Lecture Notes on Non-Identifier-Based

Adaptive Control

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Adaptive Control: Non Identifier Based

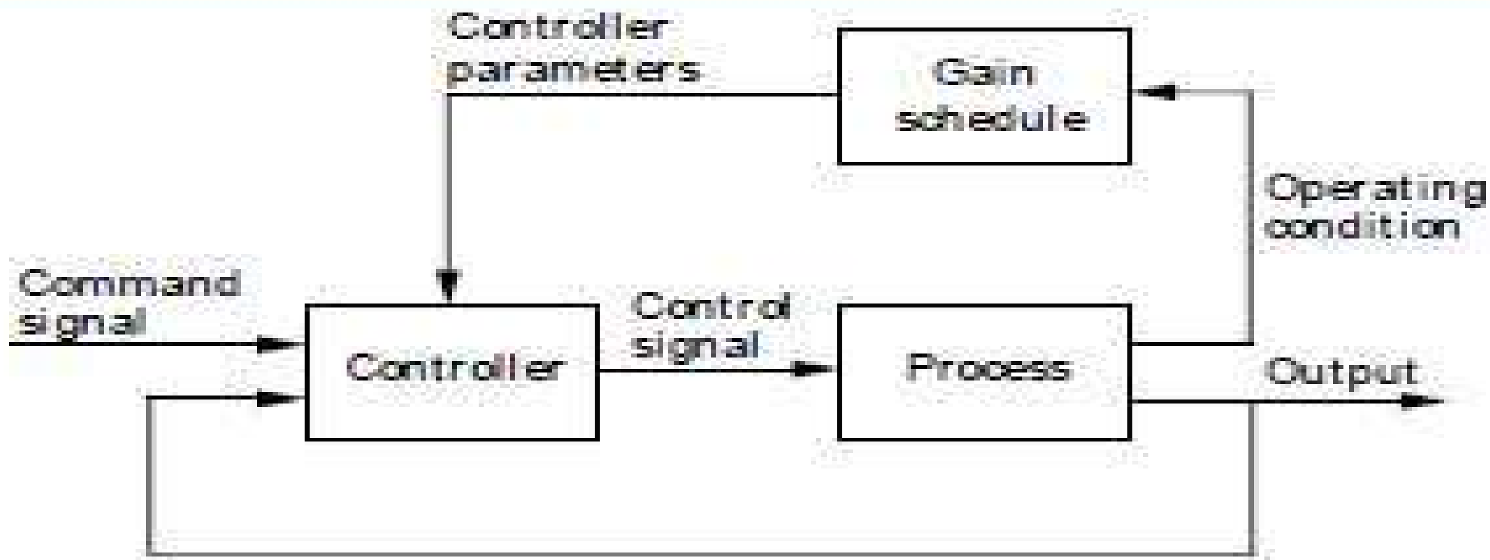
Another class of schemes that do not involve online parameter estimators is referred to as non-identifier-based adaptive control schemes. In this class of schemes, the online parameter estimator is replaced with search methods for finding the controller parameters in the space of possible parameters, or it involves switching between different fixed controllers, assuming that at least one is stabilizing or uses multiple fixed models for the plant covering all possible parametric uncertainties or consists of a combination of these methods.

We briefly describe the main features, advantages, and limitations of these non-identifier-based adaptive control schemes. Some of these approaches are relatively recent and research is still going on.

1- Gain scheduling

Gain scheduling is a type of adaptive control that can be used in systems with nonlinear or time-varying characteristics. In essence, gain scheduling involves adjusting control parameters, such as the proportional and integral gains of a PID controller, based on changing operating conditions. The goal of gain scheduling is to maintain stable control by compensating for changes in the system behavior. Overall, gain scheduling is an essential technique for modern control systems. Its ability to adapt to changing conditions and improve system performance and robustness makes it a valuable tool for a wide range of applications.

Gain Scheduling

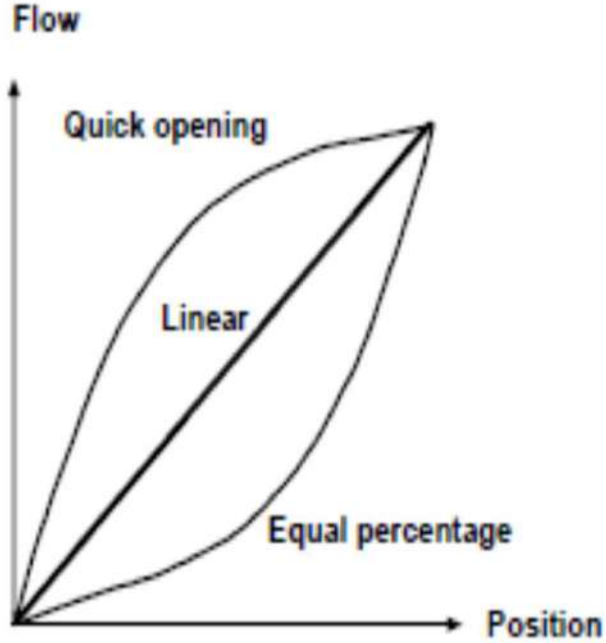


Example of scheduling variables

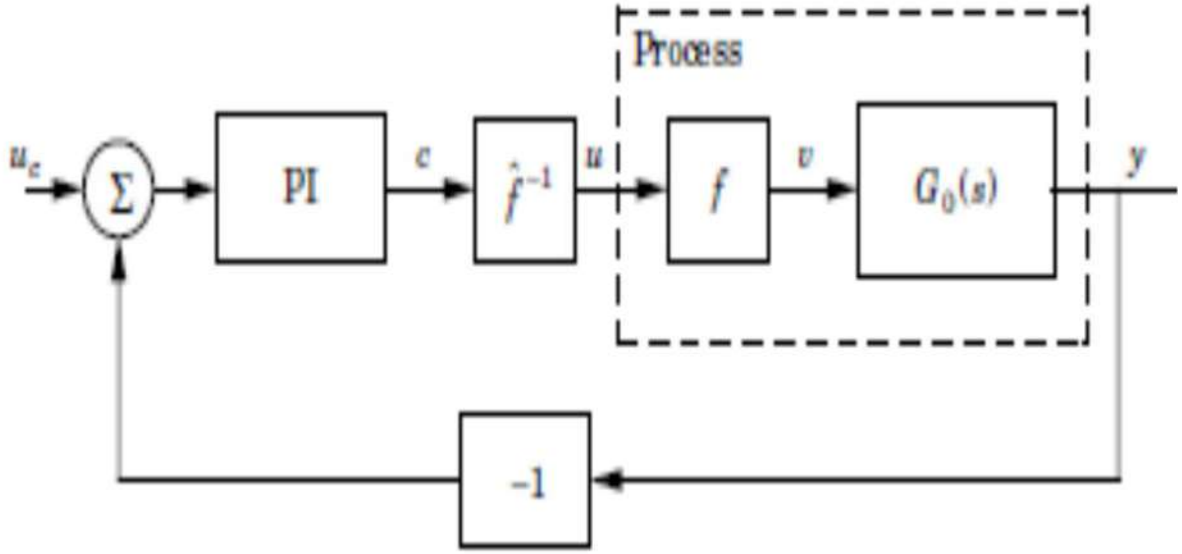
- Production rate
- Machine speed
- Mach number and dynamic pressure

Compare structure with adaptive control!

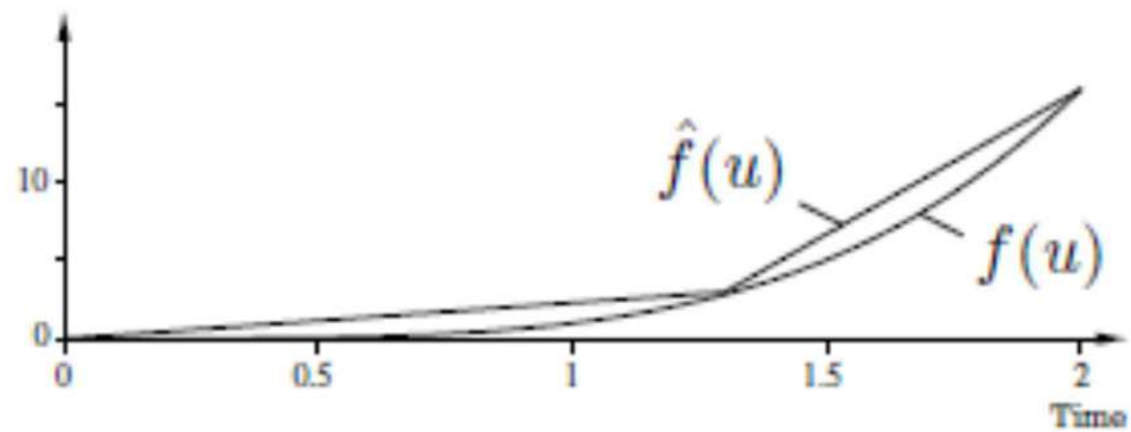
Valve Characteristics



Nonlinear Valve

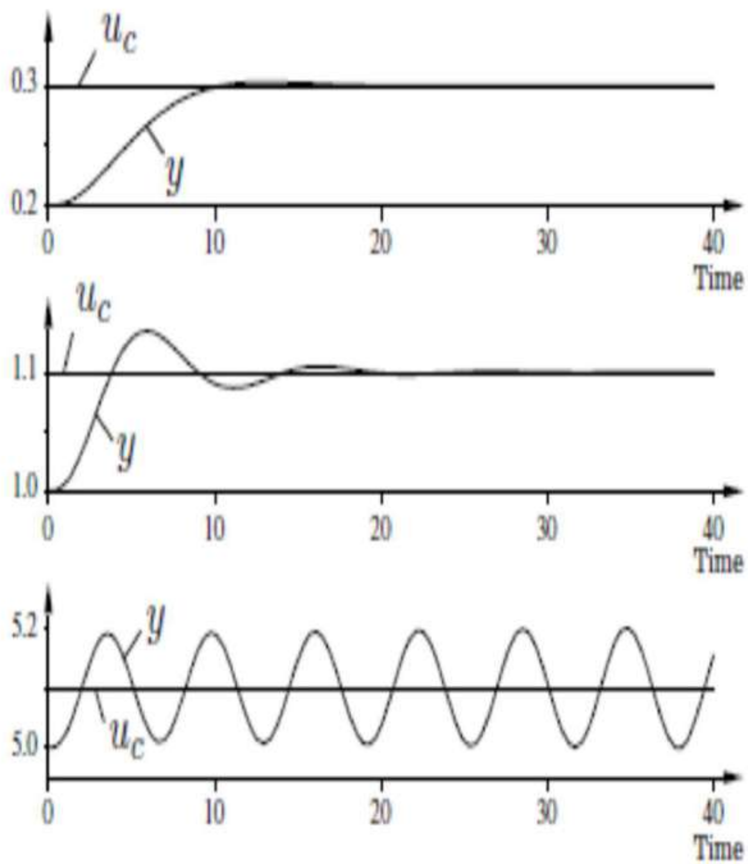


Valve characteristics



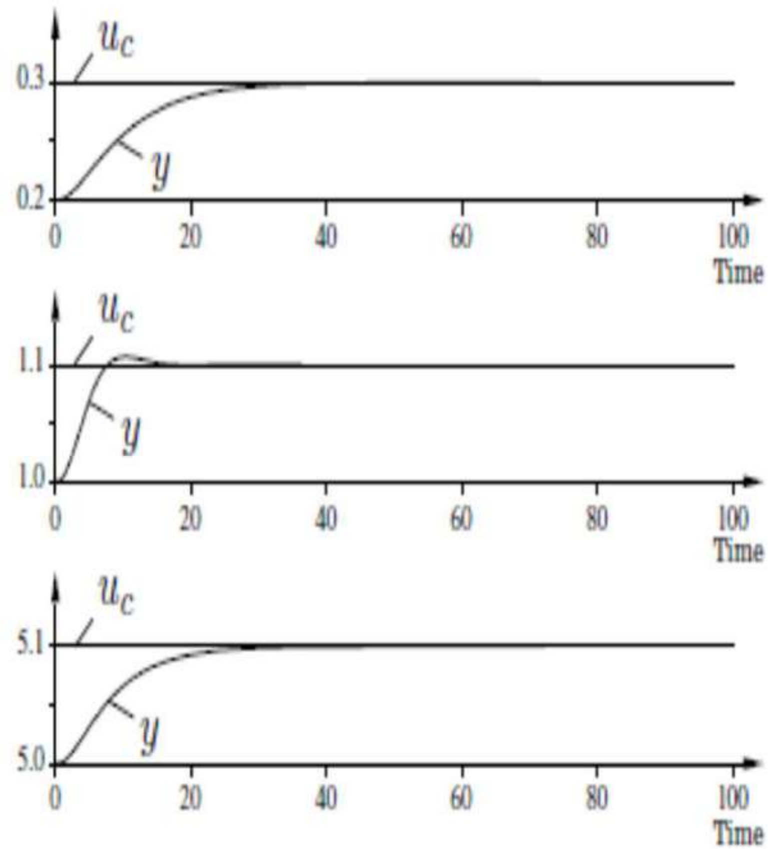
Results

Without gain scheduling



Results

With gain scheduling



Gain scheduling has been successfully applied in many industrial settings, including aerospace, automotive, and HVAC systems. For example, in an aircraft engine, gain scheduling can be used to adjust the fuel-to-air ratio based on altitude and temperature changes. This ensures that the engine operates efficiently and safely at all times. There are **three** main components of gain scheduling: **controller design**, **scheduling variables**, and **gain scheduling algorithms**.

Controller Design

A well-designed controller should be able to maintain stability and performance over the entire range of operating conditions.

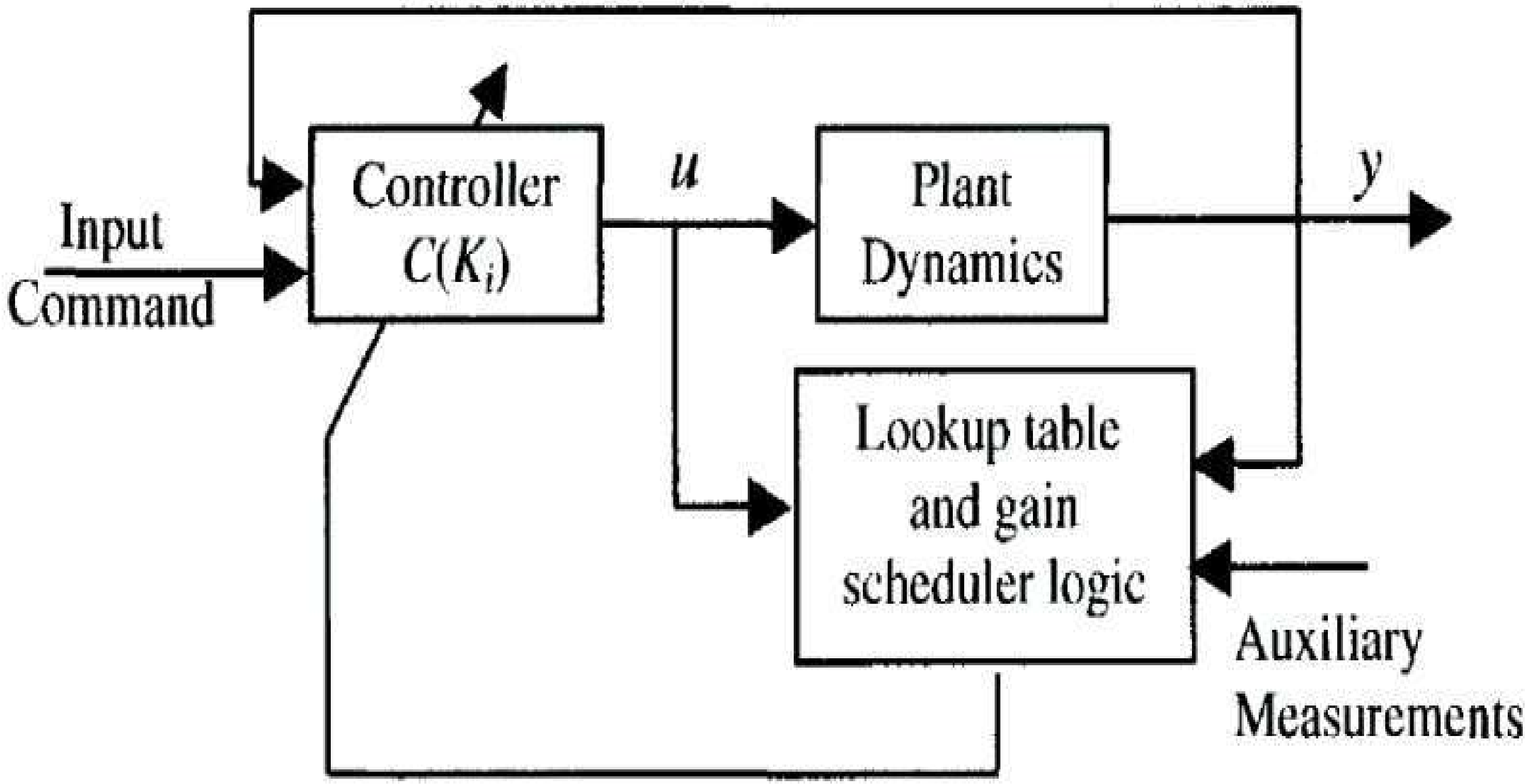
There are several methods for designing gain-scheduled controllers, including linear control design methods, nonlinear control design methods, and adaptive control methods. Linear control design methods involve linearizing the system around a set of operating conditions and designing a controller for each linearized system. Nonlinear control design methods involve designing a controller that can handle the nonlinearities of the system over the entire range of operating conditions. Adaptive control methods involve designing a controller that can adapt its gains based on the current operating conditions of the system

Scheduling Variables

The scheduling variables are the input parameters that are used to determine the appropriate control gains for a given operating condition. These variables may include system temperature, pressure, or velocity, and they may be measured directly or estimated using models or sensors.

Gain Scheduling Algorithms

There are various gain scheduling algorithms that can be used to interpolate between control gains at different operating conditions. These algorithms may be simple look-up tables or more complex nonlinear functions that map the scheduling variables to specific control gains



Gain scheduling structure.

One of the **disadvantages** of gain scheduling is that the adjustment mechanism of the controller gains is precomputed offline and provides **no feedback** to compensate for incorrect schedules. A careful design of the controllers at each operating point to meet certain robustness and performance measures can accommodate some uncertainties in the values of the plant parameters. However large unpredictable changes in the plant parameters, may lead to deterioration of performance or even to complete failure.

Despite its limitations, gain scheduling is a popular method for handling parameter variations in **flight control** and other systems. While **gain scheduling** falls into the generic definition of **adaptive control**, we do not classify it as adaptive control due to the **lack** of **online parameter estimation** which could track unpredictable changes in the plant parameters.

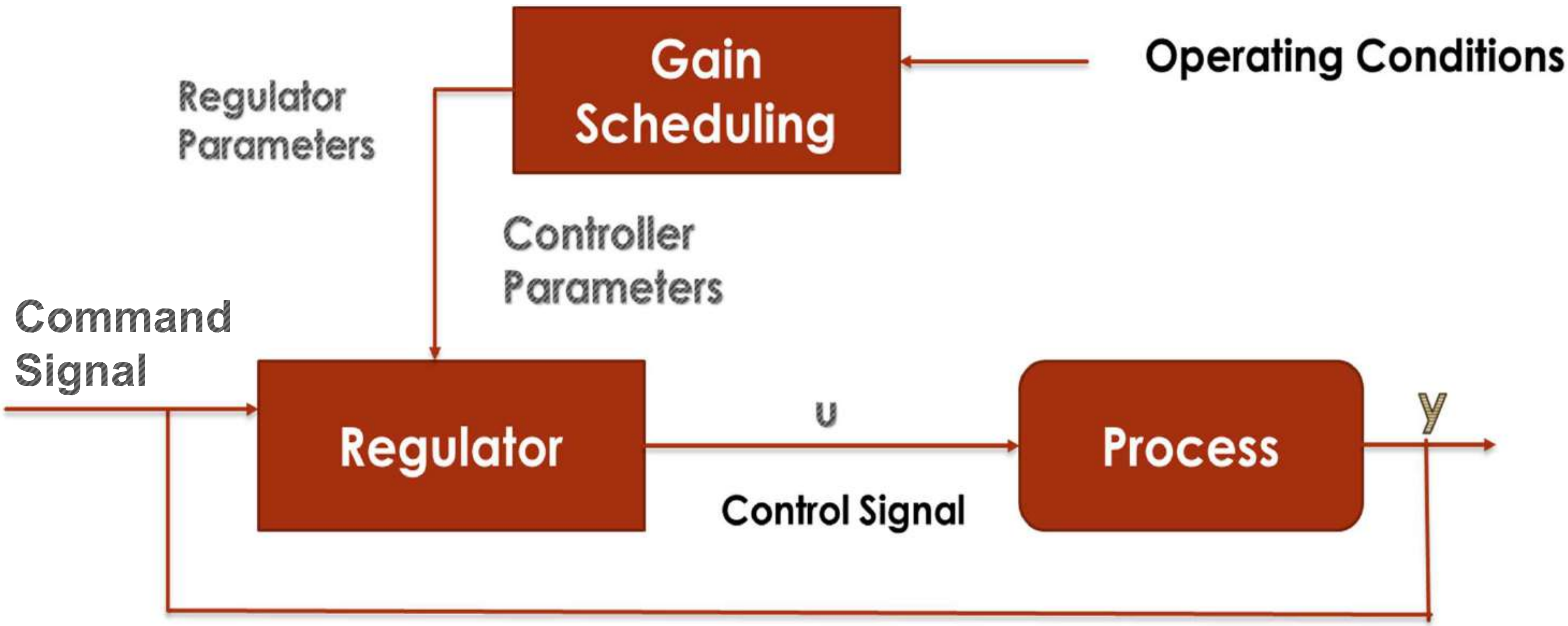
In many situations it is known how the dynamics of a process change with the operating conditions of the process. One source for the change in dynamics may be nonlinearities that are known.

It is then possible to change the parameters of the controller by monitoring the operating conditions of the process. This idea is called gain scheduling.

Its principle is to reduce the effects of parameter variations by changing the parameters of the regulator as function of auxiliary variables that correlate well with these changes in process dynamics. Gain scheduling was used in special cases: such as autopilots for high-performance air-craft.

Principles

It is sometimes possible to find auxiliary variable that correlate well with the changes in process dynamics. It is then to reduce the effects of parameter variations simply by changing the parameters of the regulator as functions of auxiliary variables as shown in figure below:



Design of Gain Scheduling regulators

It is difficult to give general rules for designing gain scheduling regulators. The key question is to determine the variables that can be used as scheduling variables. It is clear that these auxiliary signals must reflect the operating conditions of the plant. The following general ideas can be useful:

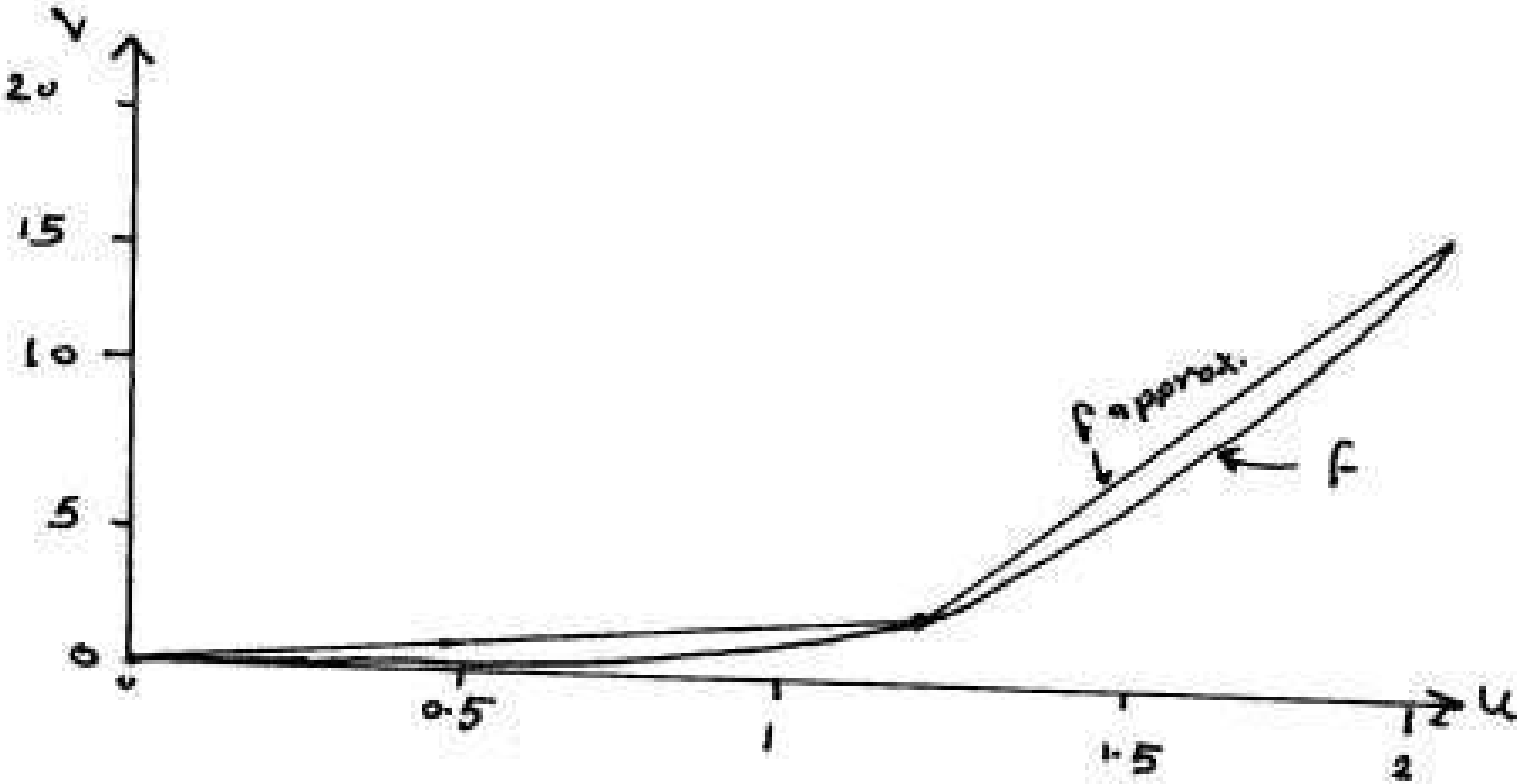
1) Linearization of nonlinear actuators.
2) Gain scheduling based on measurements of auxiliary variables.
3) Time scaling based on production rate.
4) Nonlinear transformation.

Example 1: Nonlinear Actuator:

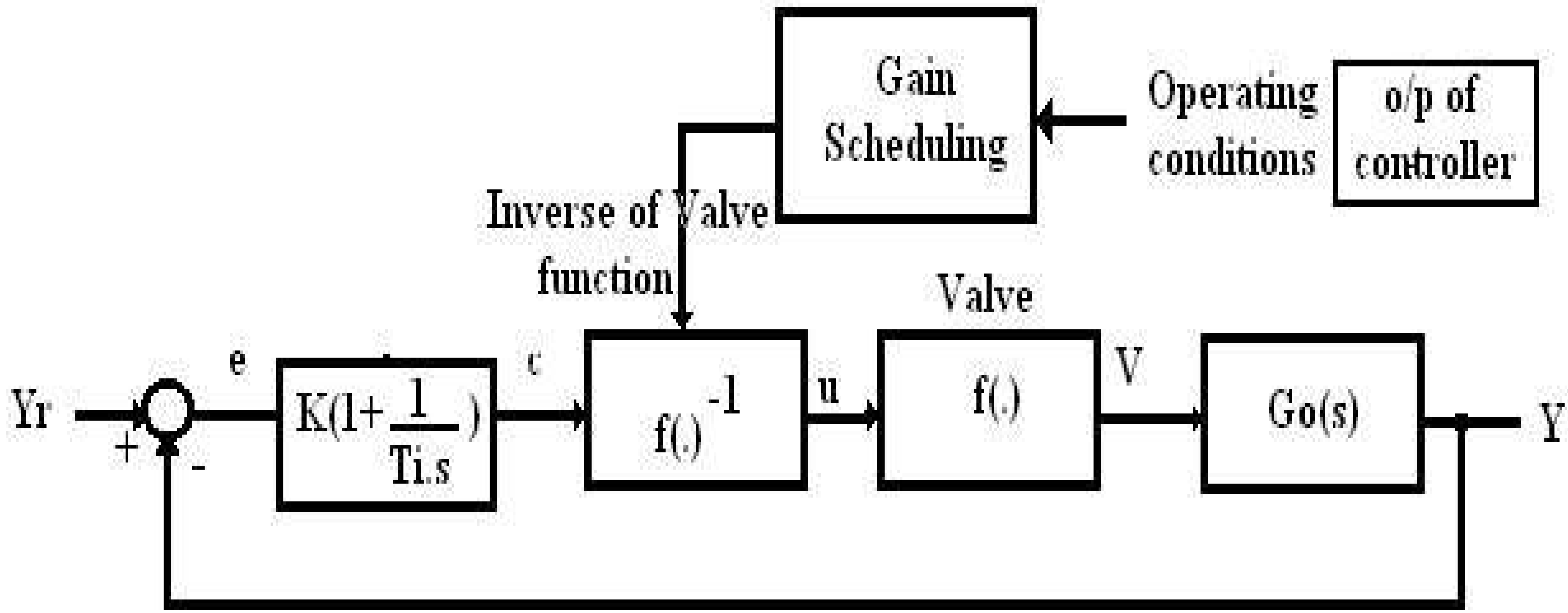
Consider the system with a nonlinear valve characteristics. Its nonlinearity is assumed to be: $V=f(u)=u^4$ $u\geq 0$

Let f^{-1} be an approximation of the inverse of the valve characteristics. To compensate for the nonlinearity; the output of the regulator is fed through this function before it is applied to the valve. This gives the relation: $V=f(u)=f(f^{-1}(c))$

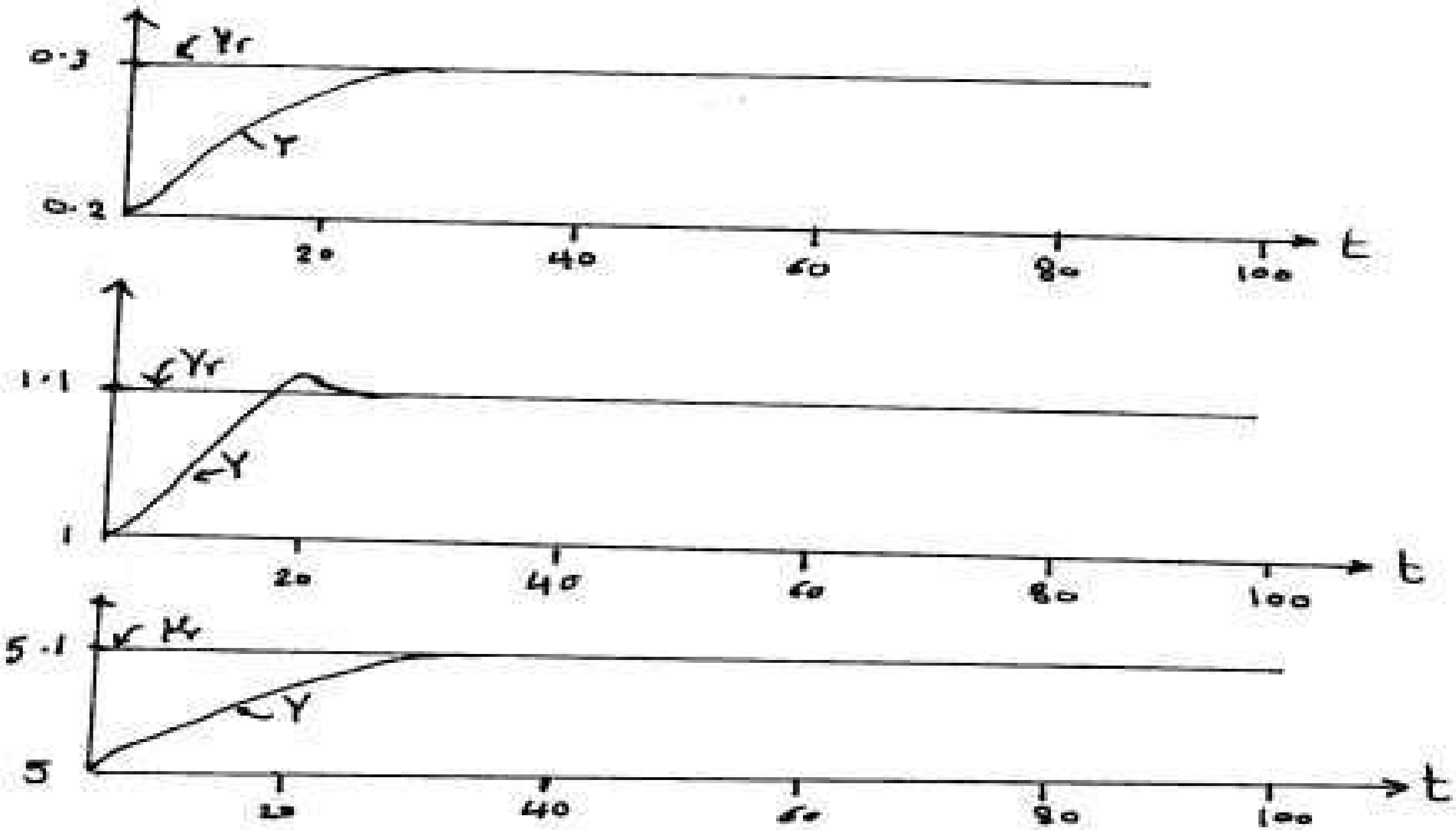
where c is the output of the PI regulator. The function $f(f^{-1}(c))$ should have less variation in gain the f. If f^{-1} is the exact inverse, then v=c. Assume that f(u) is approximated by two straight lines: one connecting the point (0,0) and (1.3,3), and the other connecting (1.3,3) and (2,16) as shown in figure below:



$$f^{-1}(c) = \begin{cases} 0.433C & \ldots\ldots\ldots\ldots\, 0 \le C \le 3 \\ 0.0538C + 1.139 & \ldots\ldots\ldots\ldots\, 3 \le C \le 16 \end{cases}$$



The figure below shows step changes in the reference signal at three different operating conditions when the approximation of the inverse of the valve characteristics is used between the regulator and valve.



By improving the inverse it is possible to make the process even more insensitive to nonlinearity of the valve.

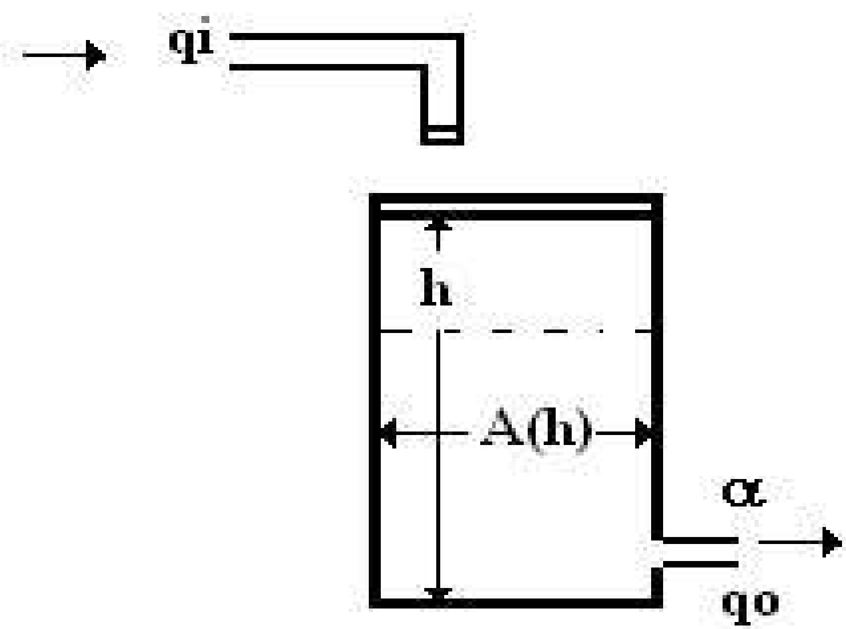
Example 2: Tank System:

Consider a tank where the cross section A varies with height h. The model is: $\frac{d}{dt}(A(h),h) = qi - a.\sqrt{2.g.h}$

Where qi is the input flow and a is the cross section of the outlet pipe. Let qi be the input and h is the output of the system. The schematic diagram of the tank is shown in figure below:

The linearized model at an operating point qi and h, function:

$$G(s)=\frac{\beta}{s+\alpha}$$



where : $\beta = \dfrac{1}{A(\overset{o}{h})}$ **and** $\alpha = \dfrac{\overset{o}{qin}}{2.A(\overset{o}{h}).\overset{o}{h}} = \dfrac{a.\sqrt{2.g.\overset{o}{h}}}{2.A(\overset{o}{h}).\overset{o}{h}}$

A good PI control of the tank is given by:

$$u(t)=K(e(t)+\frac{1}{Ti}\int e(\tau)d\tau)$$

where $K=\dfrac{2\zeta\omega-\alpha}{\beta}$ **and** $Ti=\dfrac{2\zeta\omega-\alpha}{\omega^2}$

Introducing the expressions for α and β gives the following gain schedul

$$K = 2.\zeta.\omega.A(\overset{o}{h}) - \frac{\overset{o}{qin}}{2.\overset{o}{h}}$$

$$T_i = \frac{2.\zeta}{\omega} - \frac{\overset{o}{qi}}{2.A(\overset{o}{h}).\overset{o}{h}.\omega^2}$$

ıe numerical values are often such that $\alpha << 2\zeta\omega$. The schedule can th

ıplified to: $K=2\zeta\omega A(h)$ and $Ti=\frac{2\zeta}{\omega}$

In this case it is sufficient to make the gain proportional to the cross sec

the tank. For $\zeta=0.5$ and $\omega=1$ rad/sec, the gain schedule of the system is:

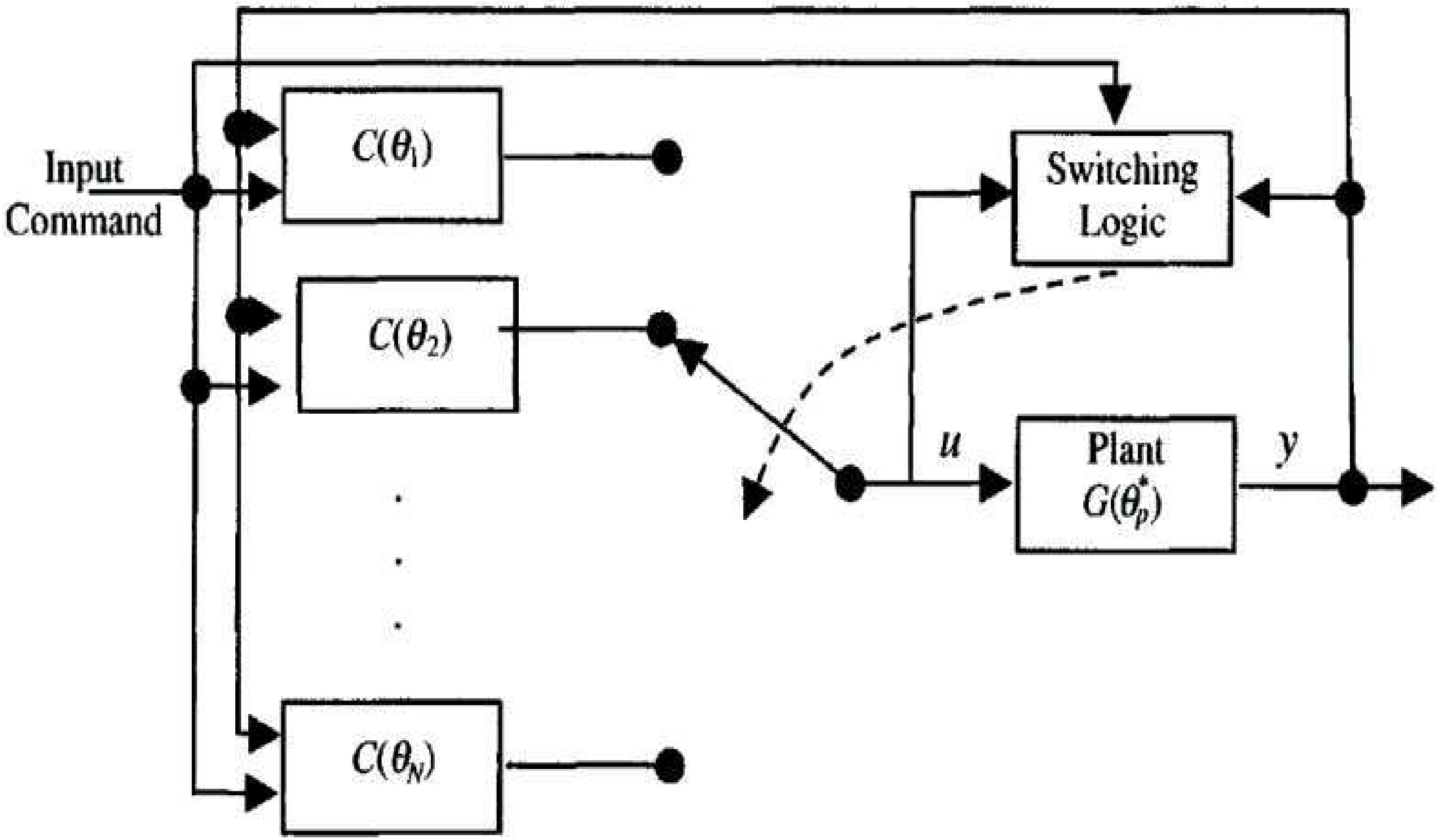
Cross section A(h), (m^2)	Gain (K)
0.2	0.2
0.4	0.4
0.6	0.6
0.8	0.8

2. Search Methods

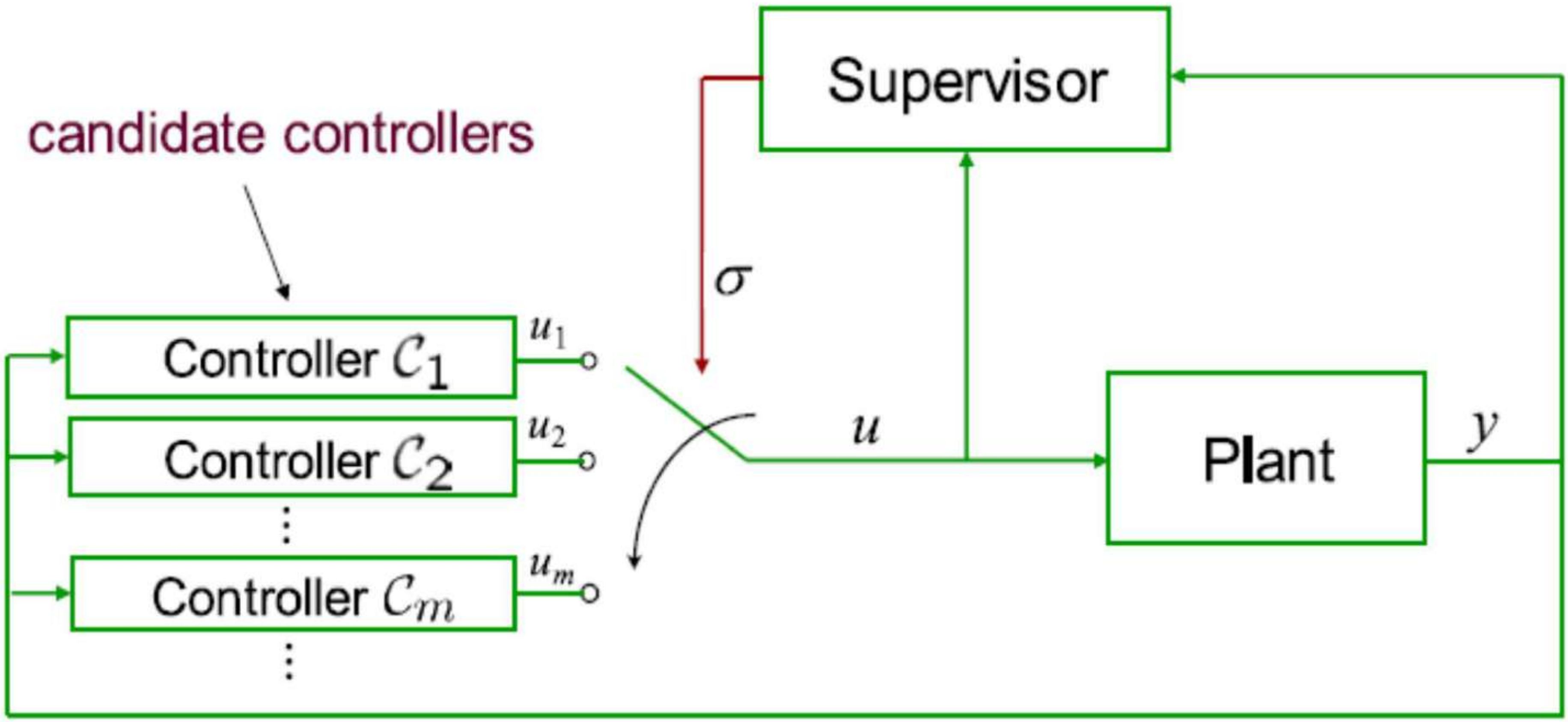
A class of non-identifier-based adaptive control schemes emerged over the years which do not explicitly rely on online parameter estimation. These schemes are based on search methods in the controller parameter space until the stabilizing controller is found or the search method is restricted to a finite set of controllers, one of which is assumed to be stabilizing. In some approaches, after a satisfactory controller is found it can be tuned locally using online parameter estimation for better performance.

3. Multiple Models and Switching Schemes

Since the plant parameters are unknown, the parameter space is parameterized with respect to a set of plant models which is used to design a finite set of controllers so that each plant model from the set can be stabilized by at least one controller from the controller set. A switching approach is then developed so that the stabilizing controller is selected online based on the I/O data measurements. Without going into specific details, the general structure of this multiple model adaptive control with switching, as it is often called, is shown in next Figure.

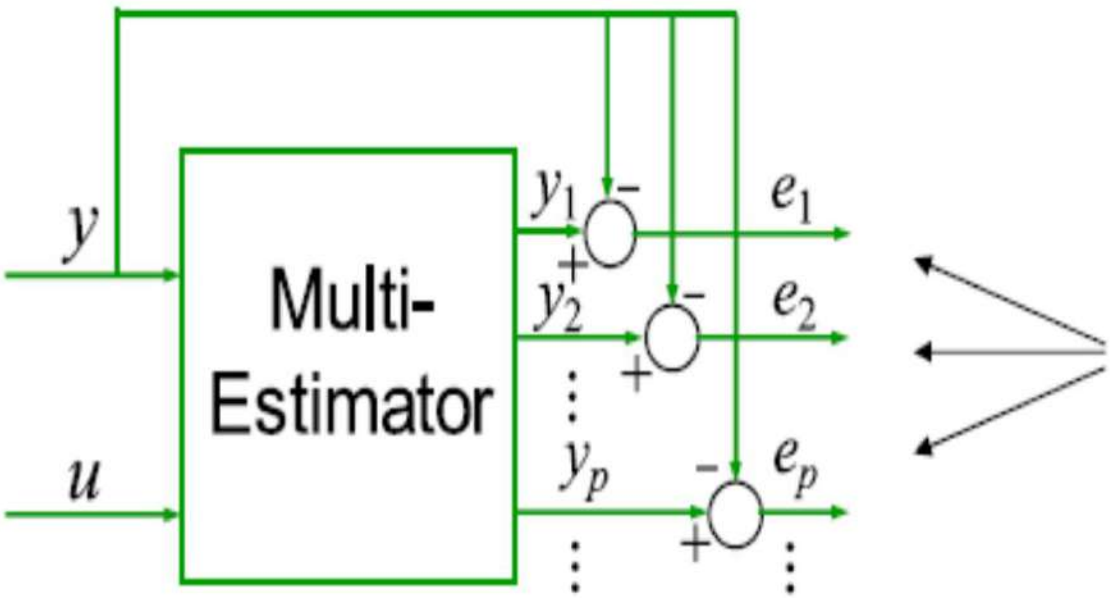


Multiple models adaptive control with switching



σ – switching signal, takes values in $\mathcal{Q}$

$\mathcal{C}_\sigma$ – switching controller



estimation errors:

$$e_p := y_p - y,\ \ p \in \mathcal{P}$$

Want e_{p^*} to be small

Then e_p small indicates $p = p^*$ likely

EXAMPLE

$$\dot{y} = y^2 + p^* u$$

Multi-estimator:

$$\dot{y}_p = -(y_p - y) + y^2 + pu, \ \ p \in \mathcal{P}$$

$$e_p = y_p - y, \ \ p \in \mathcal{P}$$

$$\Downarrow$$

$$\dot{e}_{p^*} = -e_{p^*} \ \ => \ \ e_{p^*} \longrightarrow 0 \ \ \text{exp fast} \ \ \forall\, u$$

$$\dot{y} = y^2 + p^* u - d$$

disturbance

Multi-estimator:

$$\dot{y}_p = -(y_p - y) + y^2 + pu, \ \ p \in \mathcal{P}$$

$$e_p = y_p - y, \ \ p \in \mathcal{P}$$

$$\Downarrow$$

$$\dot{e}_{p^*} = -e_{p^*} + d \ \ => \ \ e_{p^*} \longrightarrow d \ \ \text{exp fast} \ \ \forall\, u$$

STATE SHARING

$$\dot{y}_p = -(y_p - y) + y^2 + pu, \quad p \in \mathcal{P}$$

Bad! Not implementable if $\mathcal{P}$ is infinite

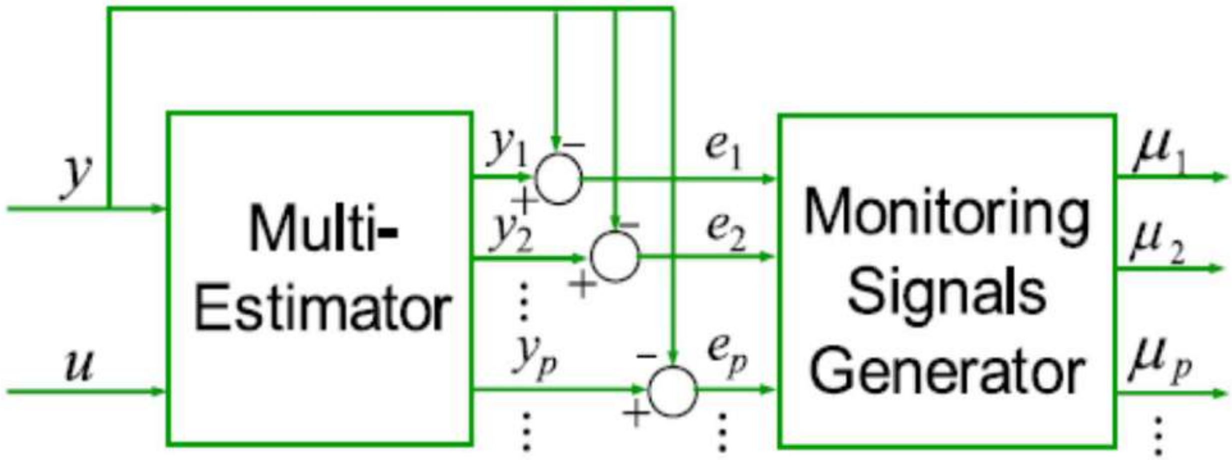
The system

$$\dot{z}_1 = -z_1 + y + y^2$$
$$\dot{z}_2 = -z_2 + u$$
$$y_p = z_1 + pz_2, \quad p \in \mathcal{P}$$

produces the same signals

$$\dot{y}_p = \dot{z}_1 + p\dot{z}_2 = -z_1 + y + y^2 - pz_2 + pu = -y_p + y + y^2 + pu$$

SUPERVISOR



Examples:

$$\mu_p(t) = \int_0^t |e_p(\tau)|^2 d\tau \Leftrightarrow \dot{\mu}_p = |e_p|^2, \; \mu_p(0) = 0$$

$$\mu_p(t) = \int_0^t e^{-\lambda(t-\tau)} |e_p(\tau)|^2 d\tau \Leftrightarrow \dot{\mu}_p = -\lambda \mu_p + |e_p|^2, \; \mu_p(0) = 0$$

EXAMPLE

Multi-estimator:

$$\dot{z}_1 = -z_1 + y + y^2$$
$$\dot{z}_2 = -z_2 + u$$
$$y_p = z_1 + p z_2, \;\; p \in \mathcal{P}$$

$\boxed{\dot{\mu}_p = e_p^2}$ – can use state sharing

$$e_p^2 = (z_1 + p z_2 - y)^2 = (z_1 - y)^2 + 2 p z_2 (z_1 - y) + p^2 z_2^2$$

$$\dot{\eta}_1 = (z_1 - y)^2$$
$$\dot{\eta}_2 = 2 z_2 (z_1 - y)$$
$$\dot{\eta}_3 = z_2^2$$
$$\mu_p = \eta_1 + p \eta_2 + p^2 \eta_3, \;\; p \in \mathcal{P}$$

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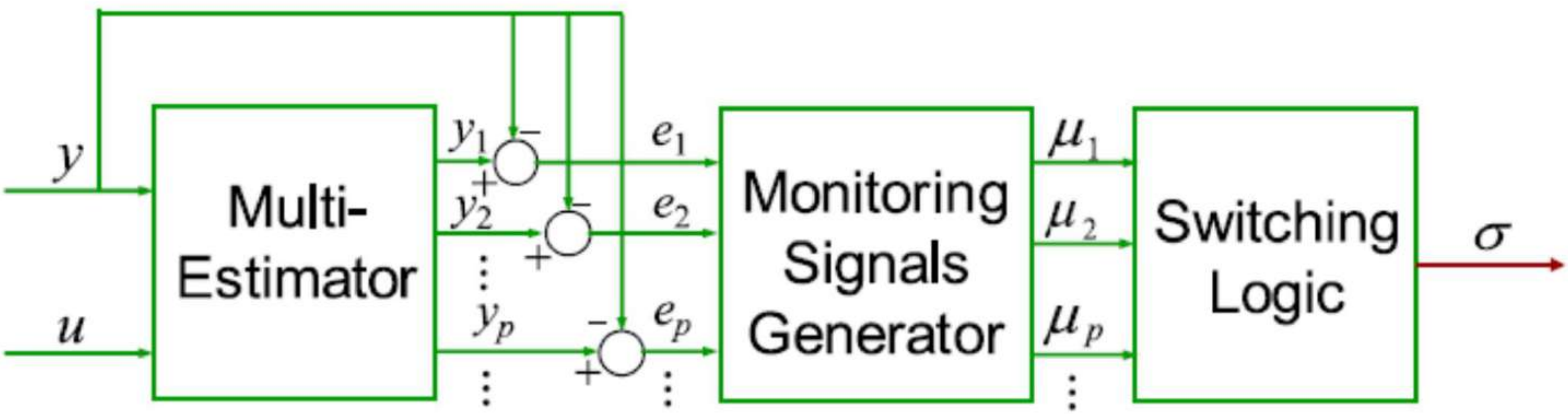

We know: e_{p^*} is small

Switching logic (roughly): $\sigma(t) = \arg\min_{p \in \mathcal{P}} \mu_p(t)$

This (hopefully) guarantees that e_σ is small

Need: e_σ small => stable closed-loop switched system