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# Program

## Session 1. Chair: Roland Richter

| | |
|---|---|
| 13:00 | Kurt Pichler: |
| | Detecting broken reciprocating compressor valves under varying load conditions |
| 13:30 | Francisco Serdio: |
| | Fault Detection by Residual Analysis - Next directions |

## Session 2. Chair: Thomas Natschläger

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|---|---|
| 14:15 | Mariya Zhariy: |
| | Graph Theoretical Approaches in Model Based Fault Diagnosis |
| 14:45 | Ciprian Zavoianu: |
| | Efficient Multi-Objective Optimization using 2-Population Cooperative Coevolution |
| 15:15 | Carlos Cernuda: |
| | Prediction of Cloud Point in Melamine Resin Production using Hybrid Adaptive Calibration Methods and Ensemble Strategy |

# Detecting broken reciprocating compressor valves under varying load conditions

K. Pichler, E. Lughofer, T. Buchegger, E.P. Klement, M. Huschenbett

Reciprocating compressors are heavily used in modern industry, for instance for gas transportation and storage. In many cases, compressors run at high capacity and without backup. Hence unexpected shutdowns lead to large losses in productivity. Furthermore, there is an economic trend towards saving labor costs by reducing the frequency of on-site inspection. Such considerations mean that compressors are run by remote control stations and monitored by automated technical systems. In this case, the system must be able to retrieve and evaluate relevant information automatically to detect faulty behavior.

The state of the art solutions for reciprocating compressor valve fault detection are designed for constant load conditions. When the load changes, operators adapt the threshold values manually. Since modern reciprocating compressors are controlled by reverse flow control systems, changing load levels are not unusual, and the fault detection methods have to cope with that fact. In this paper, we present an important step towards the goal of a load-independent method. Furthermore, the proposed method is based on vibration data. This makes sensor mounting easier and cheaper than the commonly used in-cylinder pressure measurements.

The proposed method evaluates time-frequency representations (spectrograms) of vibration measurements at the valve covers. Based on previous publications, we know that a cracked or broken valve influences the amplitudes of the power spectrum in certain frequency bands. Furthermore, it is obvious that the load control system changes the timing of the valve events. Of course, both factors are reflected in the spectrogram. Keeping that knowledge in mind, we have a look at the point-wise difference of a faultless reference spectrogram and a test spectrogram. Depending on the fault state of the valve and the load levels, it shows specifically shaped structures. The positions of the structures within the spectrogram are varying unpredictably with the valve type and the load. Hence, an automated detection would be hard to realize. Additionally, measurement noise would make the detection even more difficult. Both problems can be solved by applying two-dimensional autocorrelation to the point-wise spectrogram difference: the significant structures are centered and the noise effects are reduced. Thus makes it easier to define features that characterize the specific patterns. For example, Fig. 1 shows the autocorrelation for a faultless test spectrogram, but with changing load. In contrast, Fig. 2 shows the autocorrelation for a test spectrogram measured from a valve with a fissure. The different shapes can be seen clearly.

We tested the method with numerous real world test measurements. The measurements were recorded with different valve types, different vibrations sensors and with constant as well as varying load conditions. All of the tests proved the ability of the method to detect cracked and broken valves, cross validation using SVM classification shows very high classification accuracy.

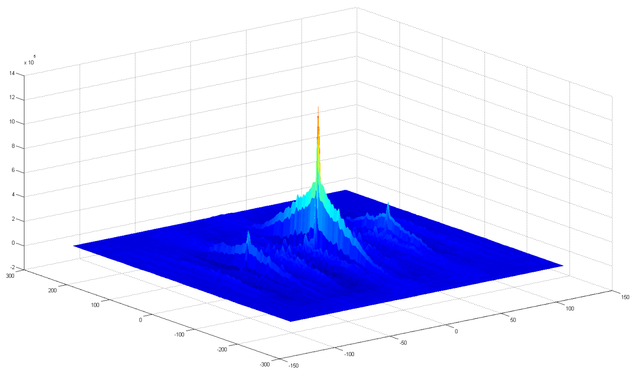

**Fig. 1: Autocorrelation representation for a test measurement from faultless valves**

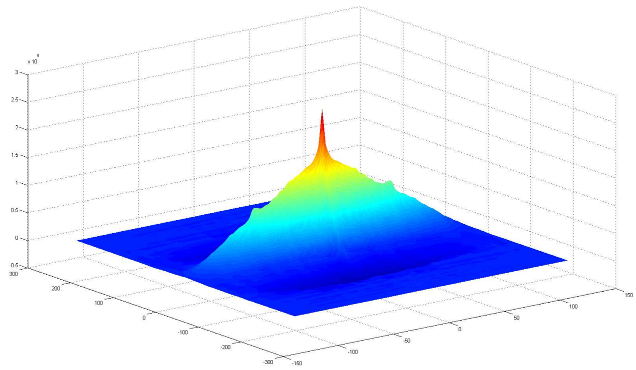

**Fig. 2: Autocorrelation representation for a test measurement from a cracked valve**

# Fault Detection by Residual Analysis - Next directions

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**Abstract**

Fully automatic monitoring and fault diagnosis systems are one way to increase the efficiency of monitoring processes.

There are cases in where the traditional fault diagnosis approaches using model-based techniques relying on analytical process (system) models [9] [8] [15] and often employing a robust observer design such as [17] [18] [6] or [16] are not deployable; the same is the case when the physical definition of the appearance of a fault is used to deduce fault models, see for instance [12] [3]. There are other cases where neither fault patterns nor annotated samples for fault and fault-free cases are available, then preventing the use of pattern recognition and classification approaches - techniques mainly relying on supervised machine-learning (ML) based classifiers [11] [2] built up on some pre-collected training data sets including samples affected and not affected by faults, as in [1] [13].

There are other cases where the measurement signals are not all smooth and continuous in their time line appearance, showing jumping patterns in case of fault-free states. Such this situations makes the application of approaches relying on time-series analysis [10] [5], pattern recognition [7] or (vibration monitoring [4] in) frequency spaces (spectrograms etc.) [14] inapplicable.

For all these reasons, previous research on fault detection was focused in a Residual Analysis approach, where the residuals were obtained through data-oriented system identification (SysId) models characterizing implicit relationships of the system which are valid in the fault-free nominal case, expecting some of these dependencies to be violated in case of faults. With this approach, neither a supervision phase nor an (time-intensive) annotation process is required. Furthermore, the models also serve as smoothening filters for instable, discontinuous measurement signals. Additionally, a fault detection system designed this way includes the capability of being cascadable, allowing *hot* inclusion and exclusion of channels, not requiring a re-calibration or re-training phase of older established models for already existent channels.

In that previous research, three different architectures were explored -in order to examine the degree of non-linearity implicitly contained in the system- and compared against a well-known state-of-the-art approach based on principal component directions combined with Hotelling- and Q-statistics.

Even when the experiments where successfully conducted, two important observations were

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depicted on the final fault detection system: sometimes residuals were showing a non-constant, but a highly changing behavior. In this case, a simple threshold-type $\mu + n\sigma$ tolerance band often could not follow the real trend of the residual signal, thus producing in some cases unnecessary over-detections, in other cases miss-detections. Hence, we extended our approach to a more sophisticated pattern recognition-type approach, where we extract features from local windows over the residual signals and characterize them through a one-class SVM classifier (which is incrementally updated through the sliding window). In particular, this approach will move the problem to the feature space, where extracting good enough descriptive features from the residual signals should suffice. It will not need pre-collected training data sets including samples not affected by faults (assigned to class #1) and samples affected by faults (assigned to class #2). The approach will then characterize a hull on the feature space during the phase of the classifier training, whereas in the online phase those features are expecting to change under a fault presence, moving out of the hull identified by the classifier and allowing it to signal the appearance of the fault in the system.

The other extension concerns an appropriate treatment of shifts in the on-line test phase, compared to the off-line training phase. We observed that residuals may be suddenly shifted to a higher value, whereas the model quality is not lost, so still the model "which produced the residuals" is valid. Such "regular shifts" are usually caused by process changes rather than by system failures. Thus, we perform an online analysis of correlations between the identified models. Those models obtained during the data-oriented system identification (SysId) process that are identified as instable but that still preserve high correlation are potential candidates to be analyzed with a different technique than the previous explored *residual tolerance band*. A strategy focused in the variation of correlations for the identified models is proposed, where the main duty is to observe how the correlation of the model varies over the time-line: whenever untypical residuals are found, the decrease in correlation is observed as well, before reporting a fault warning.

*Keywords:* Fault detection, data-driven regression modeling, dynamic residual analysis, one-class svm, correlation analysis

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# Graph Theoretical Approaches in Model Based Fault Diagnosis

M. Zhariy and T. Natschläger

**Abstract**

The main aim of model-based fault detection and diagnosis is, from the knowledge of the system model and the measured data, to determine if there is a fault, which component is faulty and the severity of the fault.

Even if the system model is given theoretically, the functional description of some system components migth be unknown or migth contain unknown parameters. Therefore, a system identification step should in general precede the fault detection procedure.

In the approach presented here we assume the causal structure between the system components to be known. In this case we show that the system identification can be basically reduced to the parametrization of each single component. Once the system identification process is done, the widely used residuum method can be applied in order to identify the faults. One of the main issues of our approach is to figure out the minimal number of measurement nodes needed for detection of all relevant faults in case of missing data.

# Efficient Multi-Objective Optimization using 2-Population Cooperative Coevolution

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**Workshop:** Theory and Applications of Metaheuristic Algorithms
**Keywords:** continous multi-objective optimization, evolutionary algorithms, cooperative coevolution, differential evolution

## Extended abstract

Our general research tasks, aimed at optimizing design parameters of electrical drives, deal with highly-dimensional multiple-objective optimization problems (MOOPs) that also display very lengthy run-times, on account of requiring very time-intensive design (fitness) evaluation functions [8]. As such, having a robust and generally efficient (# of required fitness evaluations) optimization algorithm would significantly reduce the optimization run-times. Like most MOOPs, our problems rarely have a single solution and solving them means finding (an approx. of) a set of non-dominated solutions called the *Pareto-optimal set* [1].

Because of their inherent ability to produce complete Pareto-optimal sets over single runs, multi-objective evolutionary algorithms (MOEAs) have emerged as one of the most successful techniques for solving MOOPs [1]. Among the early MOEAs, NSGA-II [3] and SPEA2 [7] proved to be quite effective and are still widely used. At a high level of abstraction, both algorithms can be seen as MOOP orientated implementations of the same paradigm: *the* $(\mu + \alpha)$ *evolutionary strategy*. Moreover, both algorithms are highly elitist and use a two-tier fitness evaluation function based on Pareto and crowding indices.

More modern MOEAs, like DEMO [6] and GDE [4], aimed at exploiting the very good performance exhibited by differential evolution (DE) operators [5], replaced the standard SBX crossover operator [2], initially used by NSGA-II and SPEA2, with various DE variants. Convergence speed benchmark tests show that differential evolution can help MOEAs to explore the decision space far more efficiently for several classes of MOOPs. For some problems though, the generally more robust SBX operator significantly outperforms the DE algorithms.

Using 2-population cooperative coevolution, we aimed to develop a hybrid MOEA that, on the one hand, retains the stable behavior of classic MOEAs and, on the other hand, profits from the fast convergence behavior induced by DE operators. Our idea was to simultaneously evolve two different genetic populations:

one that uses the SBX operator and another that relies on a DE crossover operator. The environmental selection strategy described in [7] is applied on both populations as a crowding survival operator. Empirical results showed that the way in which fitness is shared among the two populations has a crucial impact on performance. The best results were obtained when using a dual fitness sharing mechanism based on the interleave between, generational, *weak sharing* stages and, fixed interval, *strong sharing* stages.

The results we obtained on 10 benchmark MOOPs indicate that coevolution is quite successful at its aim of constructing a robust average between SBX and DE based methods. On average, our algorithm converges faster than NSGA-II and SPEA2 and it displays a more stable behavior than DEMO and GDE3.


## Acknowledgments

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# Prediction of Cloud Point in Melamine Resin Production using Hybrid Adaptive Calibration Methods and Ensemble Strategy

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**Abstract**

In many cases, both the efficiency and quality in chemical systems can be improved by applying online analytic technologies [1], fully automatizing the quantification of the substances in chemical processes [2]. Thereby, the connection of a spectroscopic measurement method [3] in conjunction with chemometric models [4] [5] plays a major role in chemical processes in general, and in melamine resin production in particular, see e.g. [6] [7] [8]. The methods in the latter references especially deals with the usage of spectrometer in melamine resin production, especially for the purpose of determination of free melamine content ([7] and [8]) as well as the monitoring of curing of UV-curable resins and of the reaction of melamine and formaldehyde ([6]).

In our case, we are interested in a concrete part of the melamine resin production process: monitoring the value of the cloud point, which indicates the best point of time to stop the condensation. Currently, the supervision is conducted manually by operators, which from time to time need to draw and analyze samples from the production process. In this paper we investigate the usage of non-linear chemometric models, which are calibrated based on near infrared (FTNIR) process spectrum measurements, in order to increase efficiency and to improve quantification quality. They rely on fuzzy systems model architecture and are able to *incrementally adapt* themselves during the on-line process, resolving changes in the composition of the educt, often leading to severe error drifts of static models and dynamic process changes which may appear on-line over time due to long-term fluctuations (e.g., caused by dirt). Extracting the most informative wavebands before training the model is essential to avoid curse of dimensionality; this is achieved by a new extended variant of forward selection, named *forward selection with bands (FSB)*. Furthermore, variants how to integrate auxiliary sensor information (temperature, pH value, pressure) together with the FTNIR spectra are presented (*hybridity*). A specific *ensemble strategy*, based on a weighted linear combination of several models, is developed which is able to properly compensate noise in repeated spectra measurements. Results on high-dimensional FTNIR spectal data from four independent types of melamine resin show that 1.) our non-linear modeling methodology can outperform state-of-the-art linear and non-linear chemometric modeling methods in terms of validation error, 2.) the ensemble strategy is able to improve the performance of models without ensembling significantly as well as avoid isolated big errors and 3.) incremental model updates are necessary in order to keep the predictive quality of the models high by preventing drifts in the residuals.

*Keywords:* melamine resin production, prediction of cloud point, NIR spectroscopy, non-linear adaptive chemometric models, waveband extraction, auxiliary sensors, ensembling

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## 1. Our Approach

In order to resolve aforementioned demands within a connected combination, we present a chemometric modeling approach, which homogenously joins the following properties in one calibration framework:

- *Non-linear modeling component* which is based on fuzzy systems architecture and which employs statistical information criteria for dimension reduction; the architecture and its learning procedure from calibration samples was already successfully applied to NIR spectra in [9] for quantifying process parameters in PEA production. The basic difference in this paper is that we propose an extended variant of forward selection in order to extract wavebands with arbitrary widths instead of single wavenumbers (as done in [9]), termed as *forward selection with bands (FSB)*; this assures significant reduction of error-proneness in case of a small signal-to-noise ratios (high noise levels) in the data. Another difference is that we will also connect fuzzy systems with PCA and PLS, achieving a sort of non-linear versions of them.

- Specific integration of different data sources, namely NIR spectra and auxiliary sensor information (which can be seen as measurement channels) in the fuzzy systems training procedure as well as in other well-known non-linear methods (used for comparison). We term this specific combination of data sources in one model as *hybrid modeling* or as *hybrid calibration model* (see also title).

- Incremental model updates including adaptation of parameters as well as evolution of structural components on demand and on-the-fly; this is necessary in order to react on process drifts over time due to changing dynamics as outlined above (different compositions of the educt etc.), preventing time-intensive re-calibration cycles; in the context of incremental learning, gradual forgetting of older learned relations is helpful to react on process dynamics appropriately. This combination provides us adaptivity aspect in the paper, thus we also term our models as *adaptive calibration models*, or in combination with the former aspect as *hybrid adaptive calibration models*.

- Additionally, we will employ a model *ensembling strategy*, based on an independent modeling process in the subsets of repeated measurements ensembling then the predictions by means of a weighted average, for exploring the diversity in repeated measurements, following a similar motivation as in bagging.

Due to the combination of these issues, we may also speak about *hybrid adaptive chemometric models* with an ensemble component. Additionally, we provide formulas for error bars surrounding the fuzzy systems and confidence regions, which can be used as uncertainty output levels.

Our approach will be applied to on-line process data from four different types of melamin resines (containing 1249 wavenumbers) and will show 1.) that our non-linear modeling methodology fuzzy systems combined with FSB or PLS) can outperform state-of-the-art linear and non-linear modeling methods (such as MLR, PLS, PCR, stepwise regression, GLMnet, regression trees) in terms of validation error, 2.) that the usage of auxiliary information in different variants in the modeling process can not improve the predictive performance, whereas ensemble strategy is able to improve the performance of models without ensembling significantly and 3.) incremental model updates are necessary in order to keep the predictive quality of the models high during the further ongoing on-line process (static models may deteriorate in performance significantly showing drifting residuals).

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