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PCA-Based Fault Detection in High-Volume Production Using Machine Data

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Outline

- Basic philosophy of Data Processing Techniques
- Comparison of univariate Extraction Methods
- Software Structure for PCA Module
- Experiments: TCP ALU - DSQ process
- Summary and outlook

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Basic Philosophy of Data Processing Techniques

inter. machine Sensor Data

external Sensor Data

Tool Parameter

Product Parameter

$x_i(t)$ i=1..N

y

KEY NUMBER EXTRACTION

- multivariate extraction (concerning N measured channel's)
- univariate methods (concerning time signal $x_i(t)$ of one channel)

KEY NUMBER PROCESSING

- statistical methods
  - univariate (3σ limits)
  - multivariate (Clustering, T^2,Q)
- modelling and classification

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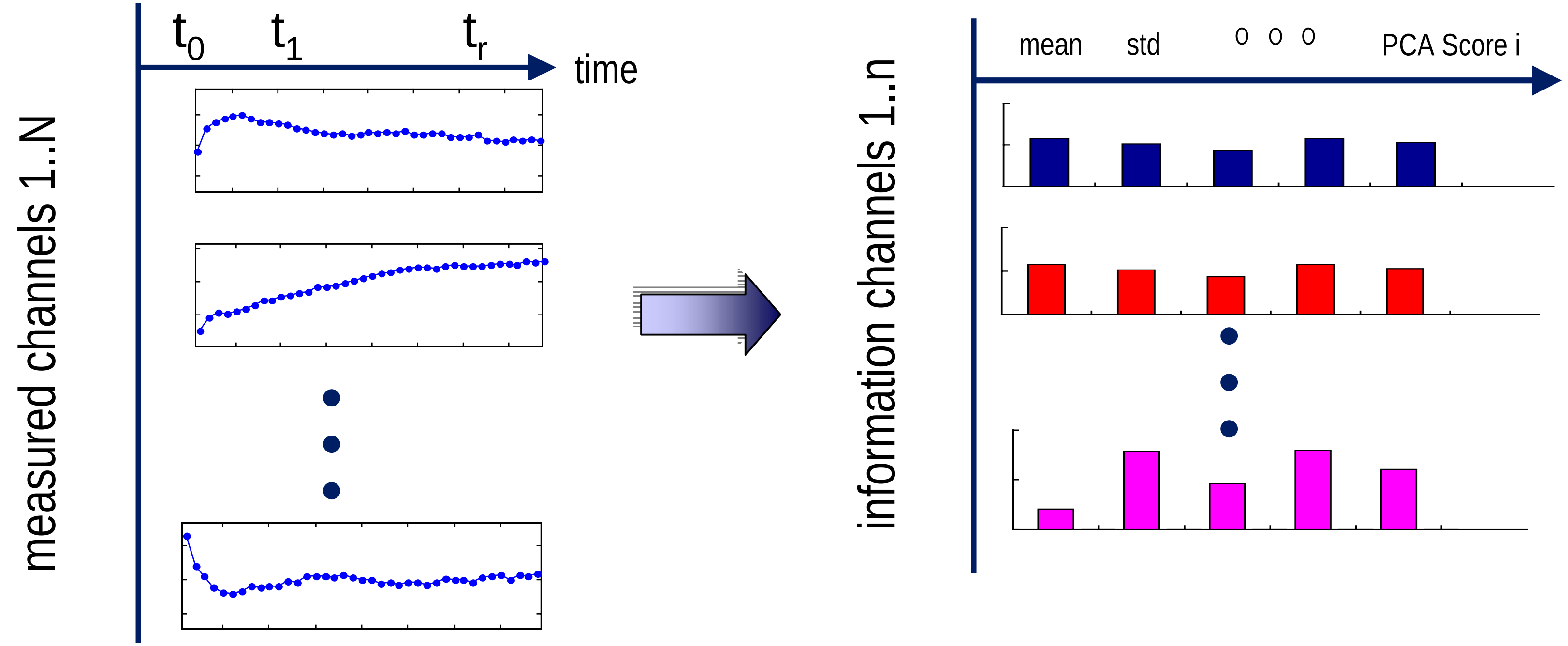
Objective of Key-Number Extraction

original measured sensor data from one wafer, lot or batch

extracted key-numbers per wafer, lot or batch



- extraction of significant information from the original data
- n extracted key-numbers (n<N) should represent the original data with a small lack of fit → important for FDC and modelling

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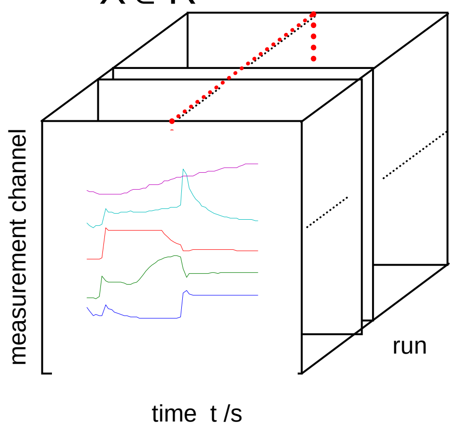
Methods for univariate Key-Number extraction for measured time signals x(t)

original data cube:

$X \in R^{channel \times time \times run}$



1. Simple Key-Numbers
   - mean values
   - standard deviation
   - duration of steps etc.

2. Extraction using signal decomposition
   - fixed signal base → Tschebyscheff
   - adjusted signal base → PCA

3. Adaptation of a nonlinear parametric signal model

⇓

Compromise between efficiency and effort

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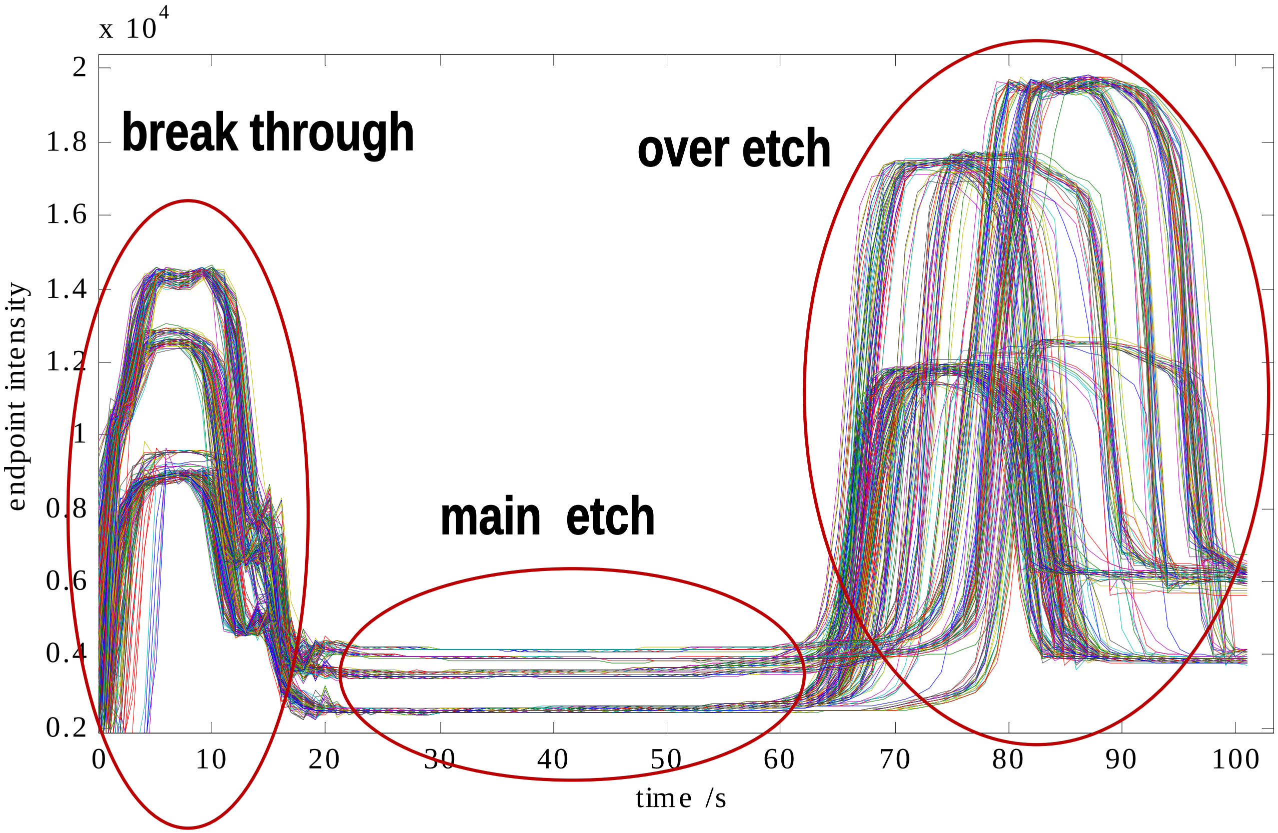
Comparison of univariate methods

- raw optical endpoint data from 335 TCP-ALU metal etches



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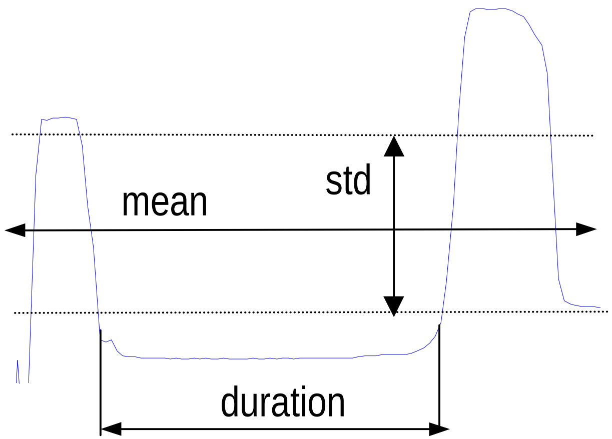
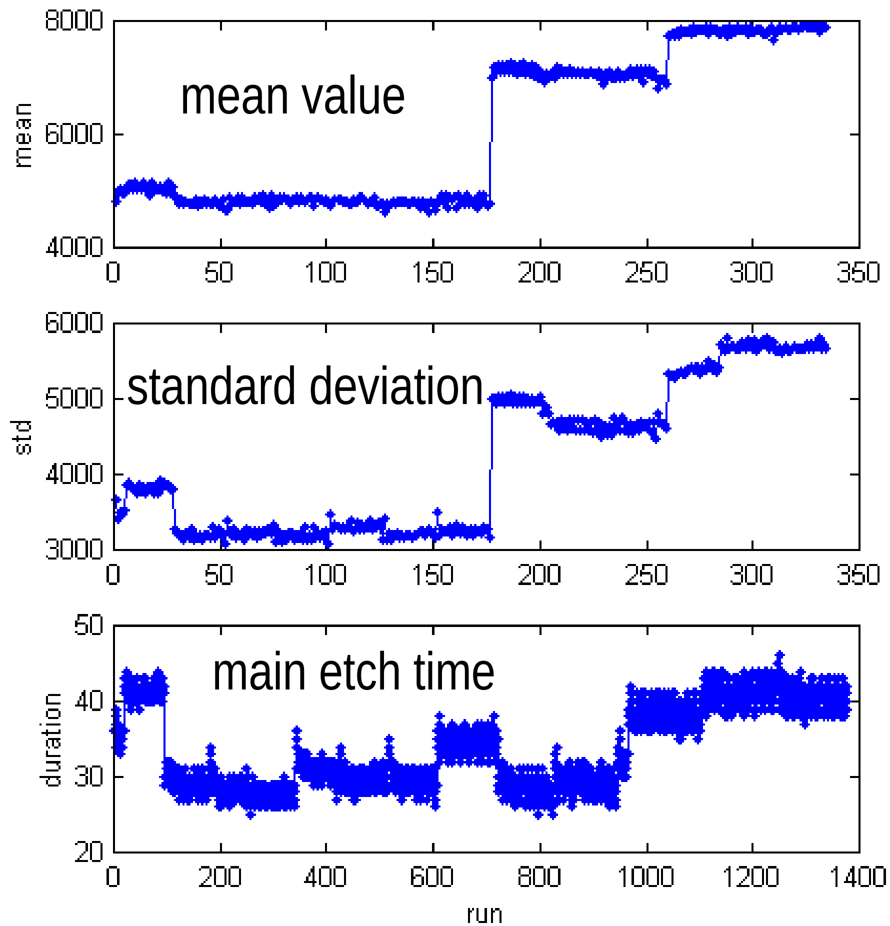
Comparison of univariate methods → Simple Key Numbers





- simple interpretation of key numbers
- no assessment of the actual signal shape

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Comparison of univariate methods
→ Signal Decomposition - Fixed Base

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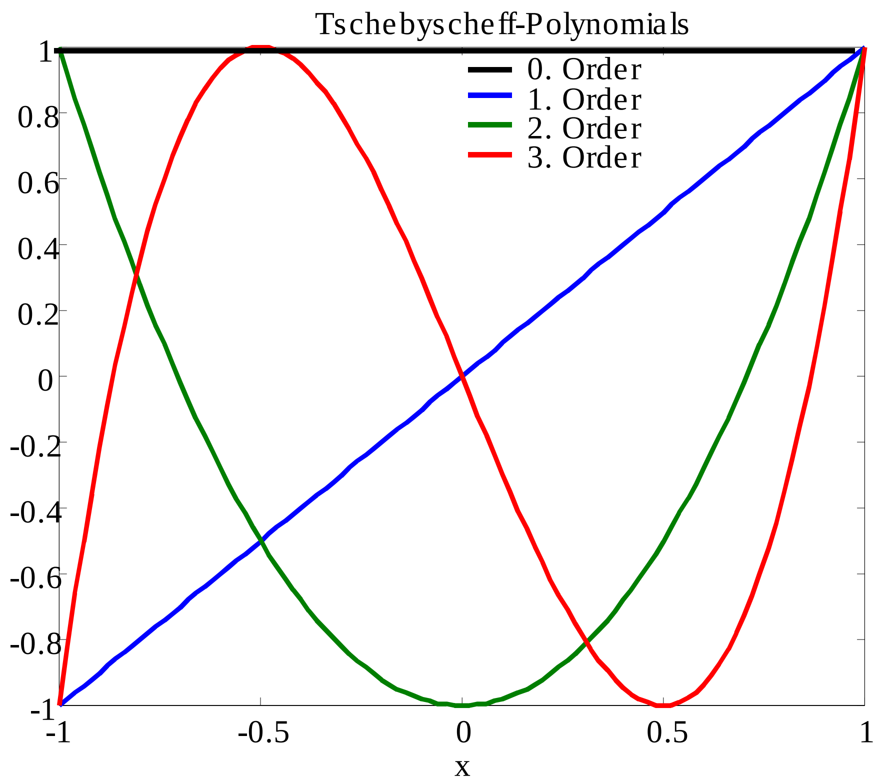
Tschebyscheff -Polynomials: $U_n = \cos(n \cdot \arccos(x))$ $\quad -1 \le x \le 1 \quad n = 1 \ldots N$



- complete non-orthogonal, polynomial signal base
- simple key-number calculation $p_n = U_n^T \cdot X$
- approximation of original signal $X = \quad p_n \cdot U_n$

→ key-numbers depend on the number N of polynomials used and must be calculated using Least Square (Fit)

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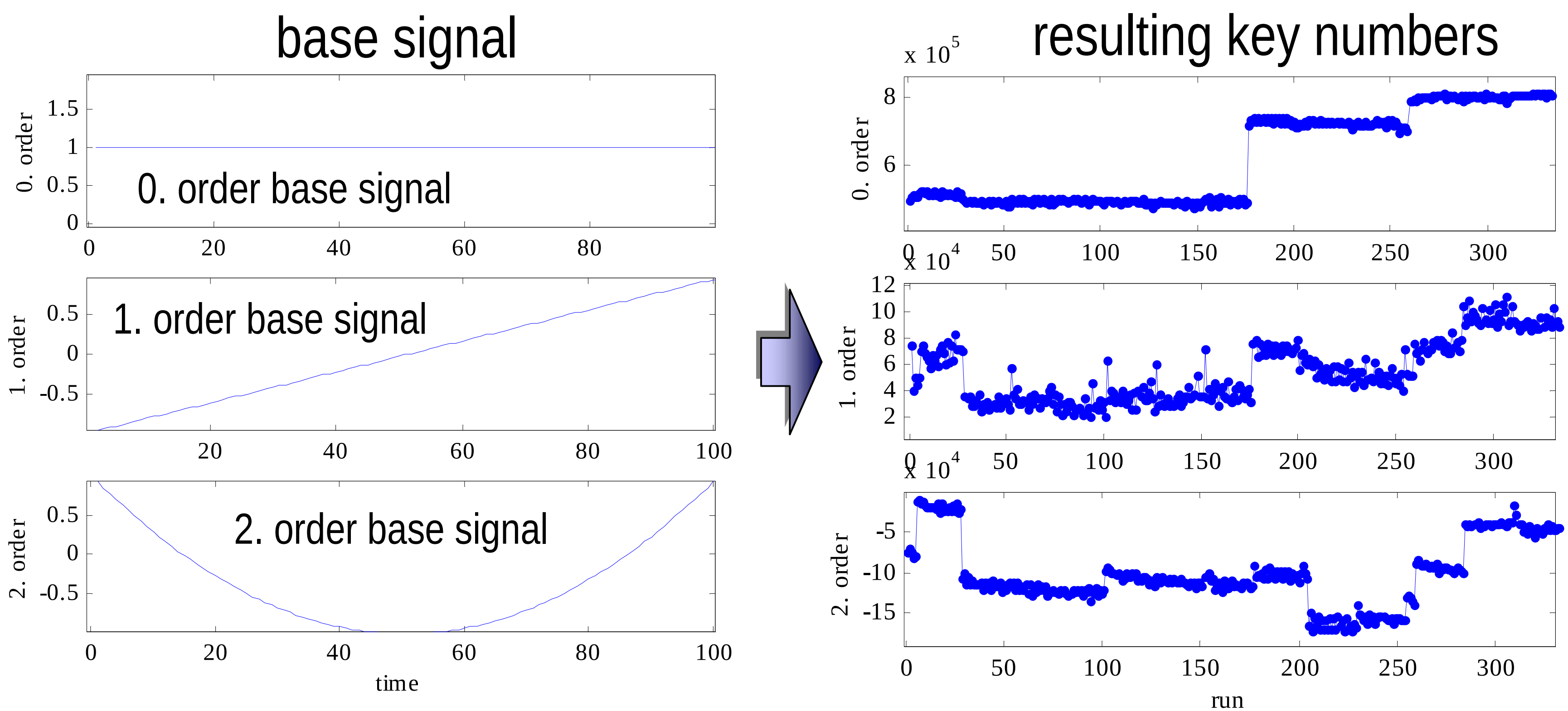
Comparison of univariate methods
→ Signal Decomposition - Fixed Base



- actual signal shapes are taken into account in an unspecific way
- poor approximation quality

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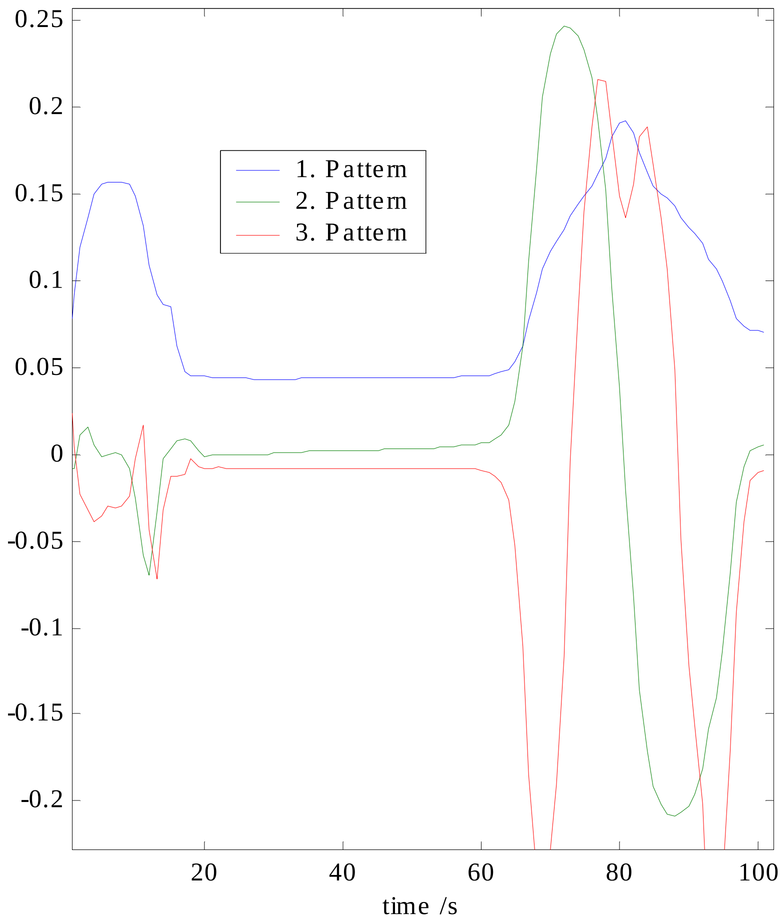
Comparison of univariate methods
→ Signal Decomposition - Adjusted Base



- Principal Component Analysis creates an adjusted signal base
- eigenvector decomposition of the original data matrix into orthogonal base signals u_n and orthogonal key-numbers p_n :

$$X = P \cdot U^T = \quad p_n \cdot u_n^T$$

- key-numbers represent the weight of the corresponding base signal in the original data sample

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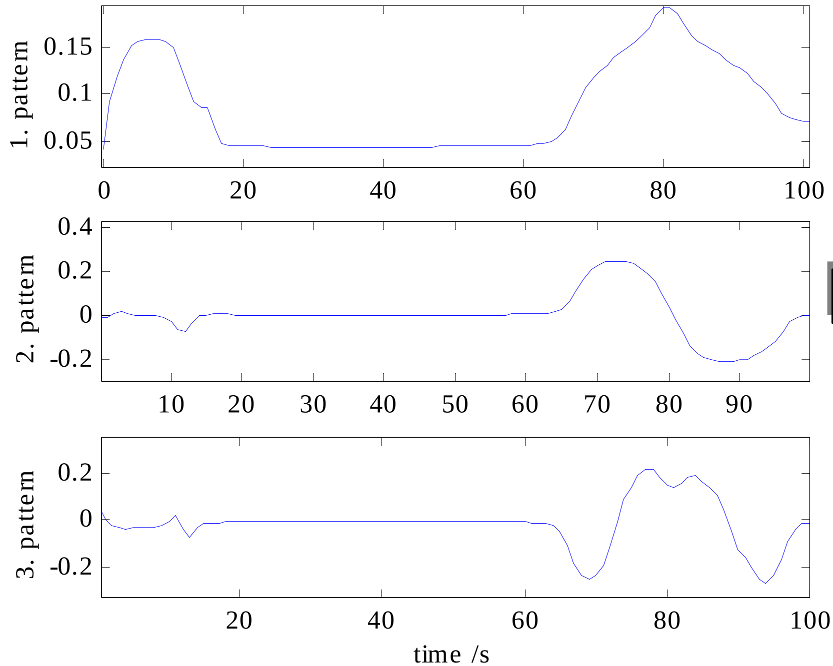
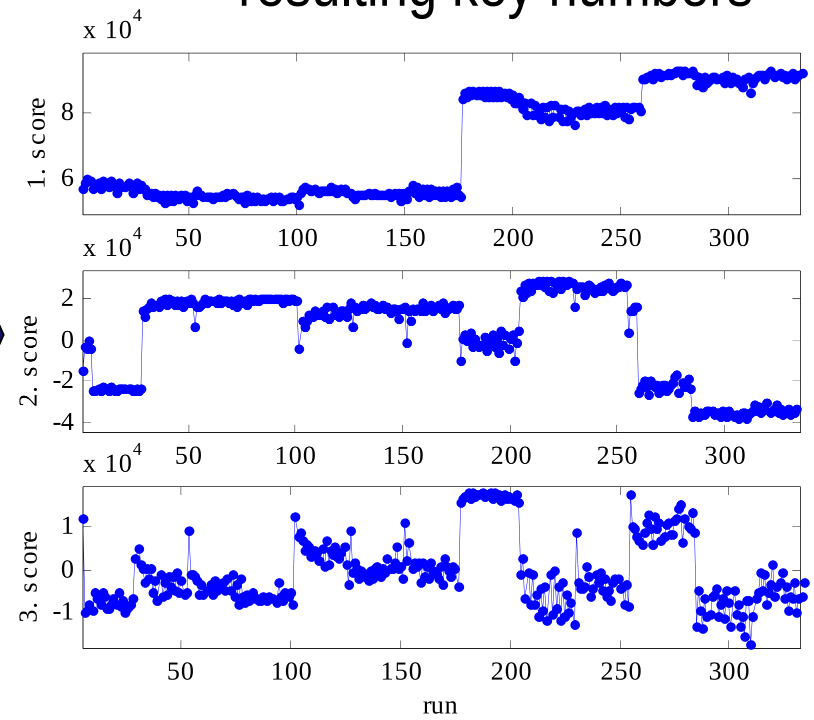
Comparison of univariate methods → Signal Decomposition - Adjusted Base

base signal



resulting key numbers



- actual signal shapes are considered in a specific way
- best approximation quality (Frobenius Norm)

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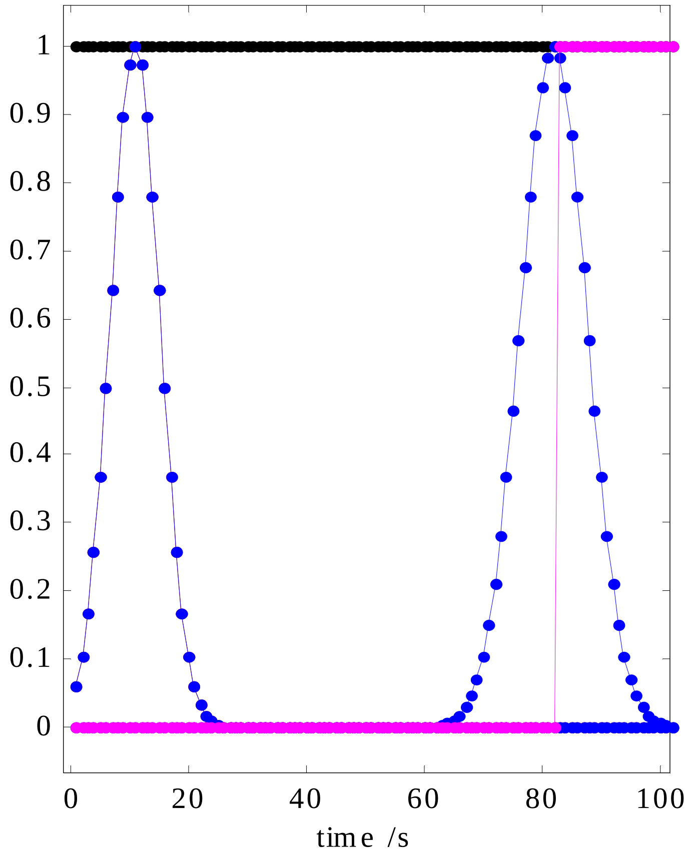
Comparison of univariate methods → Nonlinear signal model

$$y = p_1 + p_2 \cdot e^{-\left(\frac{x-p_5}{p_7}\right)^2} + p_3 \cdot e^{-\left(\frac{x-p_6}{p_8}\right)^2} + p_4 \cdot \mathrm{step}(x - p_6)$$



- calculation of the key numbers by adaptation of a nonlinear signal model with linear model parameters p_1 .. p_4 and nonlinear model parameters p_5.. p_8
- minimize the lack of fit using an optimization algorithm for nonlinear parameters and Least Squares algorithm for linear parameters

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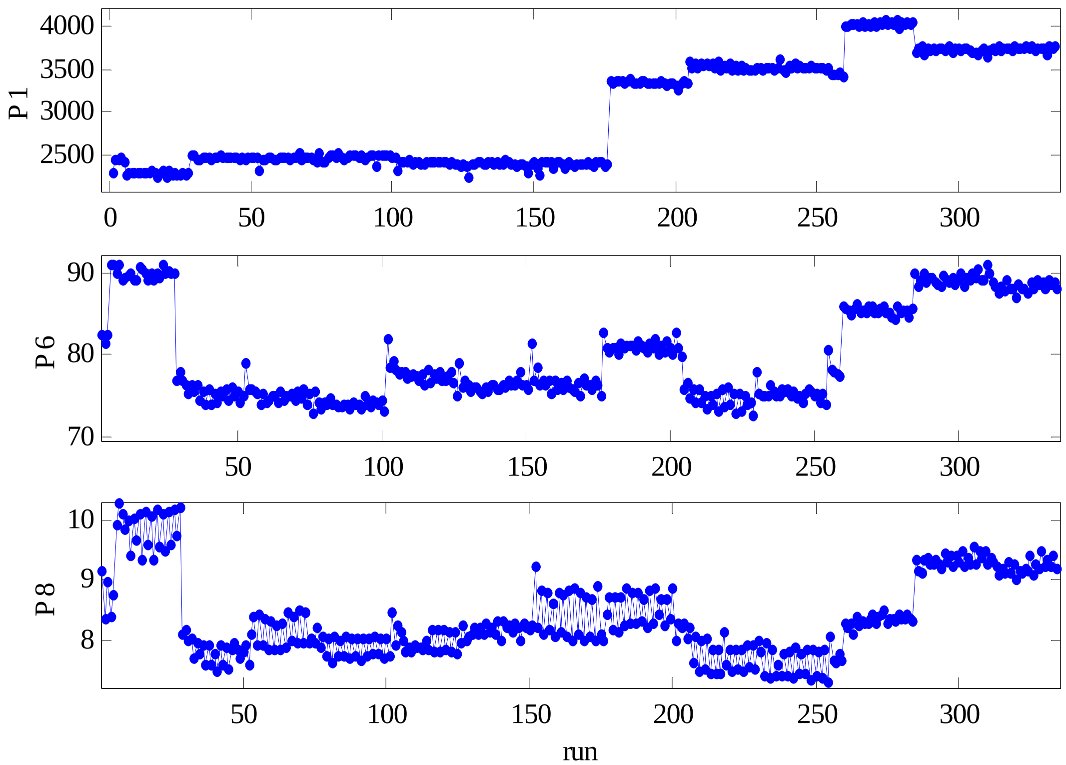
Comparison of univariat methods → Nonlinear signal model

parameter p_1
→ total power

parameter p_6
→ endpoint time

parameter p_8
→ endpoint width



- excellent interpretation of calculated key-numbers
- requires the pre-definition of an analytical signal model

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Comparison of univariate methods $\rightarrow$ Approximation Power

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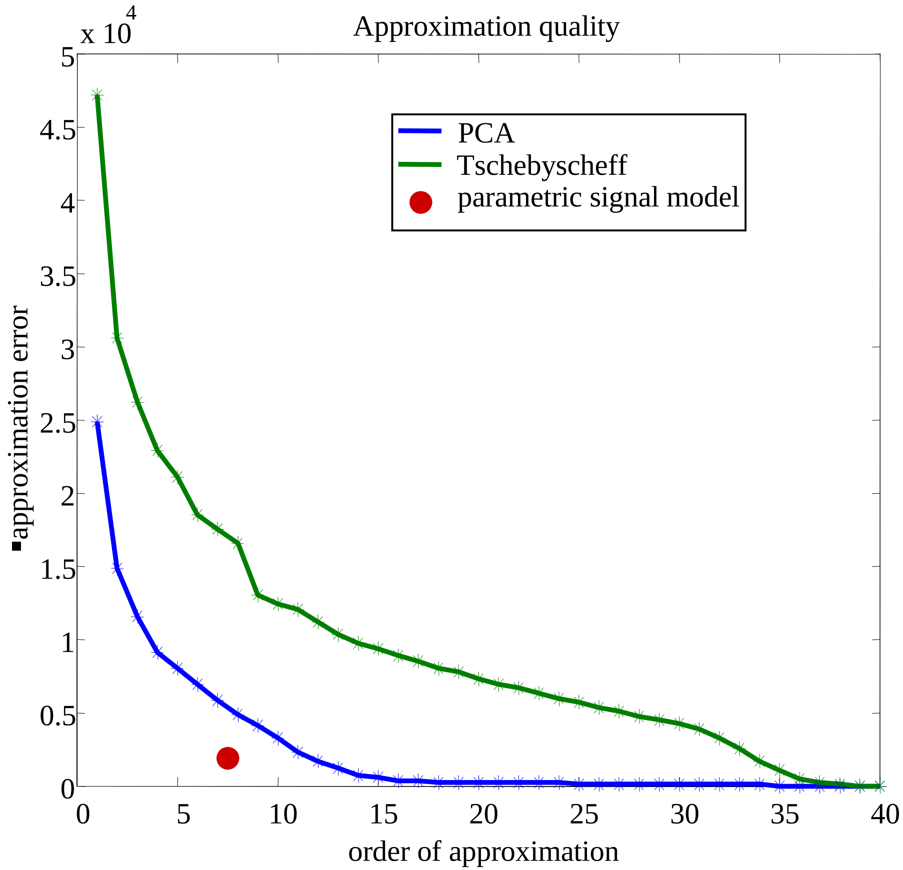
Lack of fit vs. number of key-numbers



- the overall objective is to minimize the lack of fit with as few as possible key-numbers
- PCA provides a better approximation than Tschebyscheff
- parametric signal model provides the best approximation quality

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Comparison of univariate methods → Summary

Simple Key Numbers	▪ very simple interpretation ▪ bad approximation quality ▪ no assessment of actual signal shape
Tschebyscheff Basis	▪ interpretation nearly impossible ▪ low approximation quality ▪ actual signal shapes are taken into account (unspecific)
PCA-Basis	▪ possible interpretation in conjunction with base signals ▪ good approximation quality ▪ reference data are necessary for calculation of a specific signal base
Nonlinear, para-metric signal model	▪ key numbers represent real model parameter ▪ very good approximation quality ▪ pre-definition of an analytical signal model is necessary ▪ tricky calculation of the key numbers

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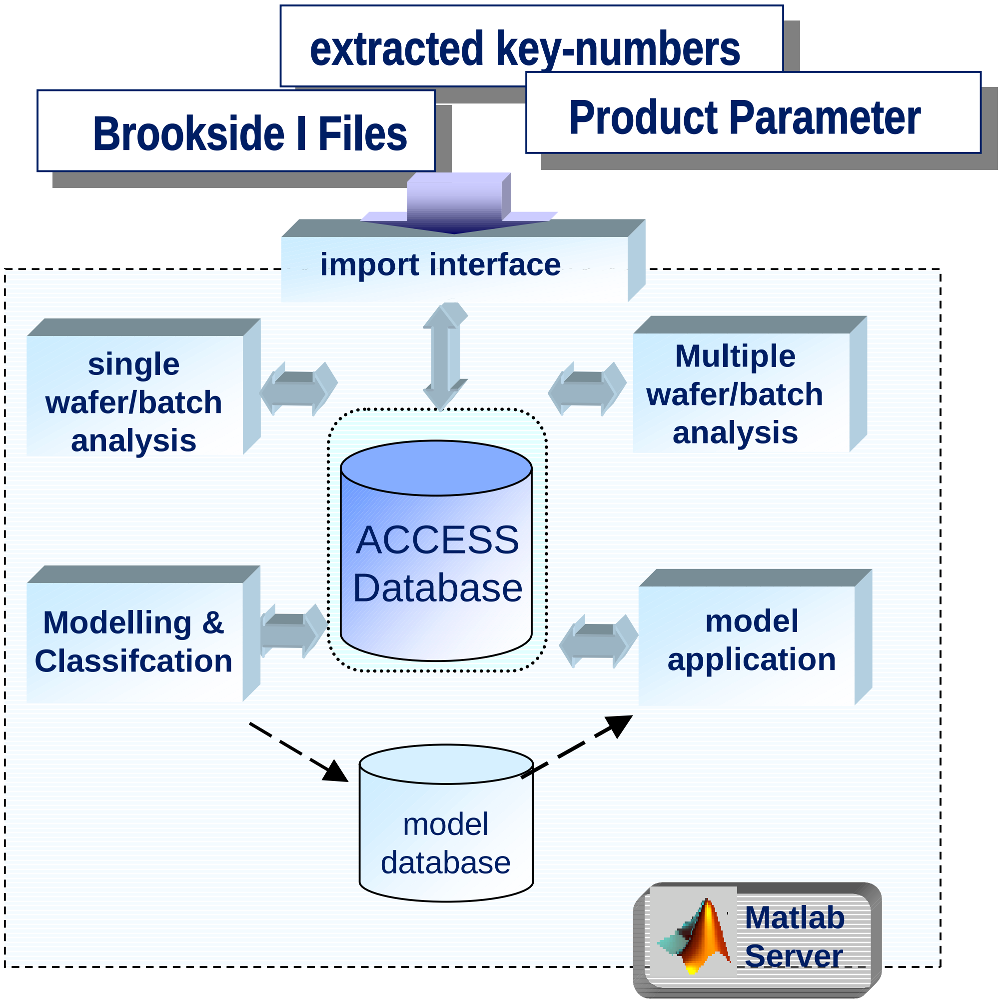
Software Prototype for PCA Data Analysis



- Database oriented storage of machine sensor data and SQL- based data access for:
  - Data visualization
  - PCA based key number extraction
  - Modelling of Product Parameter

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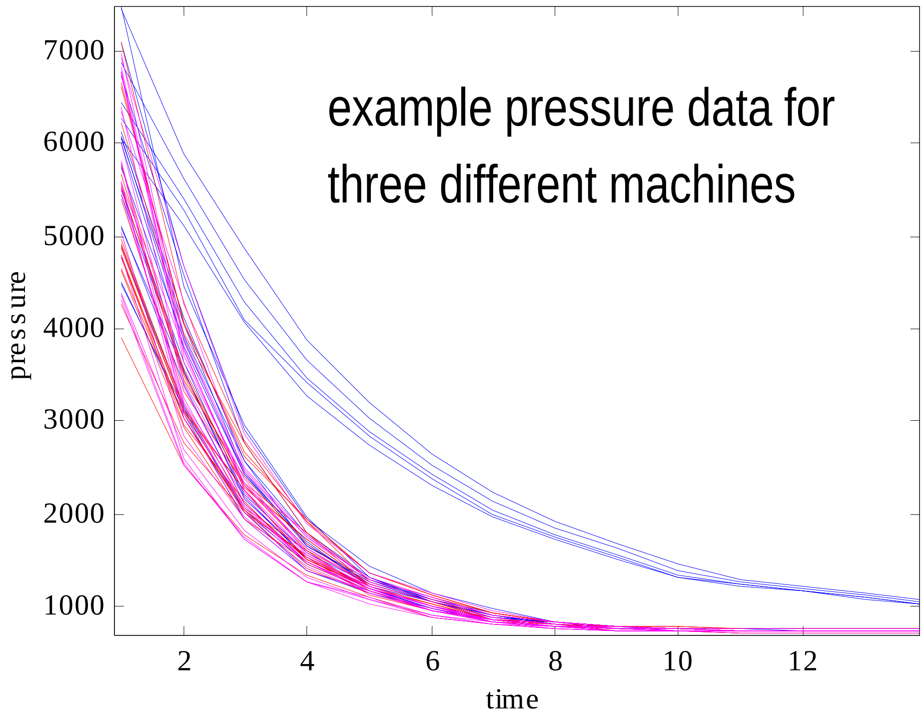
1. Example: DSQ - Pressure Analysis

- analysis of the raw pressure data from TCP-ALU DSQ-Process with PCA - method



- comparison of the pressure signal of three machines during chamber stabilization
- sudden appearance of a longer transient behavior of the pressure signal

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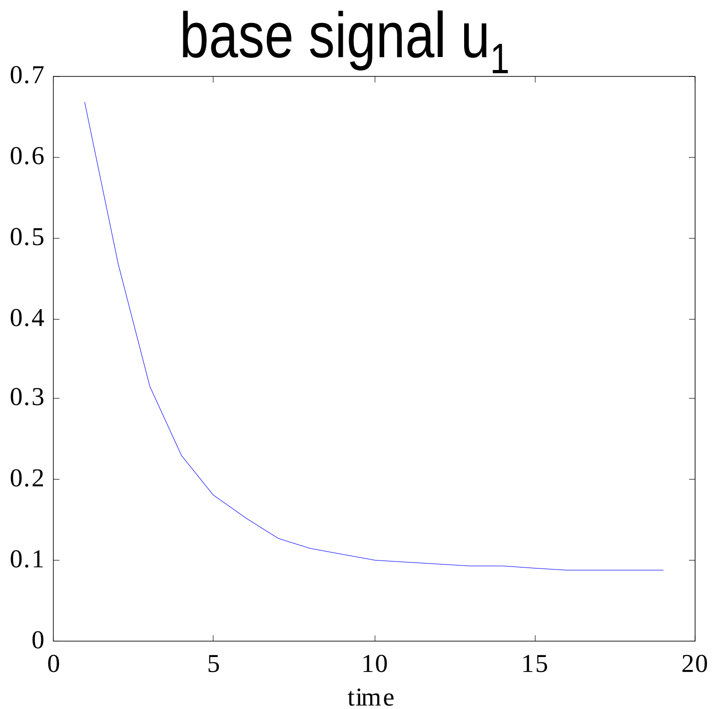
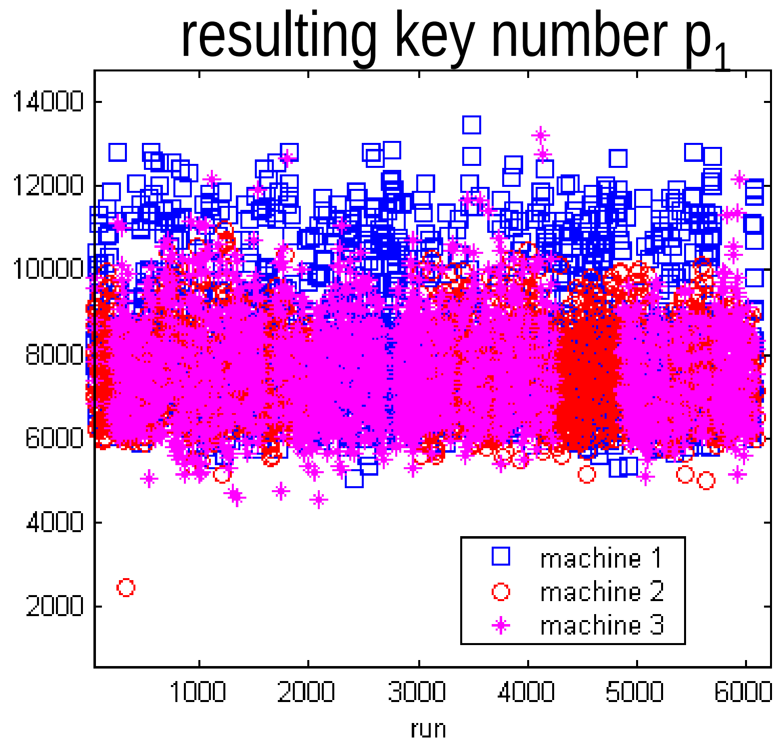
1. Example: DSQ - Pressure Analysis





- the application of the base signal u_1 results in key numbers with similar information to the mean value
- the key numbers of machine1 have a larger standard deviation

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1. Example: DSQ - Pressure Analysis

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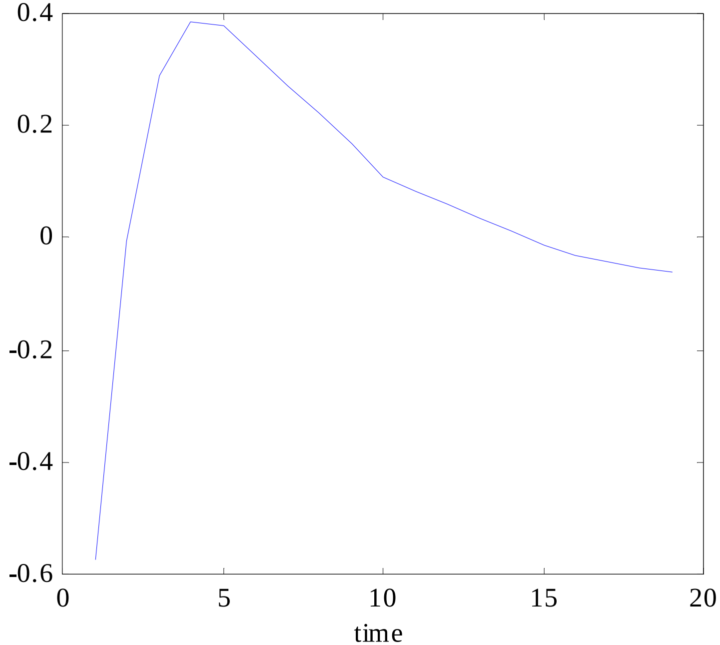
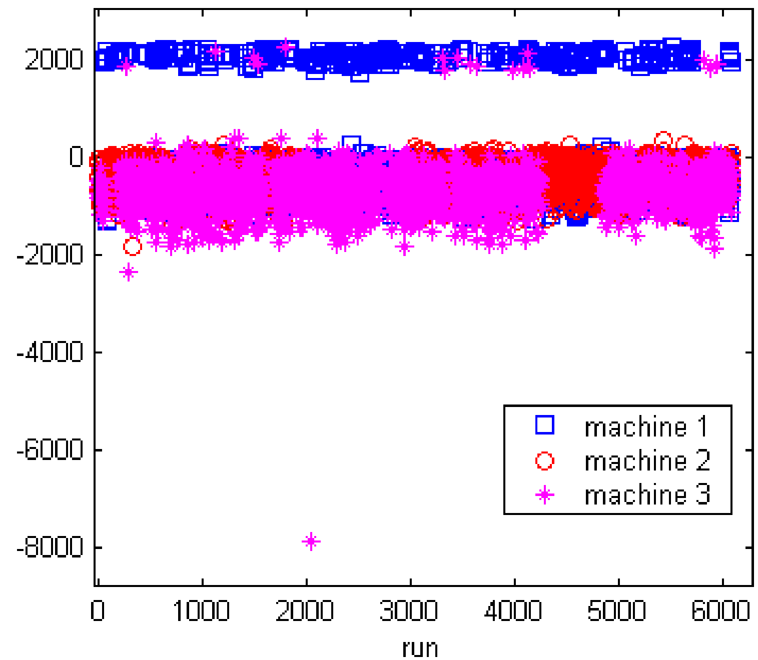
base signal u_2



resulting key number p_2



- the differences between the machines become obvious by application of the base signal u_2
- the effect can be detected clearly using fixed limits

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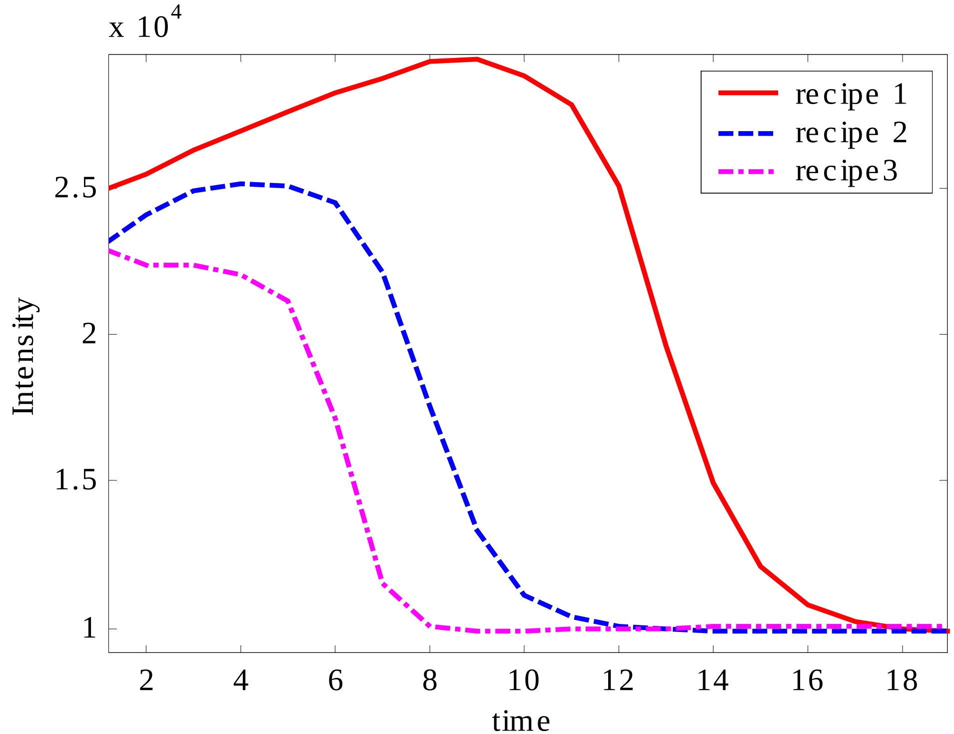
2. Example: DSQ - Endpoint Variations → Comparison of three recipes

- analysis of the endpoint data from TCP-ALU DSQ-Process with PCA - method

example of three different endpoint signals



- comparison of endpoint variations between different recipes from one machine
- reconstruction of the original endpoint signal using key numbers

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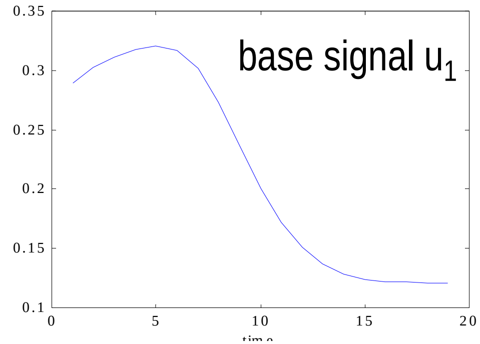
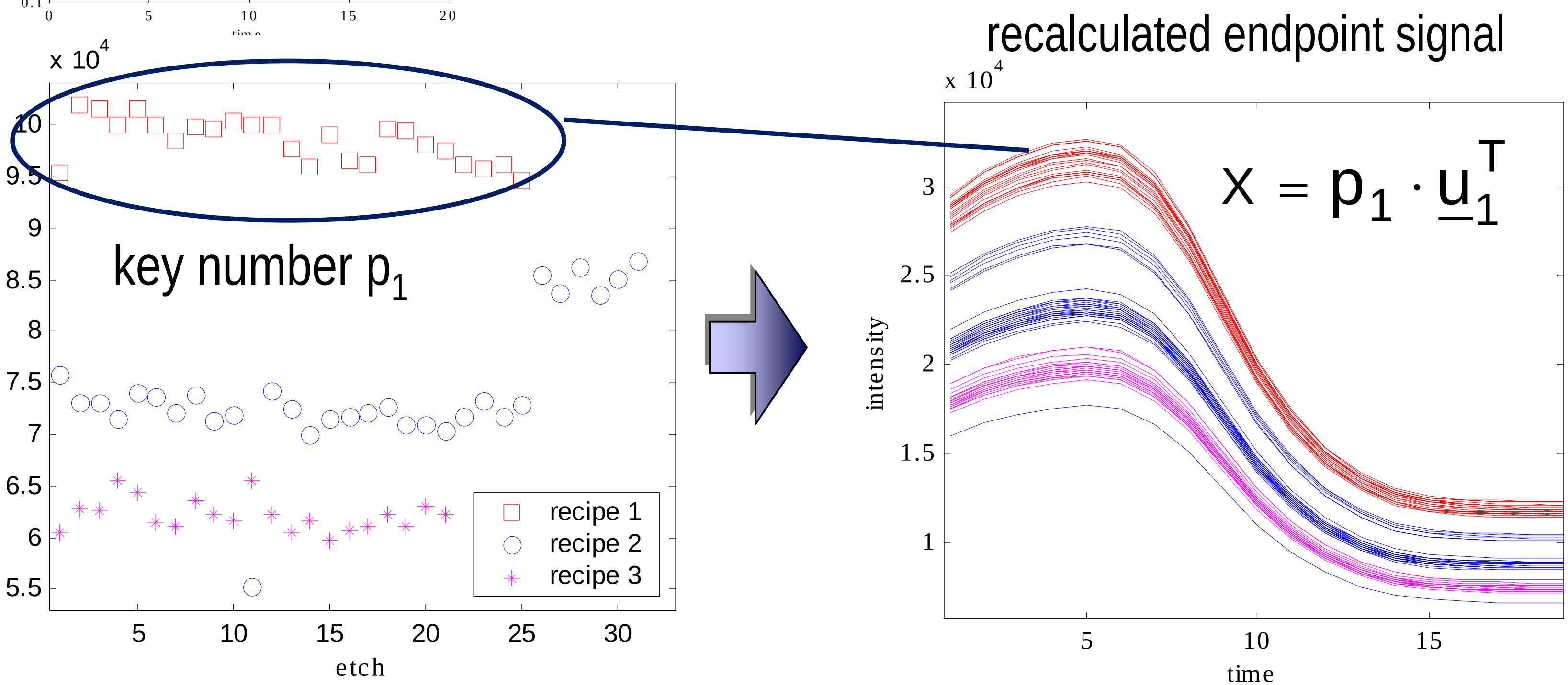
2. Example: DSQ - Endpoint Variations → Comparison of three recipes



- different total endpoint intensities are represented by the first key-number
- large variations within machine 2



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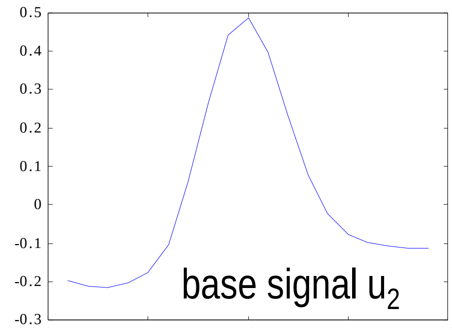
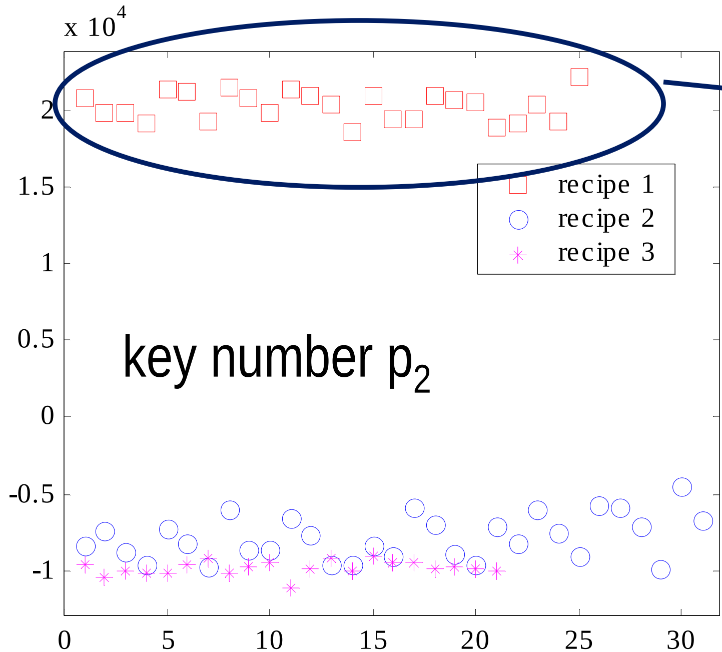
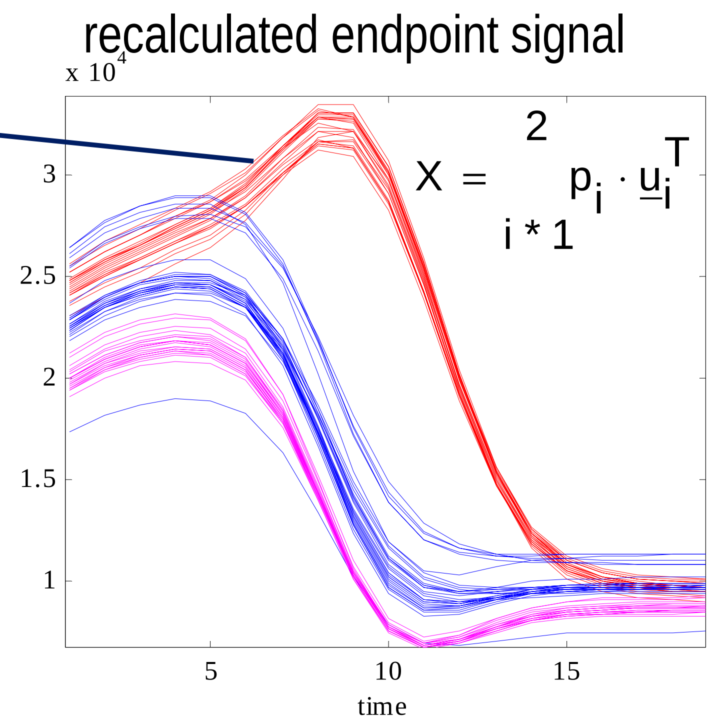
2. Example: DSQ - Endpoint Variations → Comparison of three recipes



- representation of shift-variations in the endpoint signal with key number p_2





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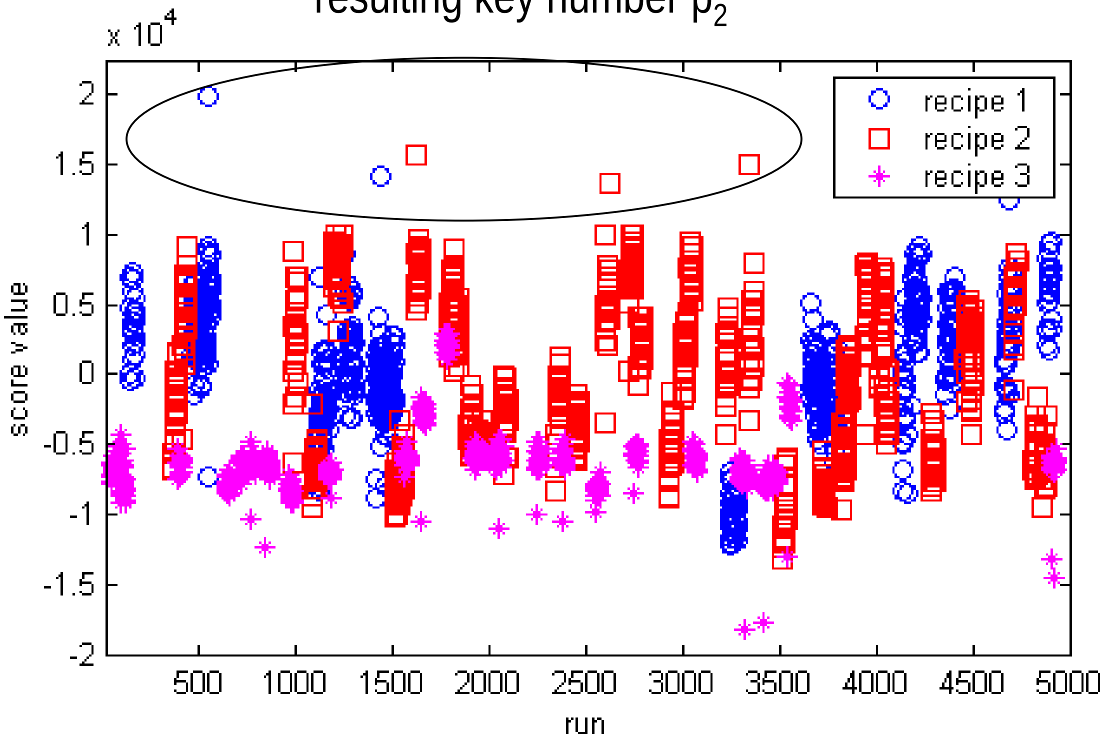
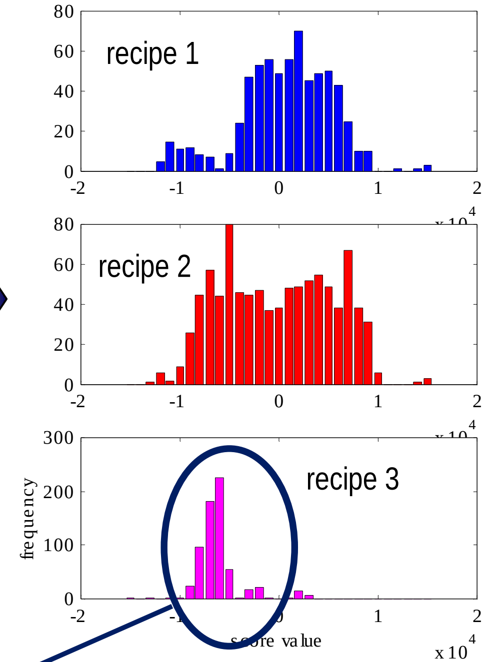
2. Example: DSQ - Endpoint Variations
→ Comparison of three recipes

- application of u_2 of the endpoint data from one machine over a 2 month period

resulting key number p_2



distribution of the key number



- the endpoint variations within recipe 3 are smaller than recipe1 & 2
- large variations in endpoint signals have been detected

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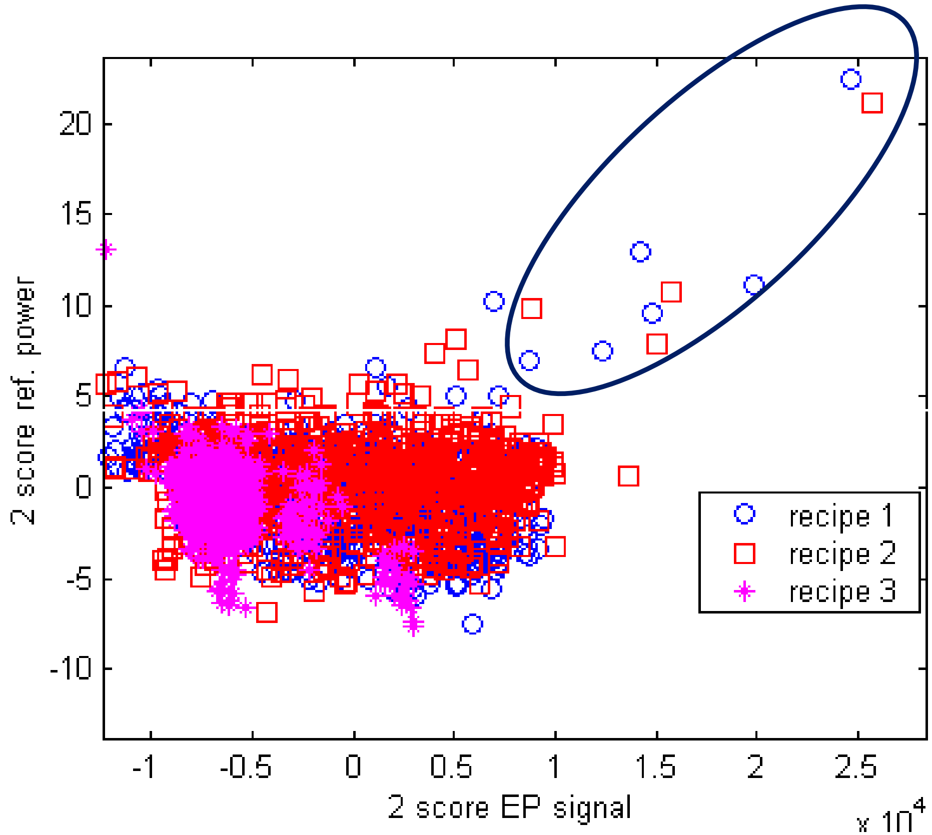
2. Example: DSQ - Endpoint Variations
→ Comparison for three recipes

- additional independent PCA calculation for reflected power signals



- the appearing outliers in the endpoint key-numbers correlate with deviations from a normal behavior in the reflected power signal

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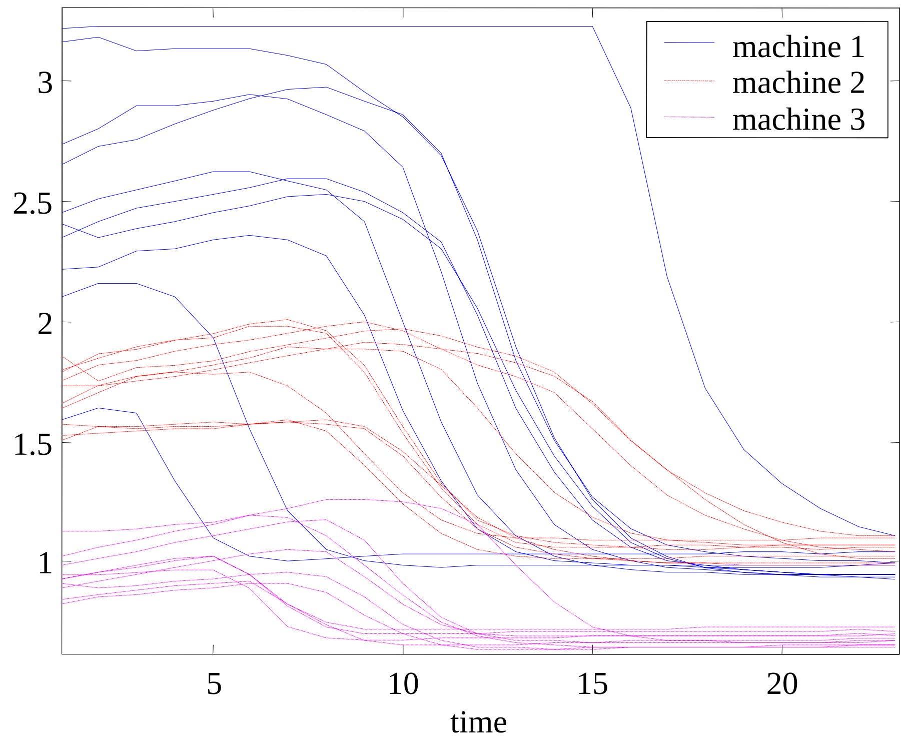
2. Example: DSQ - Endpoint Variations
→ Comparison for three machines

- analysis of the endpoint data from TCP-ALU DSQ-Process from three different machines with PCA - method

example of representative endpoint signals



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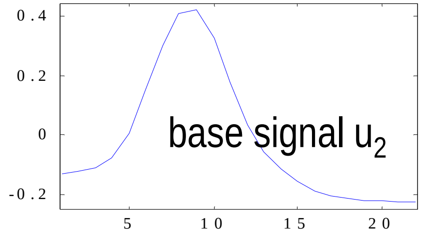
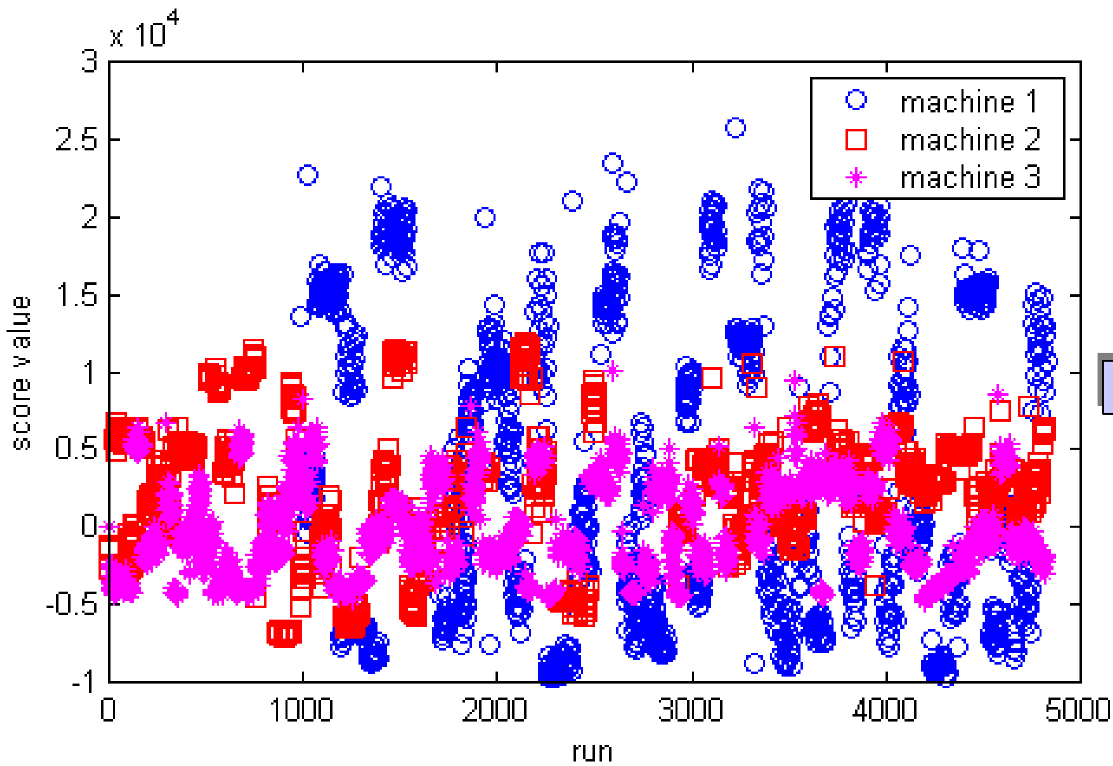
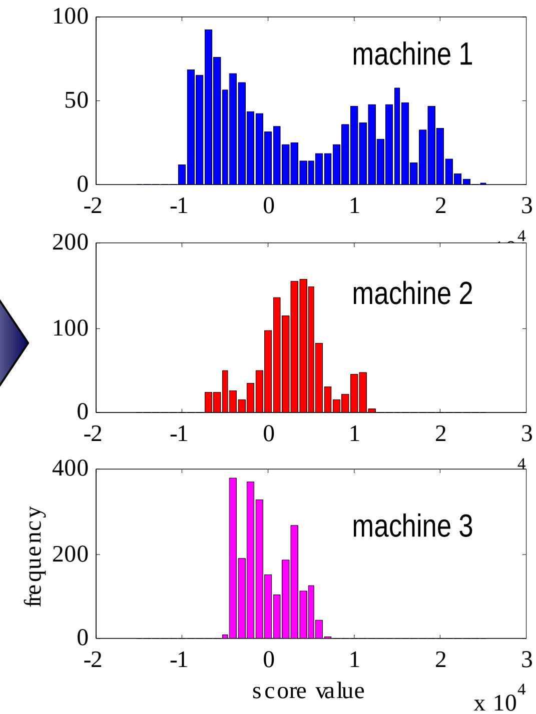
2. Example: DSQ - Endpoint Variations
→ Comparison for three machines



- the resulting key number, generated by application of base signal u_2 to all data, show that the endpoint from machine 1 has a larger standard deviation than the other





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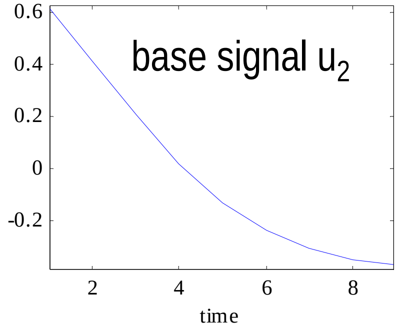
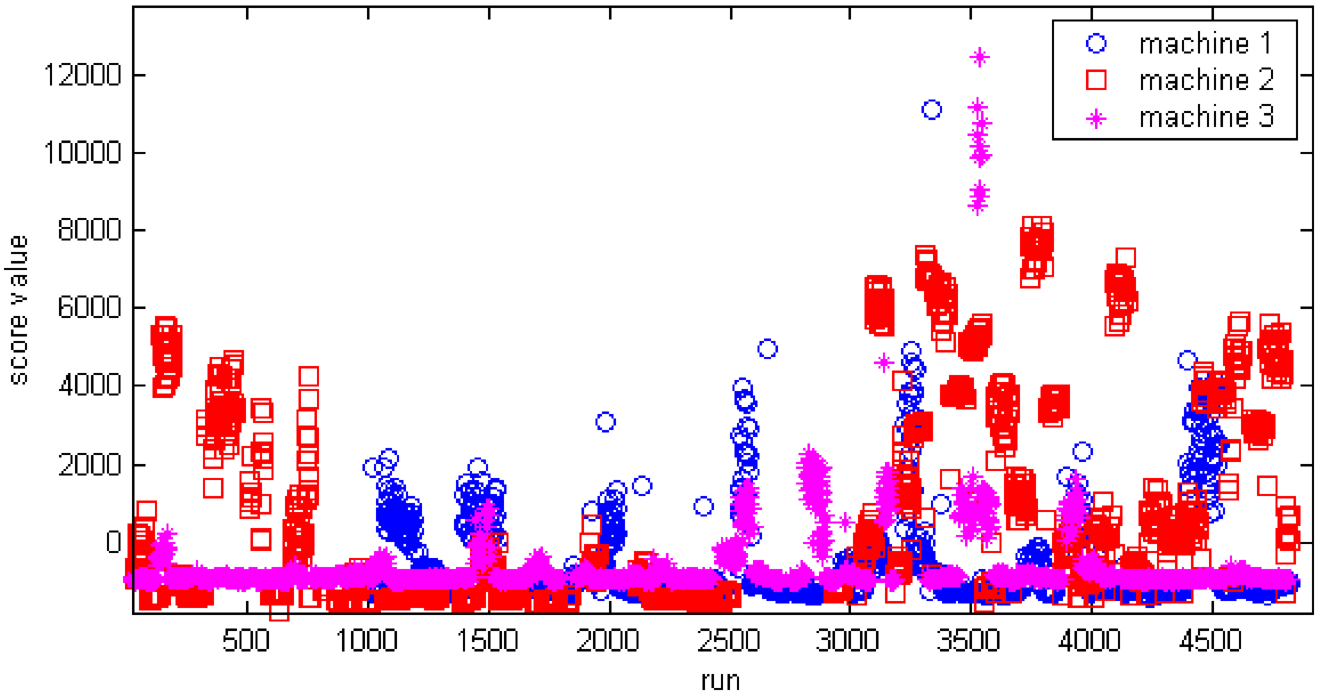
2. Example: DSQ - Endpoint Variations
→ Comparison for three machines



- PCA analysis of final time range of the DSQ process
- detection of remaining transient signal behaviour by application of u_2
- detection of incomplete resist removal



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Summary and outlook

- an efficient key number extraction is the prerequisite for a reliable, fault detection, classification and modelling
- Simple Key Numbers are suited to detect major failures and outliers
- parametric signal models are the most powerful method to get interpretable key numbers, but requires a pre-defined analytical signal model
- PCA is an efficient method to assess variations of the signal shape
- the application of the PCA was shown on Brookside traces of DSQ stripper after metal etch
- the capability of multivariate extension of the PCA (MPCA) is the focus of current investigations

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