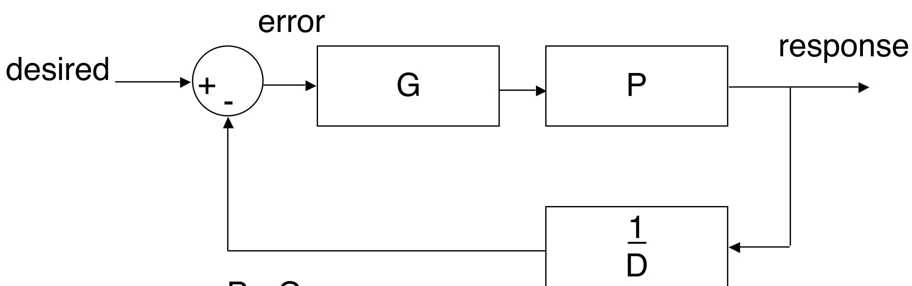


Block Diagram of Steam Engine



Classical Symbolic Reasoning (aside)

Using, for example, Laplace Transforms,
function composition is treatable as **multiplication**.



response = P • G • error

error = desired - response/D,   D a scalar

Solve for response = f(desired)

response = P • G • error
error = desired - response/D

Substituting,

response = P • G • (desired - response/D)

response(1+PG/D) = PG•desired

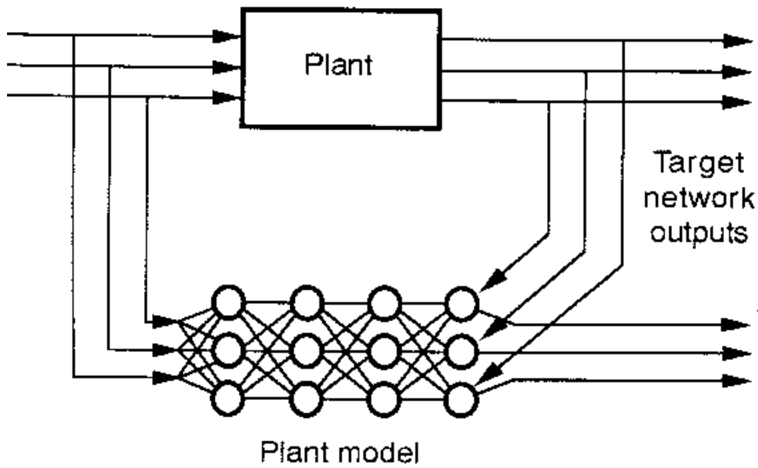
response = desired•PG/(1+PL)

where L = G/D is the **"open loop gain"**

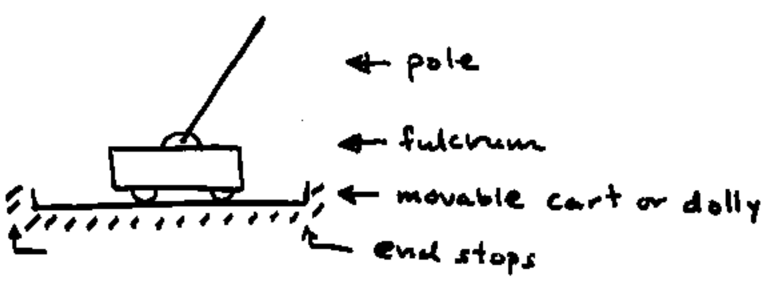
If we can make L >> 1, response = desired•PG/PL = desired•G/L

i.e. response = desired•D.

Copying a Plant as a Neural Net (Example to follow)



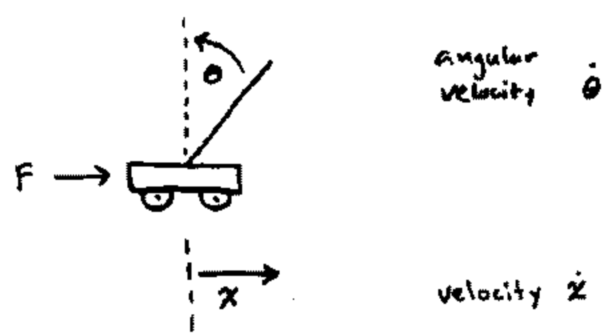
Pole-Balancing (pole-cart, broom balancing)



Approaches

- Design a controller using **classical** approach (example: matlab **pendemo**)
- Develop **parameterized controller**, then **learn parameters** using neural net by training (Widrow's approach #1)
- Widrow #2 (Tolat & Widrow)

Pole-Cart Controller



$$F(t) = a\,x(t) + b\,\dot{x}(t) + c\,\theta(t) + d\,\dot{\theta}(t)$$

Widrow Approach #1 to Pole-Cart

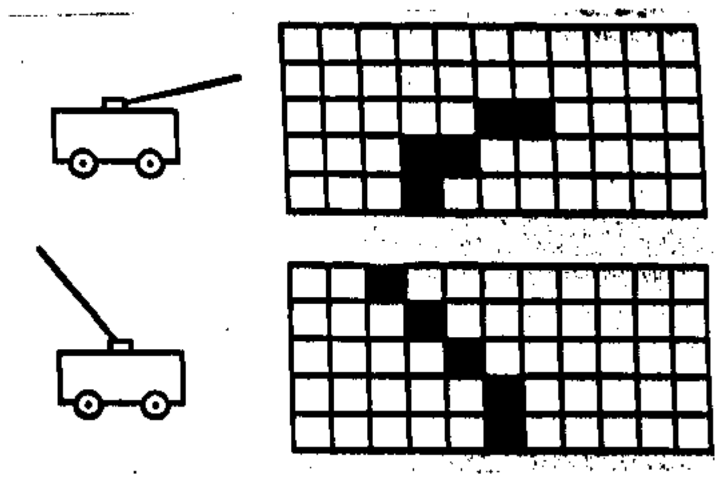
- Used Adaline to “observe” an operating controller, with input values x, x’, □, □’

- Train Adaline to emit appropriate force on cart

Widrow #2 (Tolat & Widrow)

- **Pairs of images** of pole position were input, taken at successive points 100ms apart
- 5x11 pixel image used
- Equations were not used; instead a “teacher’s input” was given indicating force on cart based on a given image pair. Only the **sign** of this force was actually used (“bang-bang” control).

States & Images (sample)

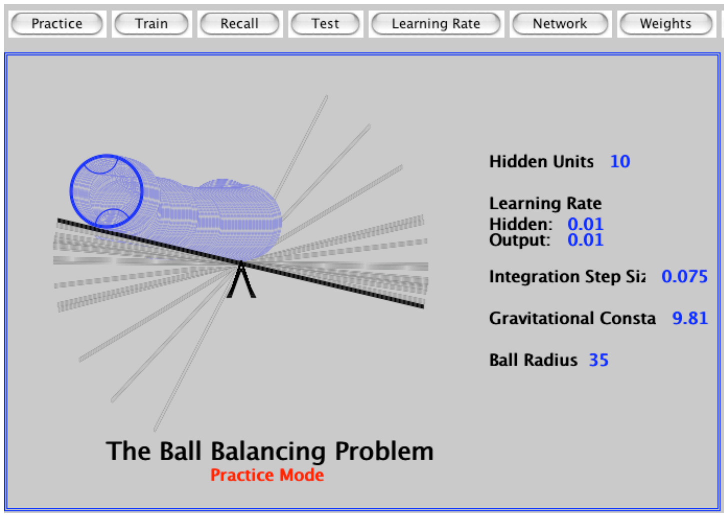


Tolat & Widrow conclusions

- 4225 image pairs used in training
- Adaline with 110 weights + threshold was sufficient to balance the pole
- Error 3.4% after only 1000 training cycles

A related train-by-watching-user Demo

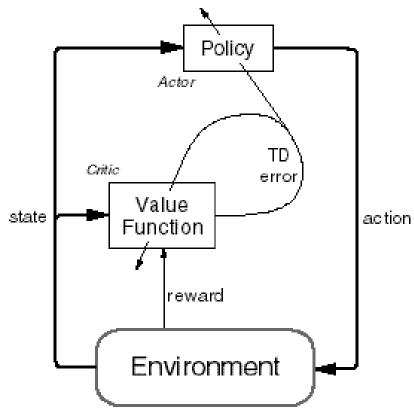
http://neuron.eng.wayne.edu/bpBallBalancing/ball5.html



Pole-Balancing Demos

- matlab/broom2: run dbroom_ndemo (2-broom demo by Wan, et al.; does not show BPTT training phase)
- Jeff Lawson '99 and Chris Lewis '99 demos, using
  - AHC (Adaptive Heuristic Critic)
  - SANE (Symbiotic Adaptive Neuro-Evolution)

Actor-Critic Methods



Explicit representation of policy as well as value function.

"Value" = expected reward from this state under a given policy = $V^{\pi}(s)$

value satisfies dynamic programming equations

value can be estimated using TD, etc.

Train both policy and value functions.

Looking Forward

- Lots of current interest in
  - neural control
  - neuro-fuzzy control
    (neural networks + fuzzy logic)
  - neuro-evolutionary control
    (neural networks + evolution programs)