

Since this was a talk, the slides were just a helper to support my presentation.

For more information and a deeper understanding please check the literature on my homepage.

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Helmut Hauser, Aug.19th 2004

Survey of Adaptive Control

by Helmut Hauser



Structure of the Presentation

- Introduction and Review to Control Theory
- Different Approaches (linear)
 - Gain Scheduling
 - Model Adaptive Control
 - Self Tuning Regulators
 - Dual Control
- Nonlinear Approaches
- Conclusions

Control Theory

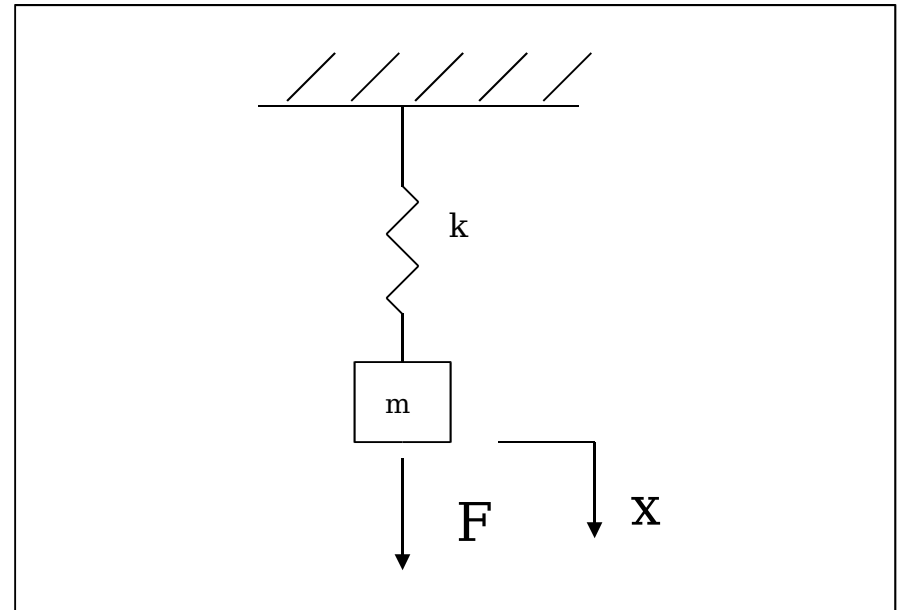
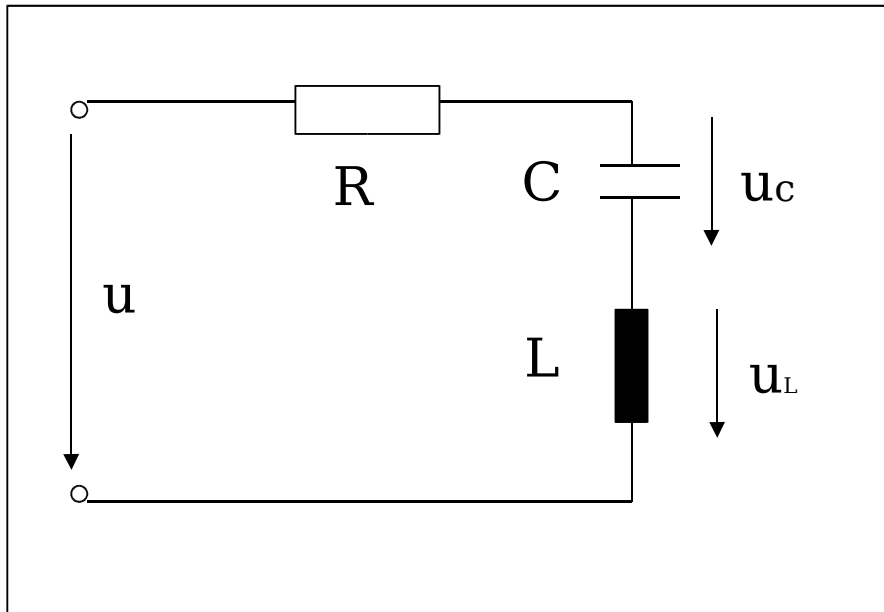
Formulation of the problem

What is Control Theory ?:

- treating with dynamical systems
- mathematical formulation
- analysing their properties

-> Trying to influence somehow the behaviour and properties by another dynamical system

Dynamical Systems - Mathematical Formulation



Description by Kirchhoff's law:

$$\sum u = 0$$

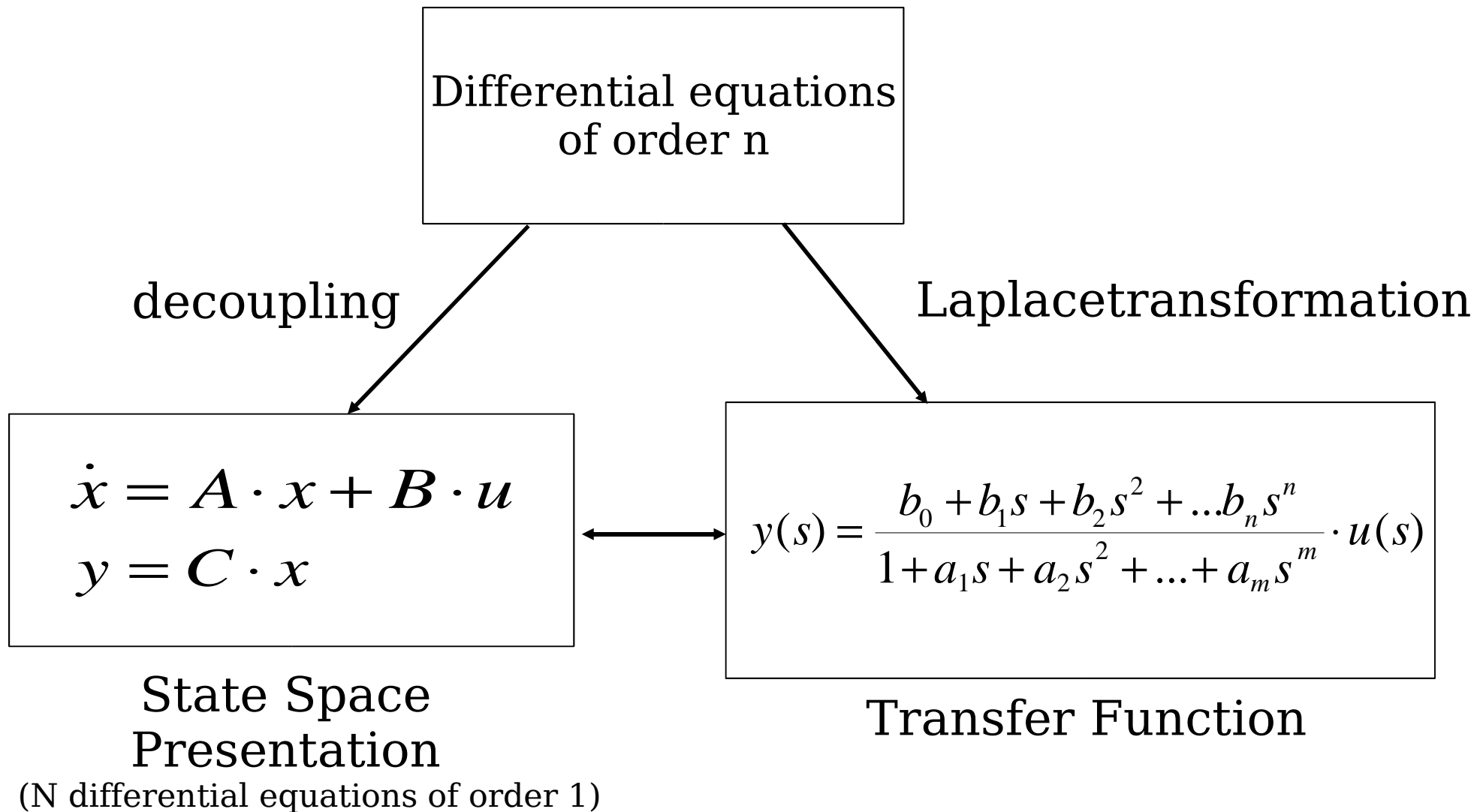
$$i_C = C \cdot \frac{du}{dt} \quad u_L = L \cdot \frac{di}{dt}$$

Description by Newton:

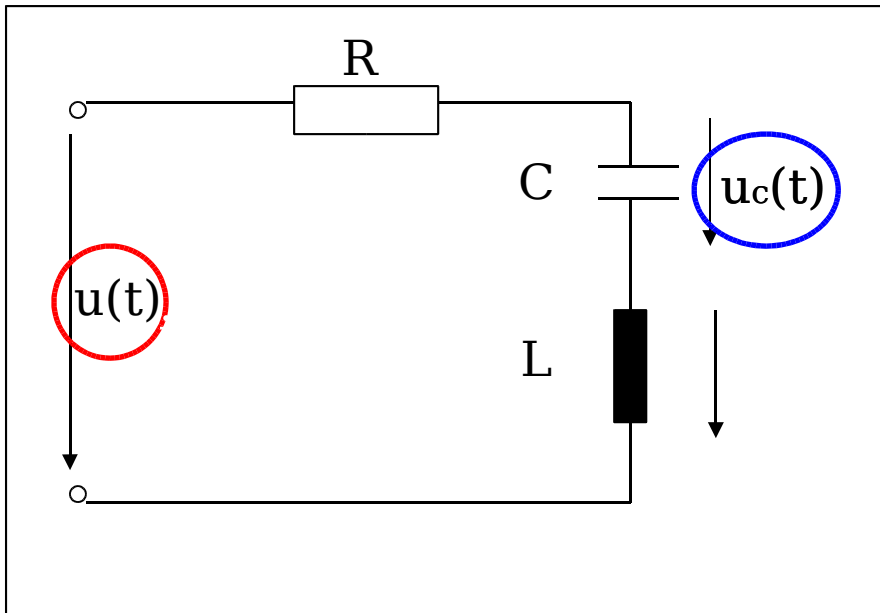
$$\sum F = \sum m \cdot \frac{dx^2}{d^2t} = 0$$

$$F_{spring} = k \cdot x$$

Mathematical Formulation of the problems



Example from before



$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{bmatrix} -\frac{R}{L} & -\frac{1}{L} \\ \frac{1}{C} & 0 \end{bmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} \cdot u$$

$$y = \begin{pmatrix} 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$\begin{aligned} \dot{x} &= A \cdot x + B \cdot u \\ y &= C \cdot x \end{aligned}$$

$$G(s) = C \cdot (s \cdot I - A)^{-1} \cdot B + D$$

Properties of Dynamical Systems

- Stability

- Impulse Response
- Observability
- Controllability
- Causality
- much more...

$$\text{real}\{\text{eigvalues}(A)\} < 1$$

State Space Representation

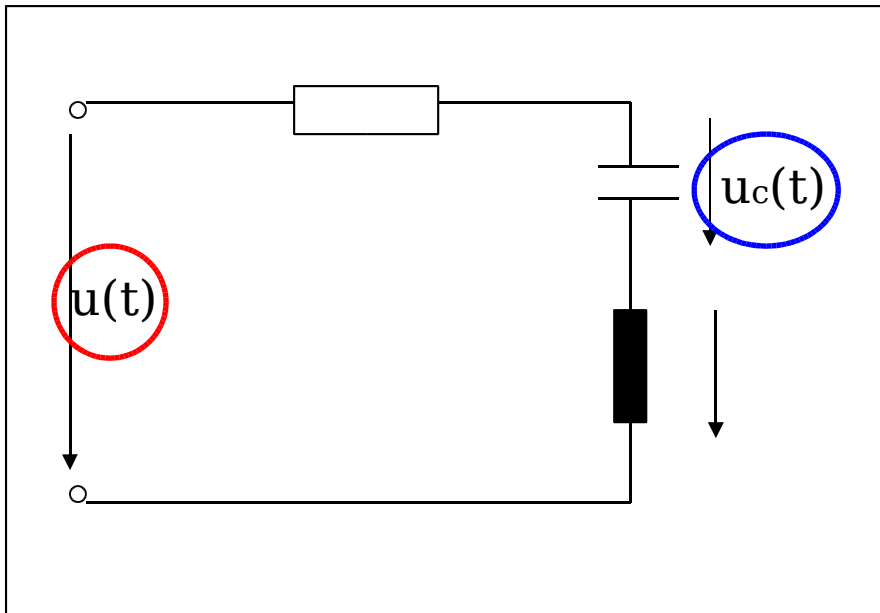
$$\dot{x} = A \cdot x + B \cdot u$$
$$y = C \cdot x$$

Transferfunction

$$y(s) = \frac{b_0 + b_1s + b_2s^2 + \dots + b_n s^n}{1 + a_1s + a_2s^2 + \dots + a_m s^m} \cdot u(s)$$

$$\text{real}\{\text{zeros}(\text{poly})\} < 1$$

Example from before

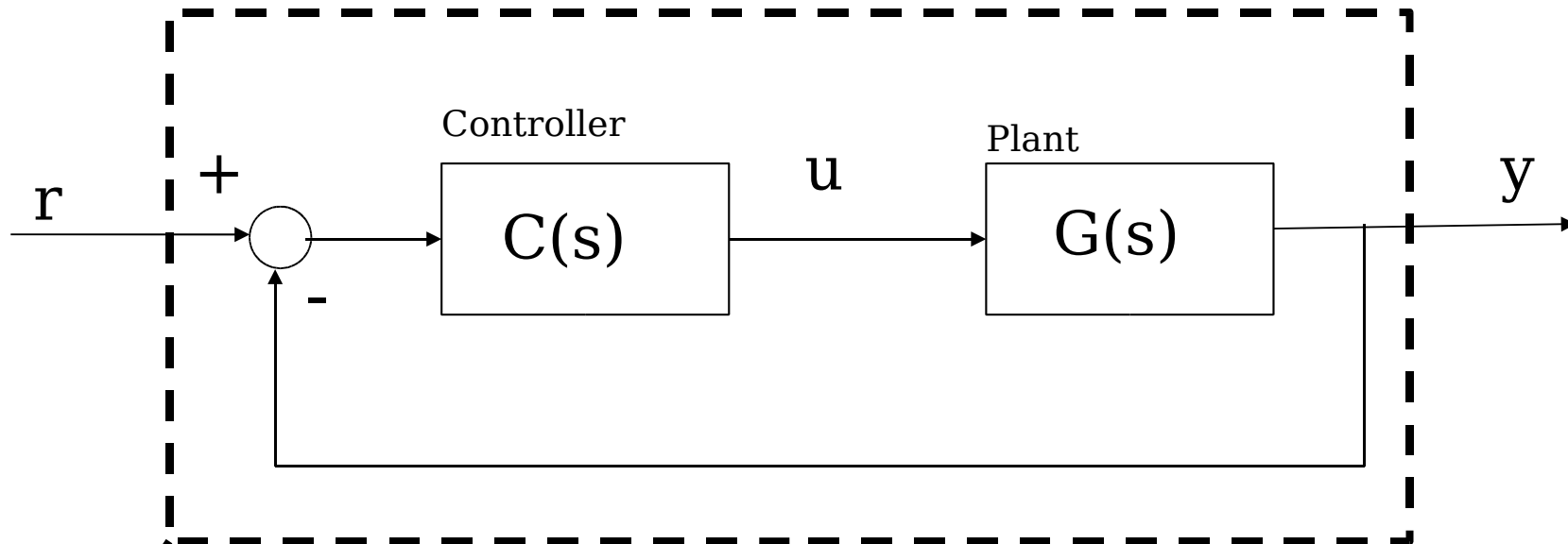


$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{bmatrix} -\frac{R}{L} & -\frac{1}{L} \\ \frac{1}{C} & 0 \end{bmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} \cdot u$$

$$y = \begin{pmatrix} 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$\begin{bmatrix} -\frac{R}{L} & -\frac{1}{L} \\ \frac{1}{C} & 0 \end{bmatrix} \longrightarrow \text{real}\{\text{eigvalues}(A)\} < 1$$

The magic of feedback



$$T(s) = \frac{C(s) \cdot G(s)}{1 + C(s) \cdot G(s)}$$

$$C(s) = \frac{Q(s)}{R(s)}$$

$$G(s) = \frac{B(s)}{A(s)}$$

$$T(s) = \frac{Q(s) \cdot B(s)}{R(s) \cdot A(s) + Q(s) \cdot B(s)}$$

Knowledge needed to control

- mathematical model of the plant (open loop)
- define wanted properties (model) of the closed loop
- some extra constraints (depend on the problem)

- That's the big problem:
- complex models
 - nonlinear models
 - disturbances
 - parameter drift, operation

One possible solution



Adaptive Control

Different Approaches

- Gain Scheduling
- Model Reference Adaptive Systems (MRAS)
- Self Regulating Tuners (SRT)
- Dual Control
- Nonlinear approaches

Gain Scheduling

Used for:

- widely changing operation points (flight control)
- nonlinear actuators $v = f(u) = u^4$

Predictable variations

Key-Idea:

Finding rules between the changes of the model and significant variables.

Feedback is nonlinear and maybe implemented as a look-up table.

Gain Scheduling

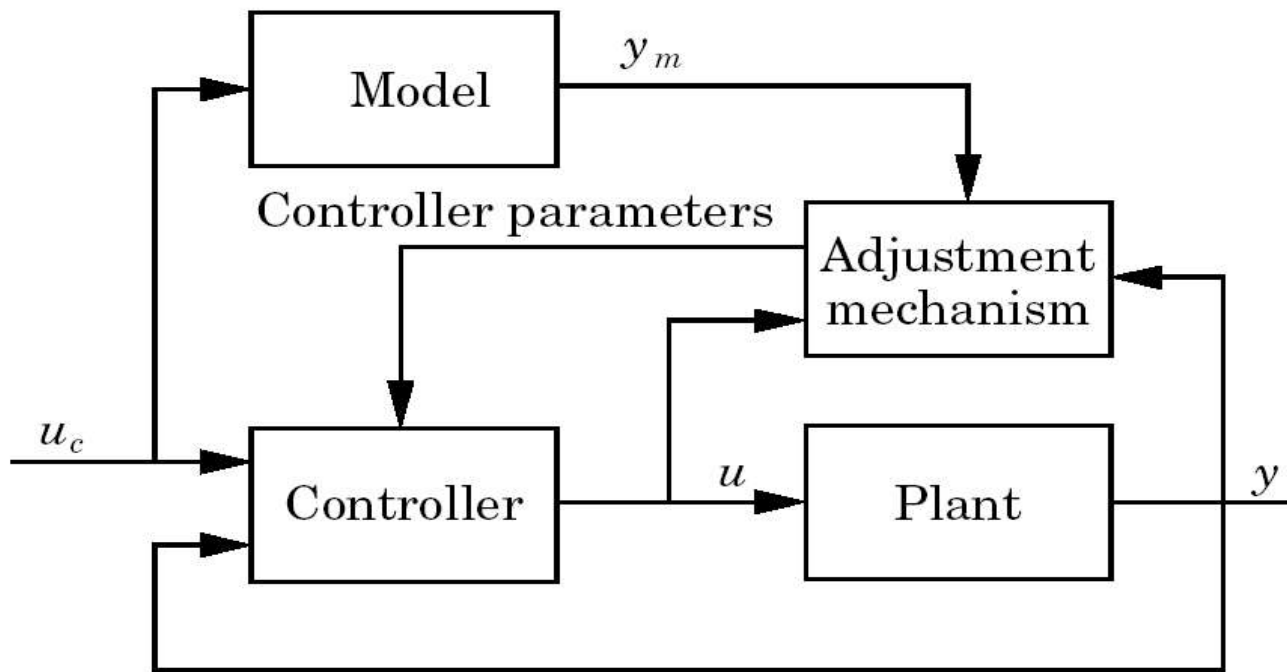
Advantages:

- very fast
- direct (no complex online calculations are needed)
- convenient if relation is known

Disadvantages:

- a lot of knowledge about the plant is needed
- quite a lot of design work before starting
- not always applicable
- no real learning possibilities

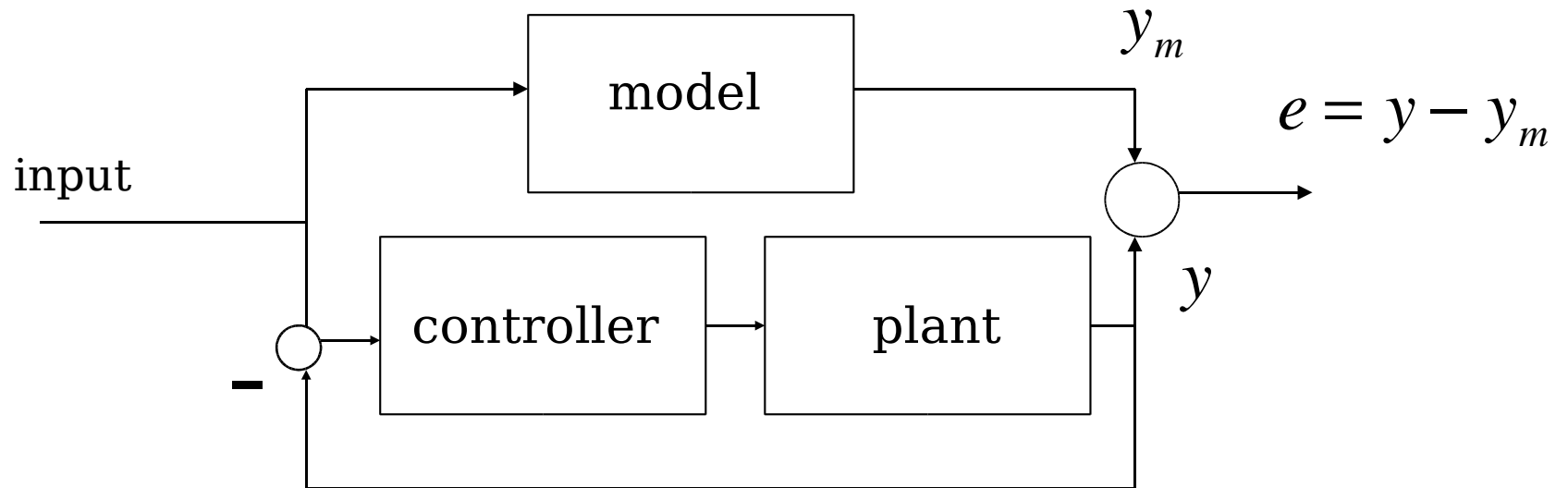
Model Reference Adaptive Control



Model Reference Adaptive Control

key idea:

To express the wanted behaviour of the closed loop by defining a reference model.



MIT-Rule

Problem

Linear feedback of the error is not adequate for parameter adjustment.

Basic Idea:

Time derivation of the control parameters is proportional to the negative gradient.

$$e = y - y_m$$

$$J(\theta) = \frac{1}{2} e^2$$

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma e \frac{\partial e}{\partial \theta}$$

MIT-Rule

$$e = y - y_m$$

$$\frac{d\theta}{dt} = -\gamma e \frac{\partial e}{\partial \theta}$$

$$\theta = f(G, G_m) = f(a, b, a_m, b_m)$$

Certainty equivalence principle !

$$G = G_m$$

$$a = a_m$$

$$b = b_m$$

MIT-Rule

Advantages

- easy principle
- convergence is proofed

Disadvantages:

- one has to know structure of the model

- stability problem

- choosing γ (small, but how small ?)

e.g. Theory of Lyapunov

Using Stability-Conditions

4 general steps:

- 1.) Determine a controller structure
- 2.) Derive the error equation
- 3.) Find a stability depending function
- 4.) Determine an adaptation law

MRAS - Summary

Advantages:

- easy formulation of behaviour due model

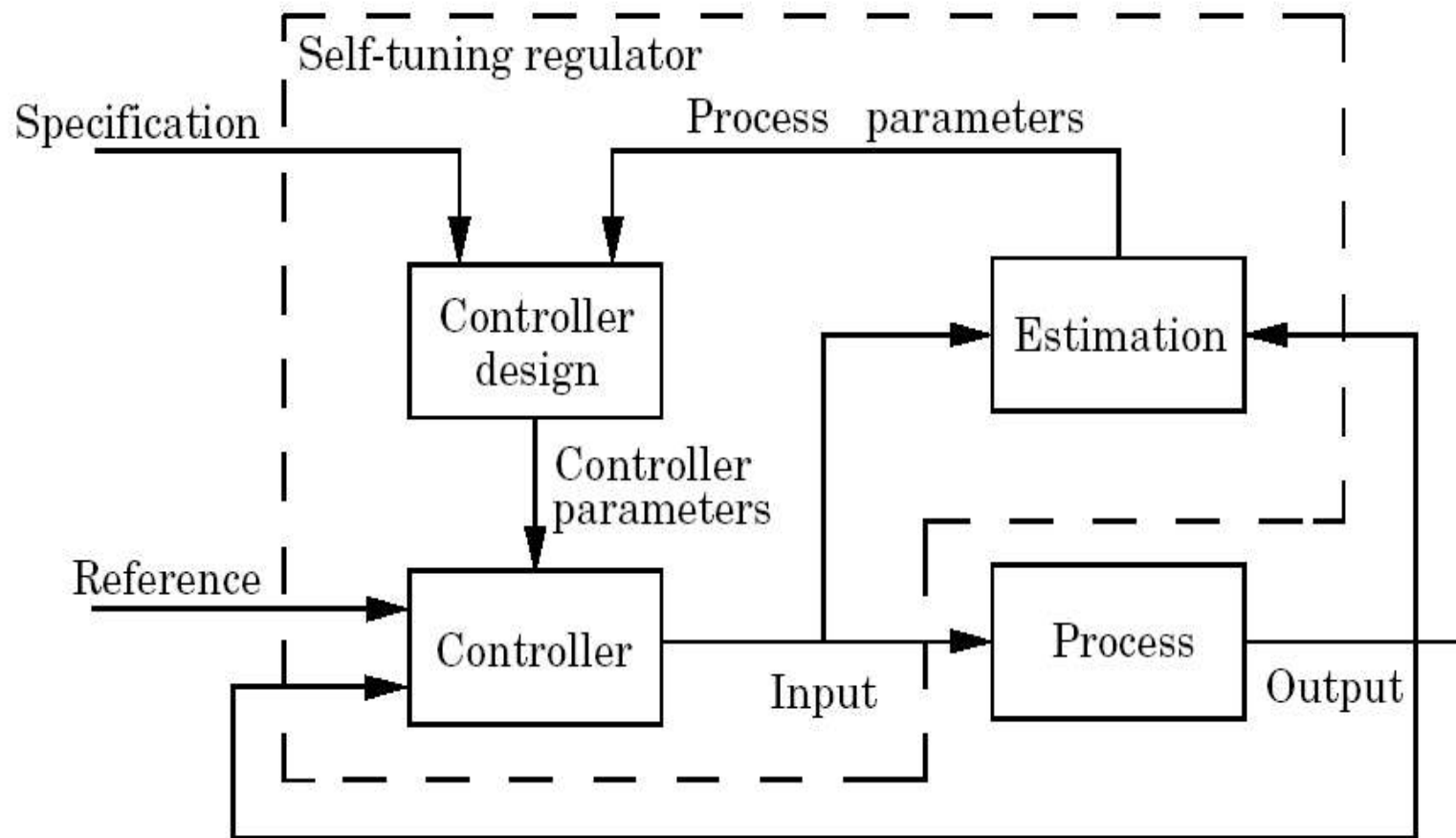
Disadvantages:

- some knowledge of the process needed
- finding adaptation law is non trivial

Algorithms

- MIT (normalized)
- Stability Design (BIBO, Lyapunov, Passivity)

Self Tuning Regulators STR



Self Tuning Regulators STR

Part 1:

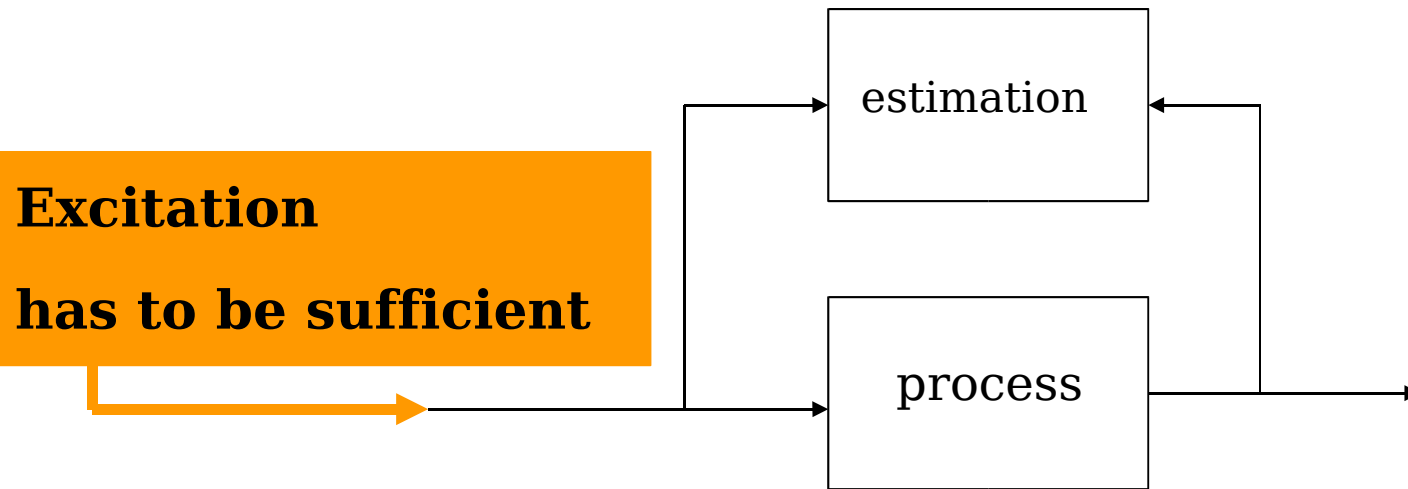
Identification of the plant
out of the input and output sequence

Certainty Equivalence Principle

Part 2

Using this model to design **online** a controller

STR - Part 1: Identification



Algorithms:

- LMS (normalized)
- Projection algorithm
- RLS
- stochastic (ELS, Ext.Kalman)

Models:

- linear (FIR, IIR, state space,...)
- ANN (feed-forward, recursive)
- Stochastic model
- and much more....

STR - Part 2: Controller Design

Possible design methods in principle all known methods:

- But, has to :**
- be fast enough (online calculation)
 - able to check for stability
 - take into account the nonlinear behaviour of adaptive systems
 - converge together with identification process

Conclusions

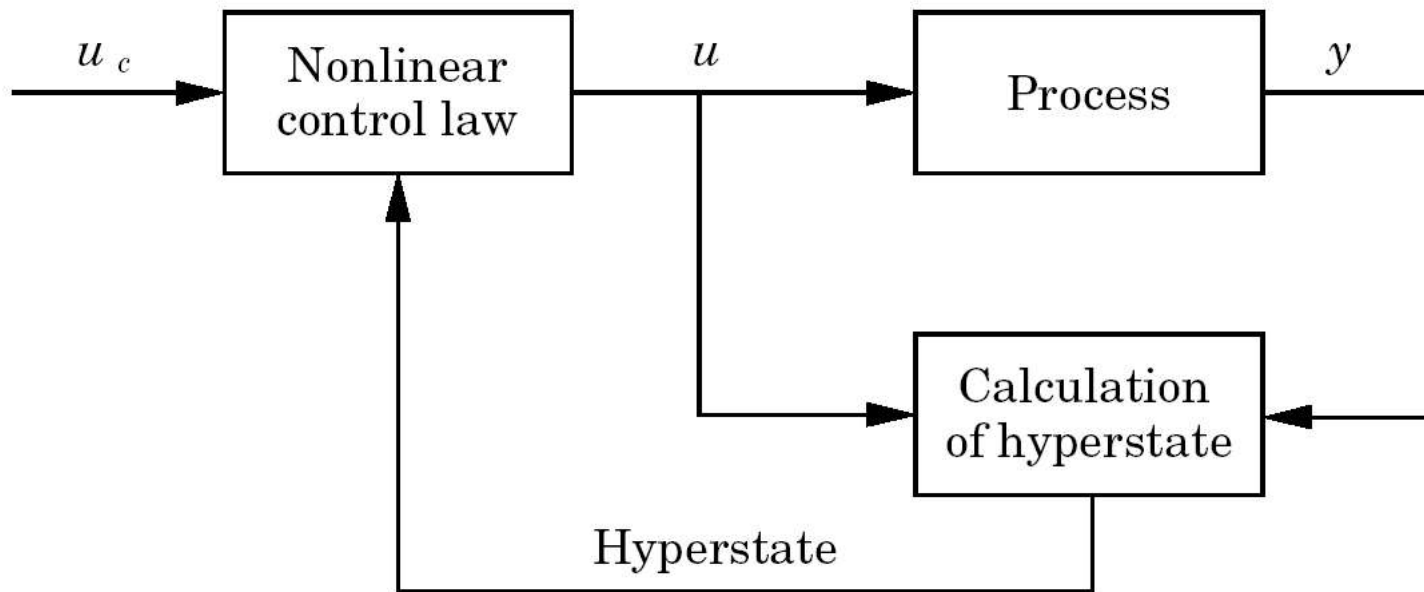
Advantages

- A lot of different possibilities for identification and for control design
- mathematical model isn't necessary, but the general structure !
- easy to implement extra knowledge
- stochastic approaches are possible

Disadvantage

- complex system -> complex analysis
- excitation of input signal is necessary

Dual Control



Dual Control - a Stochastic Approach

no separation between state variables and model parameters
uncertainties of model parameters are taken into account

leads to a hyperstate

$$z = \begin{pmatrix} x^T & \theta^T \end{pmatrix}^T$$

estimators generates a conditional probability distribution $p(z|y,u)$

Minimization of a loss function
over control signal $u(k)$

$$V = \min_{u(k-1) \dots u(N-1)} E(f(z, u))$$

Dynamic Programming

Dual Control

- Solution is time consuming, if possible
- estimator generates a conditional probability distribution $p(z|y,u)$
- controller is a nonlinear mapping
 - > from hyperstate into controller parameters

Solution can have interesting properties:

- attempts to drive the output to the desired value (controller)
- introduce perturbations (probing) when parameter uncertain

Exploration - Exploitation

Dual Control

Advantages:

- elegant design
- conceptually interesting
- takes uncertainties of the estimation into account
- probing

Disadvantages:

- very complex
- solution very time intensive, if possible

Nonlinear Approaches - Overview

- Reparameterization
- Linearization
- Nonlinear feedback
- Nonlinear models (ANN, stochastic models)

Related field:

- Robust Control Design
- Predictive Control

Conclusion

- adaptive control are designed to control a varying processes
- adaptive systems are **nonlinear** and **time variant** !!
- therefore analyse is quite complicated
- different approaches for different needs (no general theory yet)

further investigation needed:

- a general theory
- more stability proofs, convergence proofs
- get more insight into dual control (suboptimal solutions)

Thank you