Visualization of Changes in Process Dynamics Using Self-Organizing Maps

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Outline of the presentation

1. Novelty detection in FDI
2. Modeling dynamics using SOM
3. Visualization of changes in dynamics
4. Results
5. Conclusions

Novelty Detection in FDI

Common problem in FDI...

- Difficult to gather knowledge about all fault conditions:
  - neither models
  - nor fault data

... however

- Data from normal conditions are usually available

Novelty Detection in FDI

Novelty detection approach

- Look for significant changes from normal condition
- Basic idea:
  find states that lie outside the kernel of the pdf of normal data

However

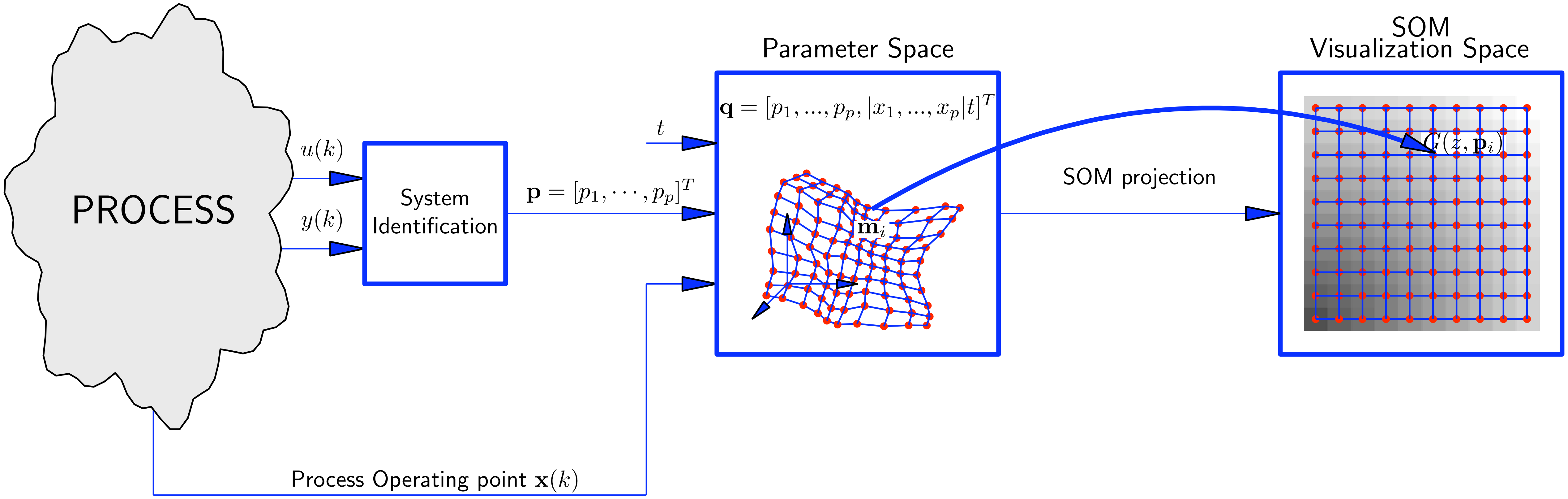
- If we apply ND to raw process data...
- ...we only analyze geometric relationships
  ...we would not consider dynamics!

We need a *model-based* approach that is, to consider dynamic models instead of static points

Novelty Detection in FDI

Maps of Dynamics (see [2])

- SOM is trained in a parametric space
- A map of models of all different dynamic behaviours is learned.
- SOM retrieval of best matching model allows to use novelty detection principles to compare models



Reference:

2. Ignacio Díaz Blanco, Manuel Domínguez González, Abel A Cuadrado, and Juan J. Fuertes Martínez. A new approach to exploratory analysis of system dynamics using SOM. Applications to industrial processes. *Expert Systems with Applications*, 34(4):2953–2965, 2008.

Modeling of Dynamics using SOM

Parametric model selection

Nonlinear dynamics (NARX):

$$y(k) = f(\varphi(k), \mathbf{p})$$

$$\varphi(k) = [y(k-1), \cdots, y(k-n), u(k), \cdots, u(k-m)]^T$$

linear case...

$$y(k) = f_L(\varphi(k), \mathbf{p}) = \mathbf{p}^T \varphi(k)$$

Linear difference equation

$$y(k) = a_1 y(k-1) + \cdots a_n y(k-n) + b_0 u(k) + \cdots + b_m u(k-m)$$

Transfer function

$$G(z, \mathbf{p}) \stackrel{\text{def}}{=} \frac{b_0 + b_1 z^{-1} + \cdots b_m z^{-m}}{1 - a_1 z^{-1} - \cdots - a_n z^{-n}}$$

Parameter vector

$$\mathbf{p} = [a_1, \cdots, a_n, b_0, b_1, \cdots b_m]^T$$

Modeling of Dynamics using SOM

Identification stage

Divide process data into *N* subsets

$$\{y(k), \varphi(k)\}_{k \in I_j}, \quad j = 1, \cdots N$$

Two alternatives

Local models
(gather data around operating point)

$$I_j = \{\text{all } k \text{ such that } \|\mathbf{x}_k - \mathbf{m}_j\| < \varepsilon\}$$

sliding time windows
(slow varying dynamics)

$$I_j = \{k_j - n + 1, k_j - n + 2, \cdots, k_j\}$$

Minimize (LS) the cost function for each subset I_j

$$J = \sum_{k \in I_j} \|y(k) - f(\varphi(k), \mathbf{p}(k))\|^2 \qquad j = 1, \cdots N$$

$$P = \{\mathbf{p}(1), \cdots, \mathbf{p}(N)\}$$

Modeling of Dynamics using SOM

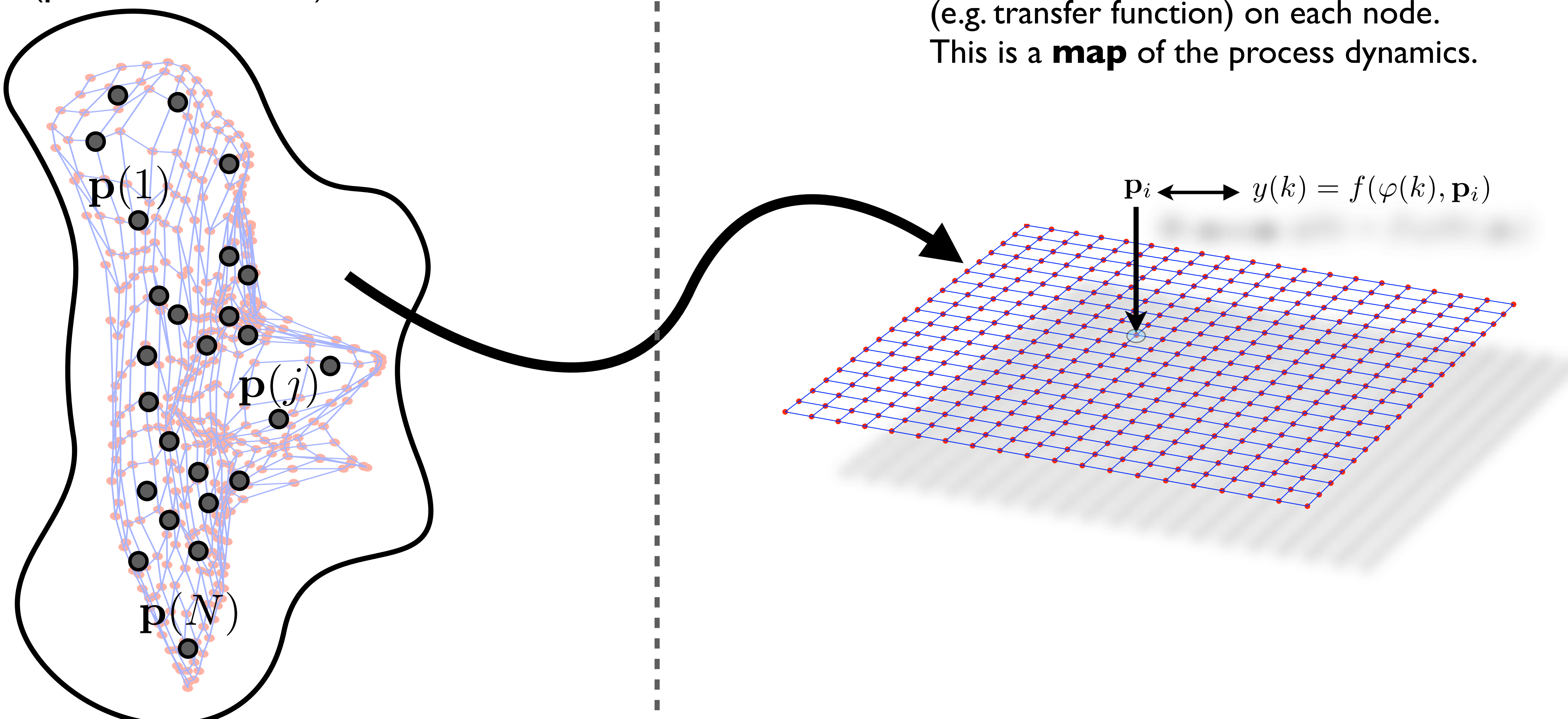
SOM projection stage

input space

(parameter set *P*)

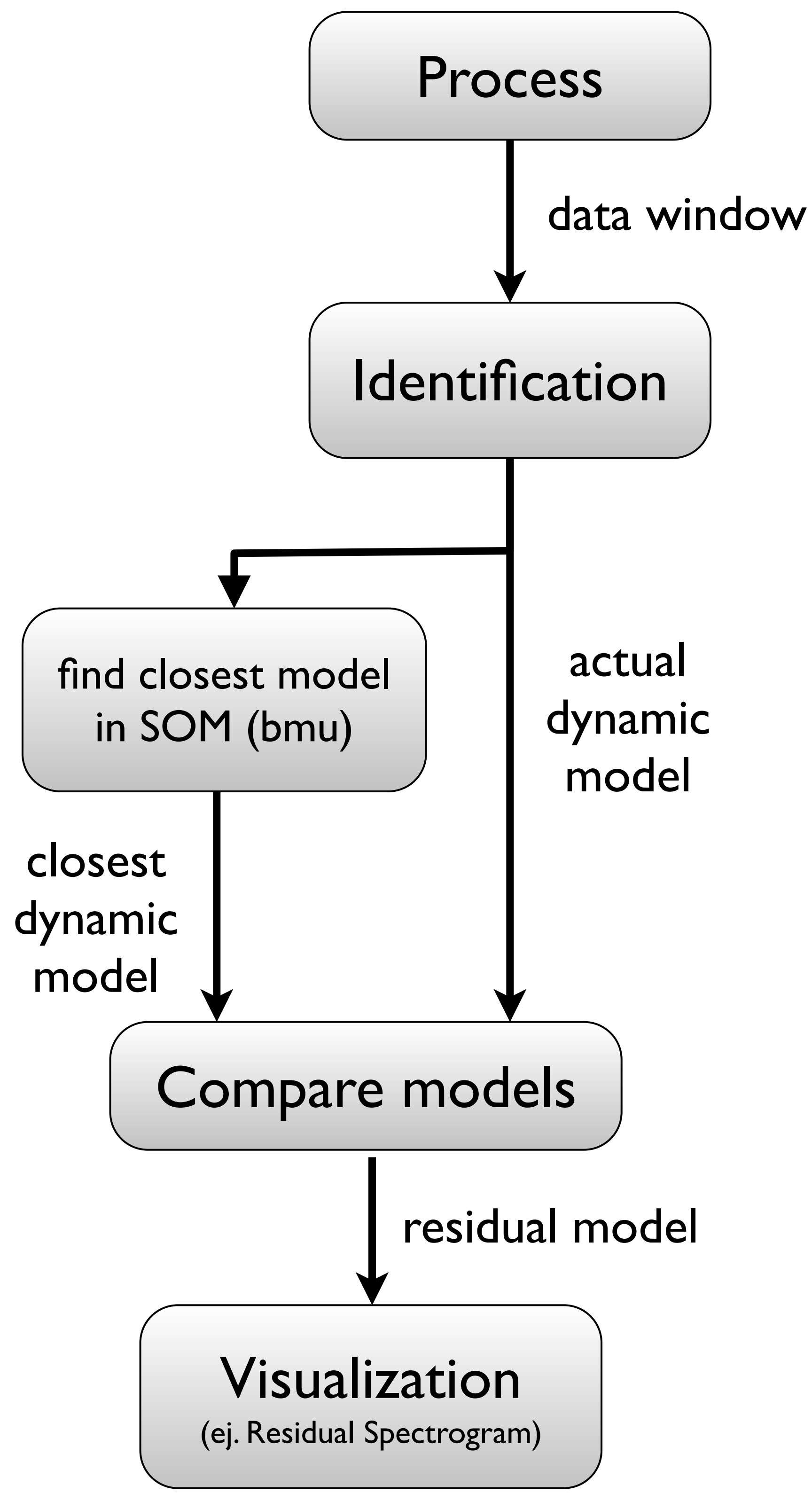
visualization space

The SOM stores a dynamic model (e.g. transfer function) on each node. This is a **map** of the process dynamics.



Visualization of Changes in Dynamics

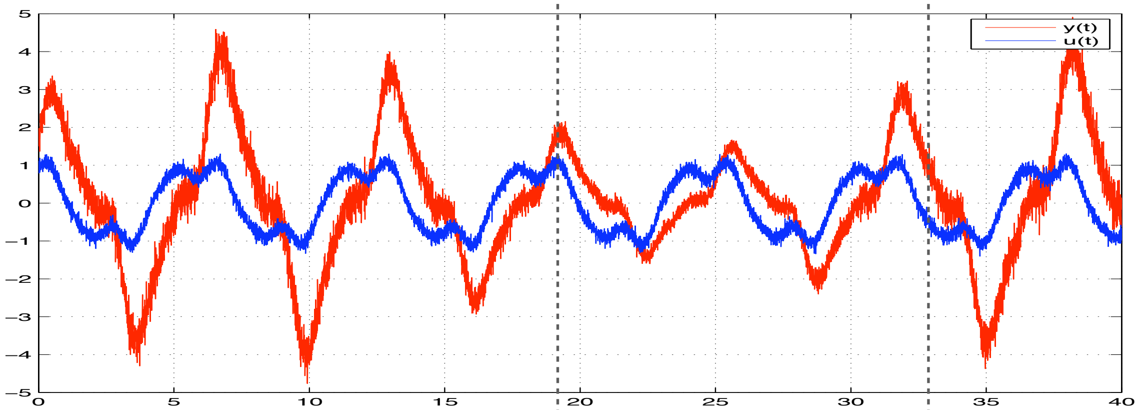
Residual model computation



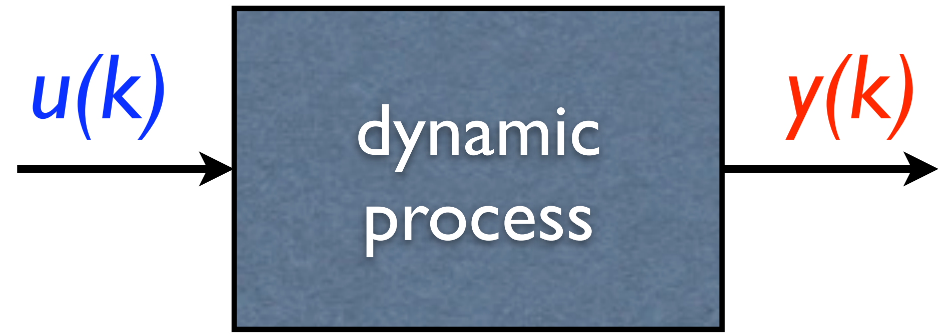
Visualization of Changes in Dynamics

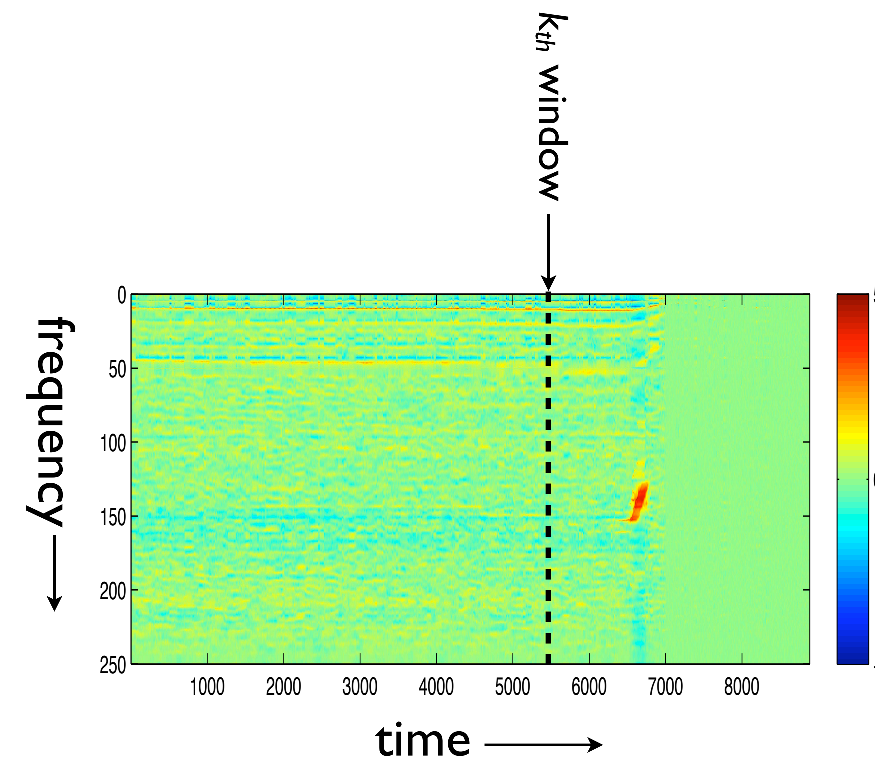
Residual model computation

Example: input (blue) and output (red) from a process



$W_k = \{k - n + 1, \cdots, k\}$





Get data from k_{th} window

$$\{y(k), \varphi(k)\}_{k \in W_k}$$

minimize:

$$J = \sum_{k \in I_j} \|y(k) - f(\varphi(k), \mathbf{p}(k))\|^2$$

SOM bmu

$$c(k) = \arg\min_i \{\|\mathbf{p}(k) - \mathbf{m}_i\|\}$$

$$\mathbf{m}_{c(k)} \leftarrow \mathbf{p}(k)$$

$G(e^{j\theta}, \mathbf{m}_{c(k)})$ (closest model)

$G(e^{j\theta}, \mathbf{p}(k))$ (actual model)

Compare models (actual vs closest)

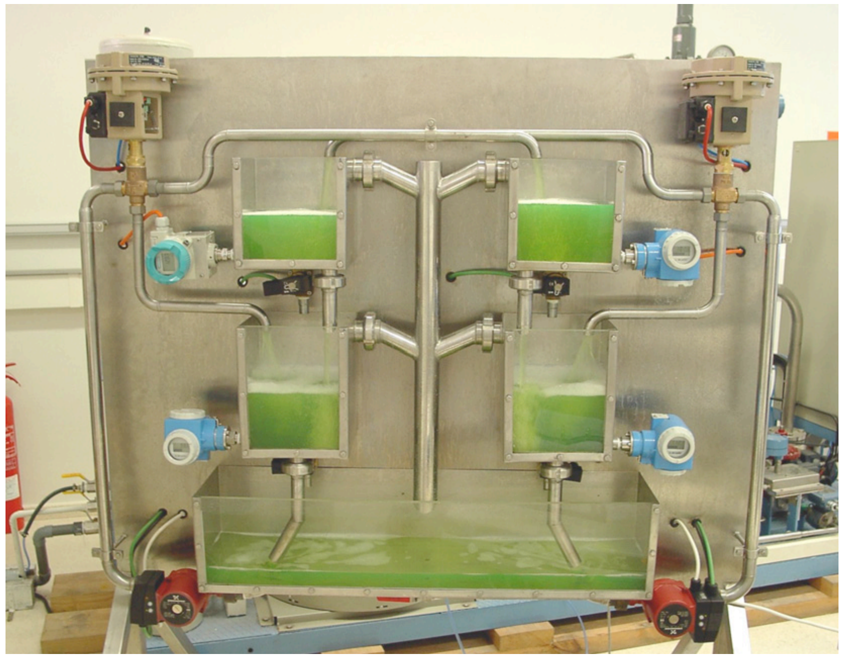
$$\mathbf{R}(e^{j\theta}, k) = \frac{G(e^{j\theta}, \mathbf{p}(k))}{G(e^{j\theta}, \mathbf{m}_{c(k)})}$$

visualize

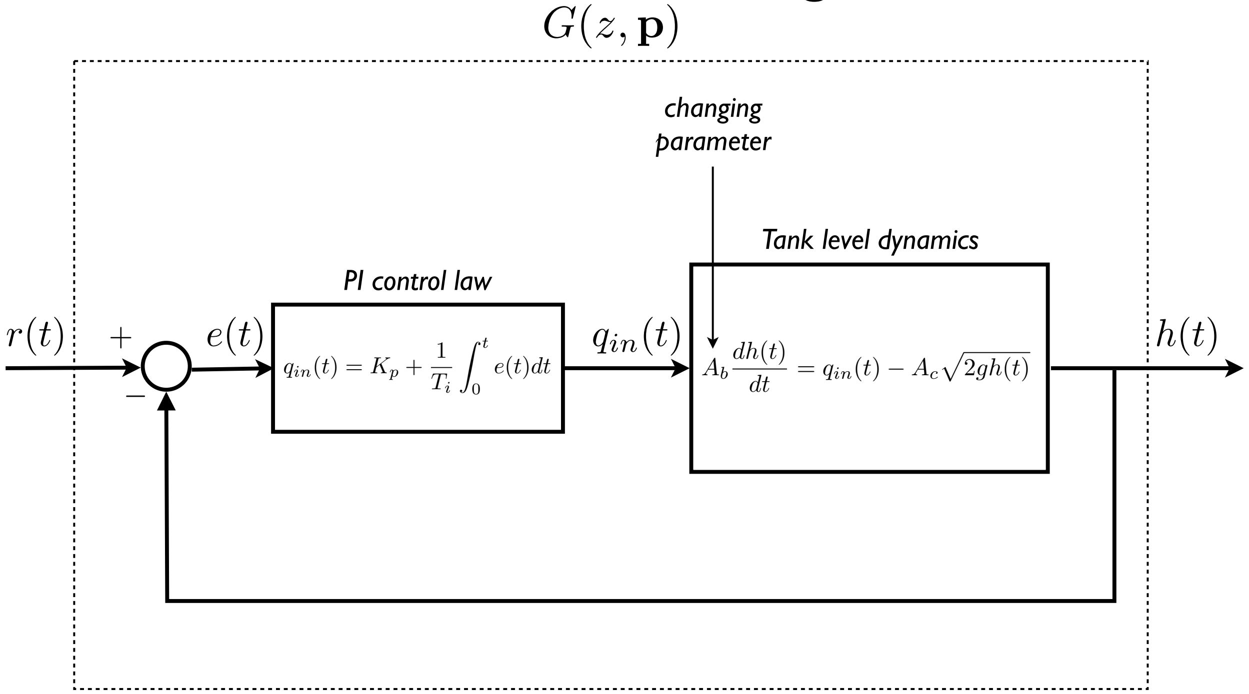
Results

Tank level control dynamics

4-Tank plant



Tank level control block diagram



Tank level dynamics: changes with A_b

$$A_b\frac{dh(t)}{dt} = q_{in}(t) - A_c\sqrt{2gh(t)}$$

Different dynamic conditions changing A_b

Condition	base area	description
1	$A_b = 389.16$ cm^2	(no objects)
2	$A_b = 332.61$ cm^2	(two small cilindric objects)
3	$A_b = 332.61$ cm^2	(two small cilindric objects)
4	$A_b = 282.35$ cm^2	(a large cilindric object + 2 small cilindric objects)
5	$A_b = 343.80$ cm^2	(a large cilindric object)
6	$A_b = 389.16$ cm^2	(no objects)

Results

Tank level control dynamics

Parametric model:

$$G(z, \mathbf{p}) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}}$$

Training parameters:

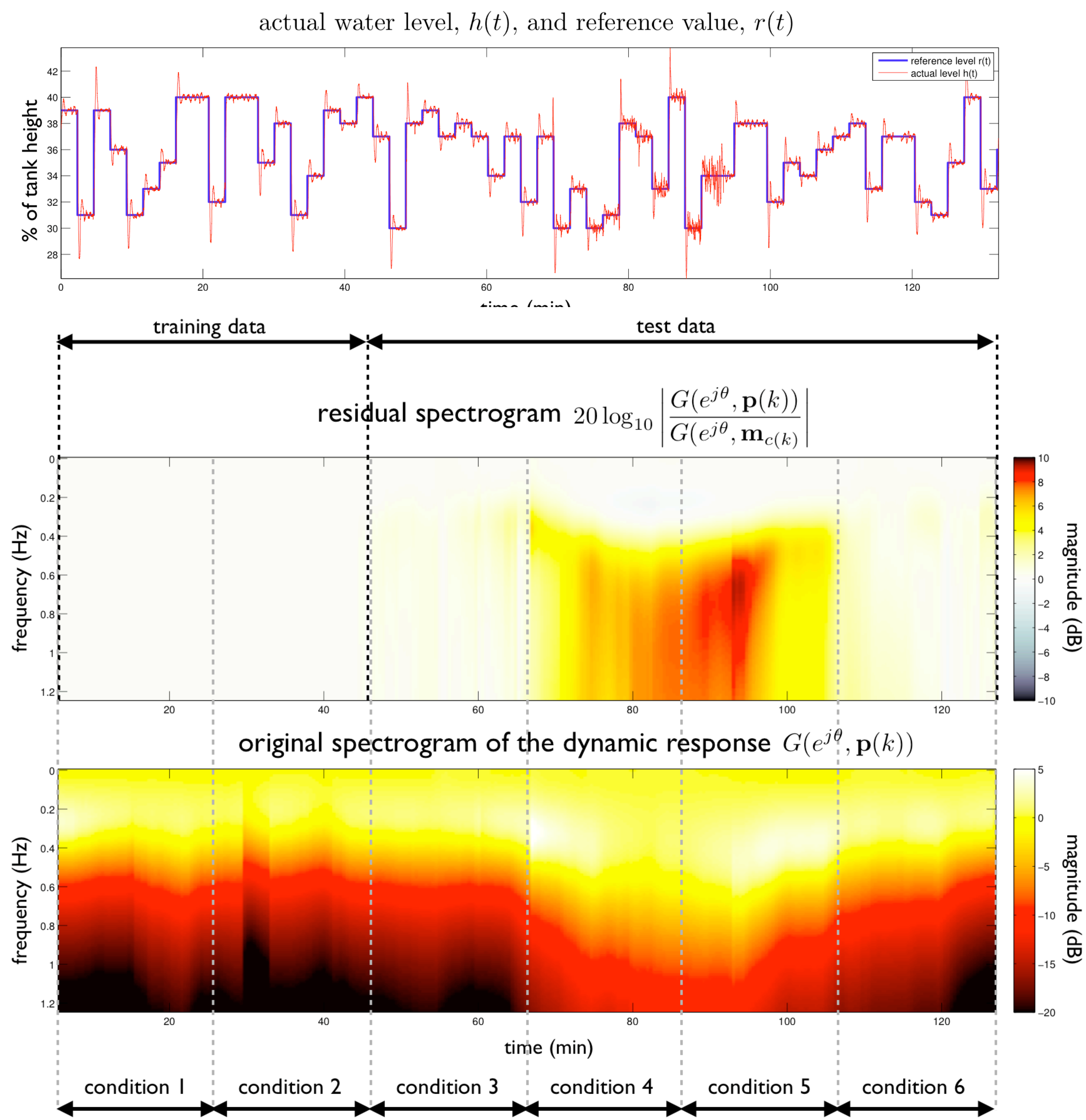
- window length: 500 samples
- windows regularly taken each 20 samples
- trained with data from conditions 1 and 2

SOM training parameters:

- 35 x 35 nodes
- 10 epochs
- gaussian neighborhood decreasing from 11.66 to 1.2

Residual spectrogram:

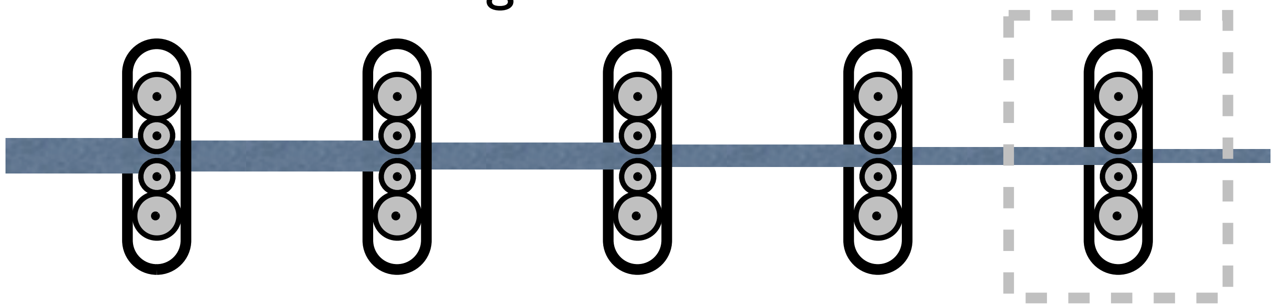
- logarithmic color scale



Results

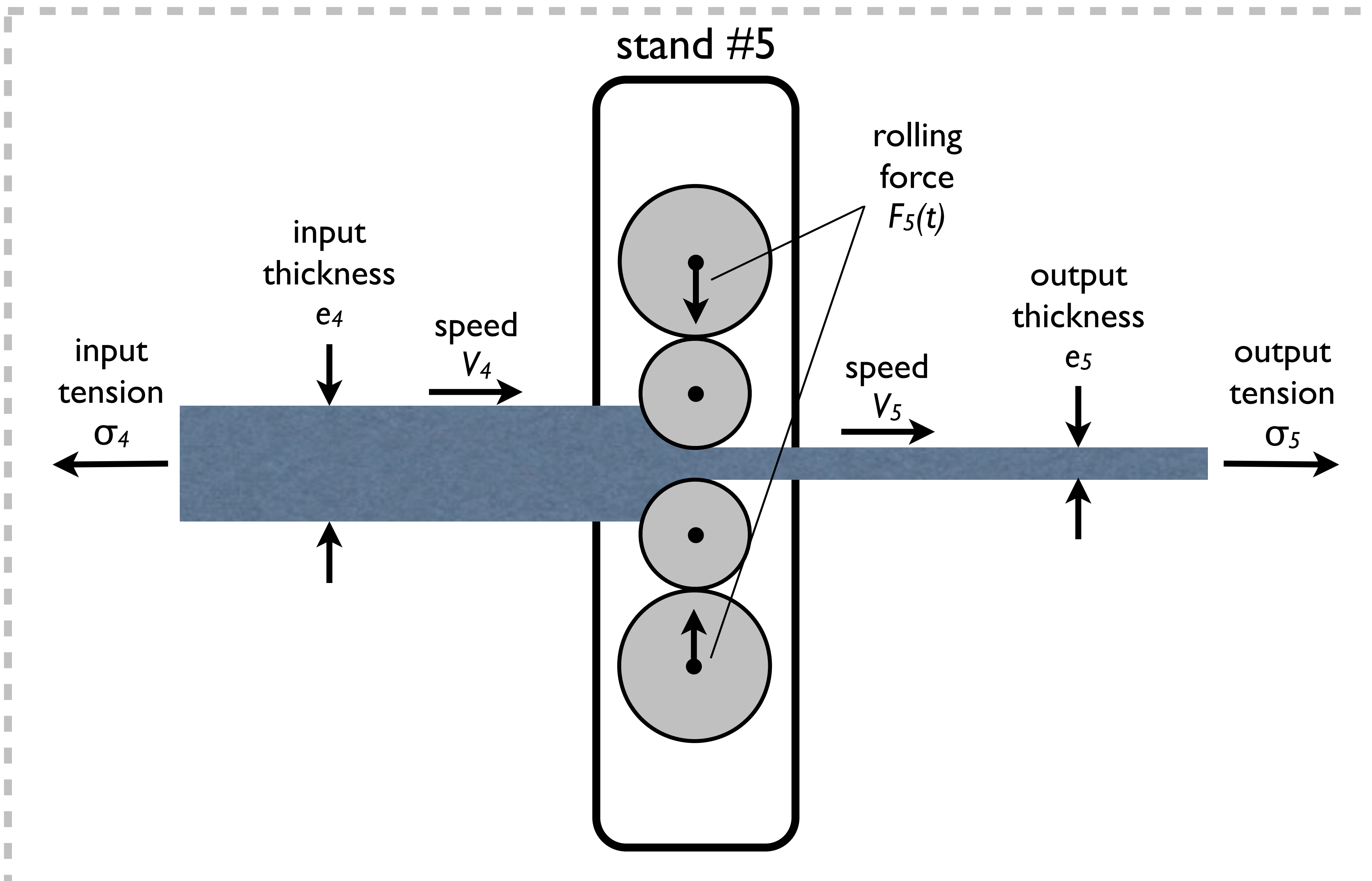
Isolation of abnormal vibrations (chatter in rolling mill)

5-stand cold rolling mill



Objective

Detect abnormal vibration modes (chatter) from data of lamination forces $F_5(t)$
measured at stand 5
of a 969mm width steel coil



Results

Isolation of abnormal vibrations (chatter in rolling mill)

Training parameters:

- sample rate: 500 Hz
  (5000 Hz with 1:10 decimation)
- window length: 1000 samples
- windows regularly taken each 10 samples
  from sample 7000 to sample 8889

SOM training parameters:

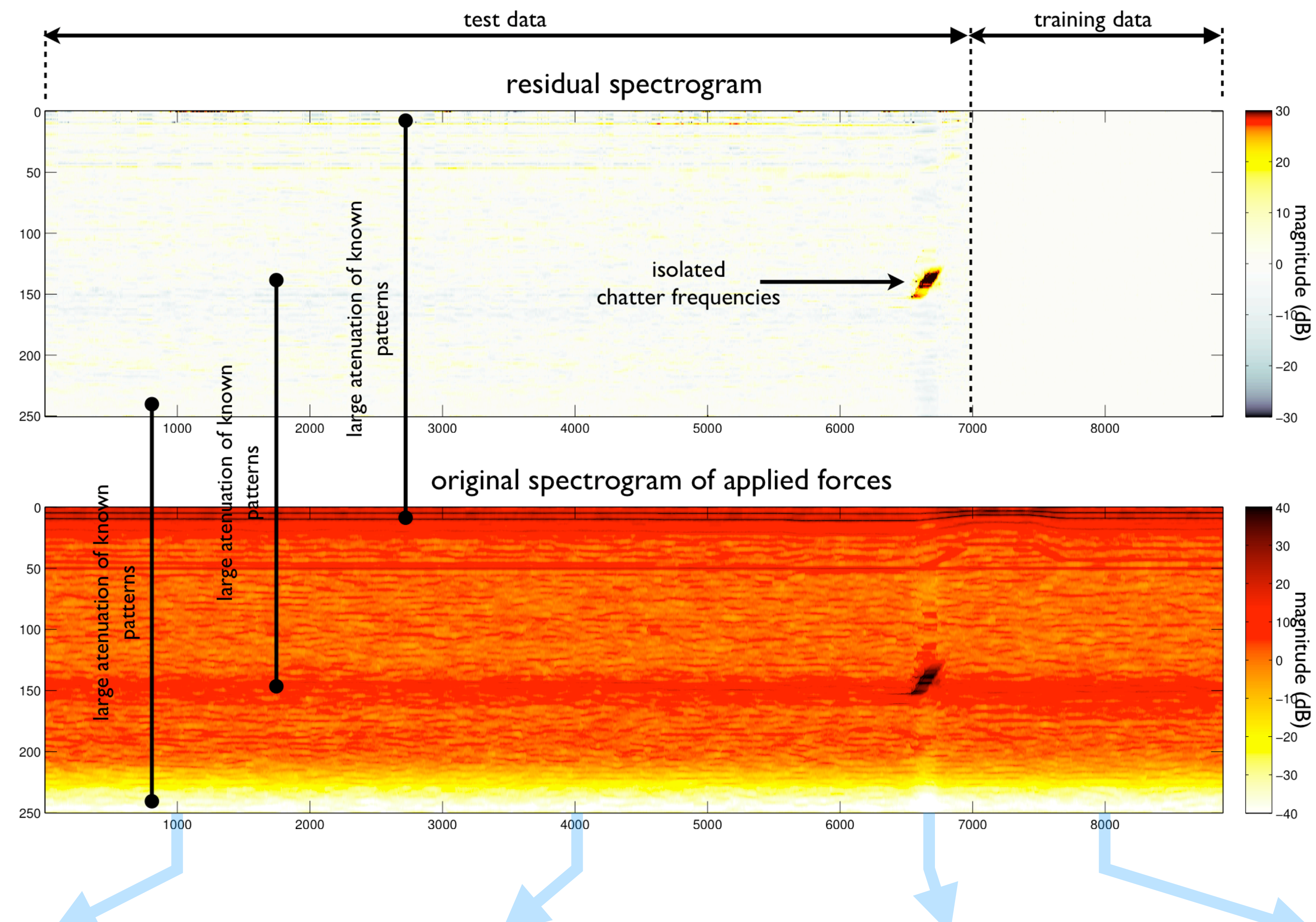
- 30 x 30 nodes
- 10 epochs
- gaussian neighborhood
  decreasing from 10 to 0.7

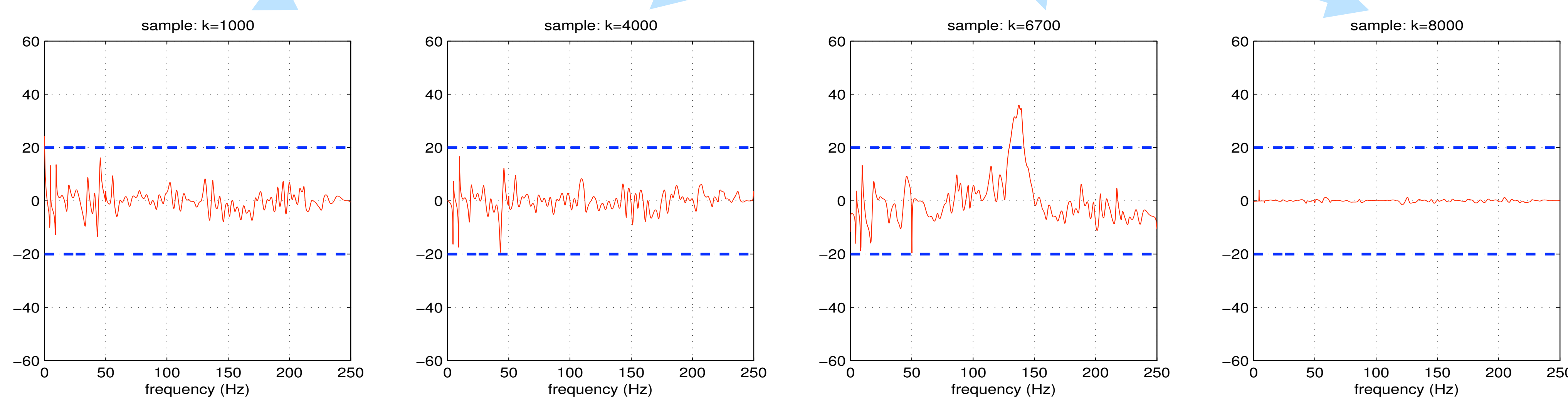
AR(110) model:

$$F_5(k) = a_1 F_5(k-1) + \cdots + a_{110} F_5(k-110) + \epsilon$$

Residual spectrogram:

- logarithmic color scale





Conclusions

Method based on Maps of Dynamics

- rooted on a model based approach
- normal dynamic behaviours are stored on a SOM

The method allows

- Detection of changes, but also...
- ... provides qualitative information on the nature of changes

Effective time frequency plot (residual spectrogram) may show:

- time where abnormal behaviour appears
- eventual time patterns (cadence of faults, trends, etc.)
- involved frequencies

Future Work

Use different metrics to compare dynamic models (e.g. H_∞)

- In the parameter space, for SOM training
- To compare actual vs. stored models

Explore new ways to produce meaningful residuals

- Use of nonlinear models
- Alternative visualizations (e.g. time-time plots)
- Plotting individual meaningful features from residual models

Questions

Thank you for your attention!