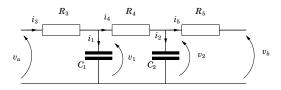


## **Principles and analogies: Electrics**

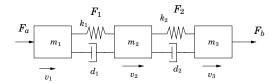
#### Example 2. An electrical system:



Potentials  $v_a$ ,  $v_b$ ,  $v_1$ , and  $v_2$ Currents  $i_1$ ,  $i_2$ ,  $i_3$ ,  $i_4$ , and  $i_5$ 

## **Principles and analogies: Mechanics**

Exempel 4. A mechanical system:



External forces:  $F_a$  and  $F_b$ Velocities:  $v_1$ ,  $v_2$  and  $v_3$ Spring constants:  $k_1$  and  $k_2$ Damping constants:  $d_1$  and  $d_2$ 

# Analogies (cont'd)

Intensity variations

$$C \cdot \frac{d}{dt}$$
(intensity) = flow

C "capacitance": hydraulic:  $A/(\rho g)$ electrical: kapacitans heat: thermal capacity mechanical: inverse spring constant Balance equations!

(More complicated if the capacitance is not constant.)

#### More phenomena

Intensity variations

$$L \cdot \frac{d}{dt}$$
(flow) = intensity

L "inductance" hydraucs:  $\rho l/A$ electrics: inductans heat: – mechanics: mass balance equations!

(more complicated if the inductance is not constant.)

### Principles and analogies: Heat

Example 3. A thermal system (heat transfer through a wall):

$T_a$	Värmekap. $C_1$ $T_1$	<i>q</i> <sub>4</sub>	Värmekap. $C_2$ $T_2$	<i>q</i> <sub>5</sub>	$T_b$

Two elements with thermal capacities  $C_1$  and  $C_2$  separated by insulating layers. Heat flows:  $q_3$ ,  $q_4$  and  $q_4$ Temperatures:  $T_a$ ,  $T_b$ ,  $T_1$  and  $T_2$ 

### Analogies

Analogies: hydraulic - electric - thermal - mechanical Two types of variables:

A. Flow Variables

- volume flow
- power flow
- heat flow
- speed

B. Intensity variables

- pressure
- voltage
- temperature
- force

For both of them addition rules hold.

### Analogies (cont'd)

Losses

flow =  $\phi$ (intensity) intensity =  $\phi$ (flow)

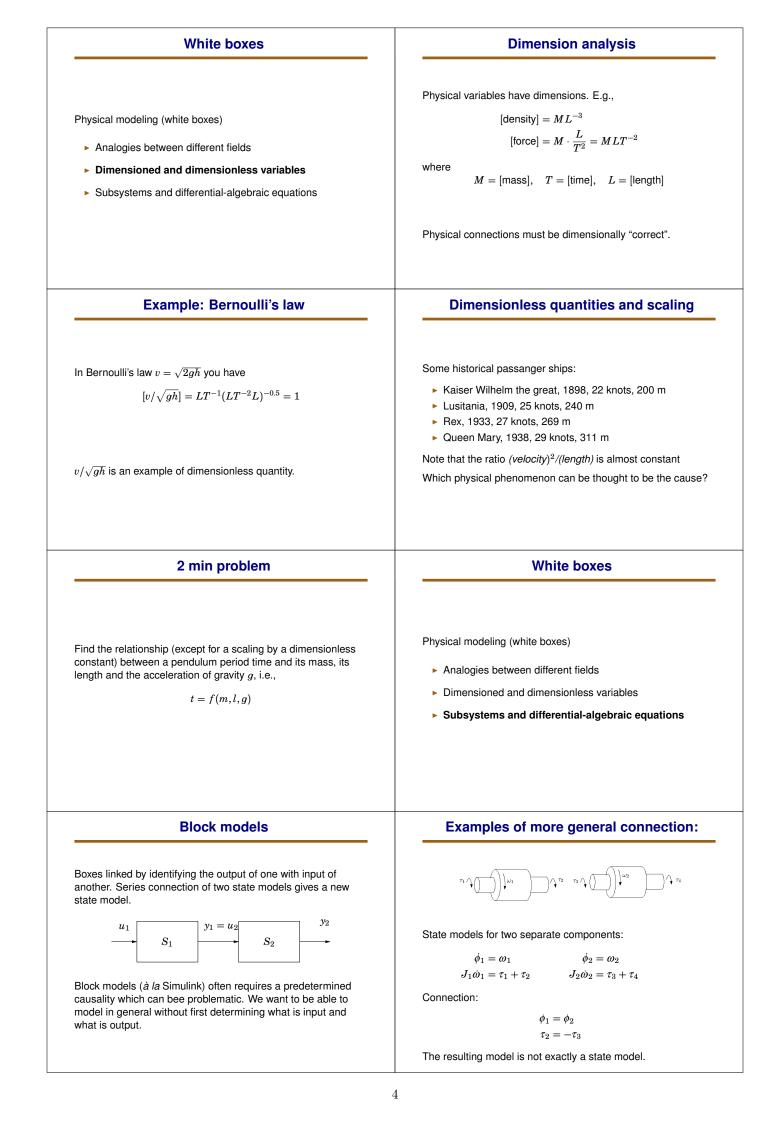
Hydraulic: flow resistance Electrics: resistance Heat: thermal conductivity Mechanics: friction

Often linear relationship in the electrical case - nonlinearly in the other (may be approximated by linear for small changes of variables)

#### **Energy flows**

Can you make a general modeling theory based on flow and intensity variables? Note the following.

pressure · flow = power voltage difference · current = power force · velocity = power torque · angular velocity = power temperature · heat flow = power · temperature



## Linear differential-algebraic equations (DAE)

$$E\dot{z} = Fz + Gu$$

If E were non-singular, one could write

$$\dot{z} = E^{-1}Fz + E^{-1}Gu$$

which is a valid state model. If E is singular, variables have to be eliminated to get a state equation. Using a DAE solver is often better, since elimination can destroy sparsity.

Example:

1	0	0	0			Γ0	1	0	0]		Γ0	0	0	0]	
0	$J_1$	0	0	$\left[\dot{\phi}_1\right]$	1	0	0	0	0	$\begin{bmatrix} \phi_1 \\ \omega_1 \\ \phi_2 \\ \omega_2 \end{bmatrix}$	1	1	0	0	$\lceil \tau_1 \rceil$
0	0	1	0	$\dot{\omega}_1$		0	0	0	1	$\omega_1$	0	0	0	0	$\tau_2$
0	0	0	$J_2$	$\phi_2$	=	0	0	0	0	$ \phi_2 $	0	0	1	1	$ \tau_3 $
0	0	0	0	$\dot{\omega}_2$		0	0	0	0	$\omega_2$	0	1	$^{-1}$	0	$ \tau_4 $
0	0	0	0			1	0	$^{-1}$	0		0	0	0	0	

## **Example: Pendulum**

A pendulum with length L and position coordinates (x, y) moves according to the equations

$$\dot{x} = u \qquad \dot{y} = v \\ \dot{u} = \lambda x \qquad \dot{v} = \lambda v - q$$

 $0 = \dot{x}x + \dot{y}y = ux + vy$ 

 $L^2 = x^2 + y^2$ 

Differentiating a second time gives

$$0 = \dot{u}x + u\dot{x} + \dot{v}y + v\dot{y}$$
$$= \lambda x^{2} + u^{2} + (\lambda y - g)y + v^{2}$$
$$= \lambda L^{2} - gy + u^{2} + v^{2}$$

and a third time

$$0 = \dot{\lambda}L^2 - 3gv$$

Finally, we have derivative expressions for all variables!

## **Black Boxes**

Statistical modeling from data (static black boxes)

- Singular Value Decomposition (SVD)
- Principal Component Analysis (Factor Analysis)
- Neural Networks / Machine learning
- Dynamic experiments (dynamic black boxes)
  - Step response
  - Frequency response
  - Correlation analysis
- Gray boxes
  - Prediction error methods
  - Differential-Algebraic Equations revisited

## Example of SVD

$$M = U \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} V^{*}$$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \underbrace{\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}}_{U} \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}}_{V^{*}}$$

What does it mean if a singular value is zero? What does it mean if it is near zero?

# Nonlinear differential-algebraic equations (DAE)

Differential-algebraic equations, DAE

$$F(\dot{z}, z, u) = 0, \quad y = H(z, u)$$

u: input, y: output, z: "internal variable"

Special case: state model

$$\dot{x} = f(x, u), \quad y = h(x, u)$$

u: input, y: output, x: state

## Mathematical modelling — Why and How?

Why modelling?

- Natural sciences: Models for analysis (understanding)
- Engineering sciences: Models for synthesis (design)
- Specification: Model of a good technical solution
- White boxes: Physical modeling Model derived from fundamental physical laws
- Black boxes: Statistical methods and machine learning Model derived from measurement data
  - Singular Value Decomposition (SVD)
  - Principal Component Analysis (Factor Analysis)
  - Neural Networks / Machine learning
  - System Identification / Time Series Analysis
- Gray boxes: Combination of the two

## Singular Value Decomposition (SVD)

A matrix M can always be factorized

$$M = U egin{bmatrix} \Sigma & 0 \ 0 & 0 \end{bmatrix} V^*$$

with  $\Sigma$  diagonal and invertible and U, V unitary:

$$\Sigma = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{bmatrix} \qquad \qquad U^*U = I \qquad V^*V = I$$

Diagonal elements of  $\Sigma$  are called singular values of M and correspond to the square roots of the eigenvalues of  $M^*M$ . Computation of SVD is *very numerically stable*.

#### Good children can have many names

Collect all the data into a large matrix. Then compute the SVD:

$$\begin{bmatrix} y_1(1) & y_1(2) & \dots & y_1(N) \\ y_2(1) & y_2(2) & \dots & y_2(N) \\ \vdots & & & \\ y_p(1) & y_p(2) & \dots & y_p(N) \end{bmatrix} = U \underbrace{\begin{bmatrix} \sigma & 0 \\ & \ddots \\ 0 & & \sigma_p \end{bmatrix}}_{\Sigma} V^*$$

Singular values  $\sigma_i$  in decreasing order on the diagonal of  $\Sigma$ . The first columns of *U* give the direction of the main data area.

**Principal Component Analysis**: By replacing the small singular values  $\sigma_i$  with zeros focuses on the essential.

The name 'factor analysis' is sometimes used as a synonymous, since large singular values  $\sigma_i$  highlight important factors.

Principal Component Analysis (PCA)	Example: Image processing								
Data from a bi-dimensional Gaussian distribution centered in $(1,3)$ :									
	What does this picture represent?								
	M =								
a start and a start and a start	1 0 0 1 1 1 0 1 0 1 0 0 0 1 0 0 1 0								
	$\begin{array}{cccccccccccccccccccccccccccccccccccc$								
	1 1 0 0 1 0 1 0								
Principal component (0.878, 0.478) has standard deviation 3. Next component has standard deviation 1.									
[Kālla: Wikipedia]									
Example: Image processing with SVD	Example: Image processing with SVD								
>> [U,S,V]=svd(M)	<pre>round(U*S1*V') =</pre>								
υ =									
-0.4747 0.8662 0.0000 -0.1559 0.0000	1 0 0 0 1 0 0 1 0								
-0.4291 -0.1371 -0.0000 0.5450 -0.7071 -0.4508 -0.3256 -0.7071 -0.4368 -0.0000	1 0 0 0 1 0 1 0 1 0 0 0 1 0 1 0								
-0.4291 -0.1371 -0.0000 0.5450 0.7071 -0.4508 -0.3256 0.7071 -0.4368 0.0000	1 0 0 0 1 0 1 0								
S =	round(U*S2*V') =								
4.5638 0 0 0 0 0 0 0 0 0	$\begin{array}{cccccccccccccccccccccccccccccccccccc$								
0 1.3141 0 0 0 0 0 0 0 0 0 1.0000 0 0 0 0 0 0 0	1 0 0 0 1 0 0 1 0								
0 0 0 0.6670 0 0 0 0 0 0 0 0 0 0.0000 0 0 0 0	1 0 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0								
Example: Image processing	Example: Correlations genes-proteines								
H + + + + + + + + + + + + + + + + + + +									
	4 <b>1</b>								
rat rath rath									
12 50 120									
The original image has 897-by-598 pixels. Tacking red, green	Cancer research: microarrays (glass) with human genes are								
and blue vertically gives a 2691-by-598 matrix. Truncating all but 12 singular values gives the left picture. 120 gives the right.	exposed to healthy cells, then to sick ones. Make a SVD of the data to find out which genes are important!								
Black Boxes	Tomorrow								
<ul> <li>Statistical modeling from data (static black boxes)</li> </ul>									
<ul> <li>Singular Value Decomposition (SVD)</li> </ul>	More on black and grey models								
<ul> <li>Principal Component Analysis (Factor Analysis)</li> <li>Neural Naturates / Machine Learning</li> </ul>									
<ul> <li>Neural Networks / Machine learning</li> <li>Dynamic experiments (dynamic black boxes)</li> </ul>	<ul> <li>Registered students will get a project</li> </ul>								
<ul> <li>Step response</li> <li>Frequency response</li> </ul>	Karl Johan Åström will lecture on bicycle modelling!								

- Frequency response
   Correlation analysis
- Gray boxes

  - Prediction error methods
     Differential-Algebraic Equations revisited

Karl Johan Åström will lecture on bicycle modelling!