ON EVALUATING CONTROL PERFORMANCE ON LARGE DATA SETS

Alexander Horch [1], Friedrun Heiber[2]

[1]*ABB Corporate Research, Germany*
[2]*University of Stuttgart, Germany*

Abstract: The evaluation of control performance by means of performance indices from large amounts of measurement data is investigated. The focus is twofold: Firstly to assess information that can be deduced from *many* data sets and secondly to investigate the usefulness of *simple* performance measures. Established methods and some useful new ideas are evaluated on many industrial data sets and the results are discussed.

Keywords: Performance indices, control loops, signal processing, data collection.

1 INTRODUCTION

The evaluation of control performance mostly deals with the computation of performance indices. These indices range from very simple ones, e.g. the control error mean and variance (e.g. [Salsbury, 1999]) up to rather complex ones involving e.g. subspace identification [Bezergianni and Georgakis, 2000].

Obviously, simple indices are very appealing since for performance monitoring, typically many control loops are assessed regularly. Unfortunately, complexity and information are usually correlated such that simple indices mostly imply simple answers. One exception is the minimum-variance control performance index by Harris [Harris, 1989]. It combines low computational effort with important information about the current loop performance. This fact contributed to its popularity over the last decade.

Traditionally, control loop performance assessment deals with the kind of information that can be deduced from the evaluation of a specific data set. This approach is sound and valid but carries some pitfalls: the data set may reflect unusual behaviour of the control loop in question. In the industrial practice, single data batches are often erroneous since plant shut downs or other unusual events might have been reflected in the data.
Such data sets will in general not be able to give a fair picture of the control loop performance. They should ideally be excluded from performance evaluation; however, a mechanism to automatically discard all such cases seems to be very difficult to achieve.

This paper attacks control performance assessment from a slightly different point of view: Given the fact that the time constant of good control is in the range of months rather than days, it would make sense to base a performance assessment on much more than only a few data sets.

The first issue discussed in this paper is: can useful information be found in simple control performance indices when evaluated on many data sets? Some indices (both simple and more advanced ones) will be evaluated for 20 control loops from a pulp mill. For each of the control loops more than 400 data batches were analysed.

A second aspect discussed is the continuous collection of information that can be combined to new knowledge about a control loop. The availability of many data sets can be used to build a nonlinearity map of the process. Such information is of great use for tuning procedures.

The paper is organised as follows: In Section 2 the data used in this study is described and presented. Section 3 presents the evaluation of some performance indices for all data sets and conclusions thereof. Section 4 discusses the use of data in order to build a knowledge database that grows with each data set that was analysed.

Examples accompany both sections and the paper concludes with a summary and requirements for industrial control performance monitoring tools.

2 INDUSTRIAL DATA SETS

This study makes intensive use of more than 400 data sets containing control loop data from a stock preparation section in a pulp mill. Each data set contains about 20 minutes of data at a sampling rate of 1 second. The loop setpoint (SP), the process variable (PV) and the controller output (OP) were logged.

A typical data batch containing 20 control loops (11 flow loops, 3 level loops and 6 composition loops) is shown in Figure 1.

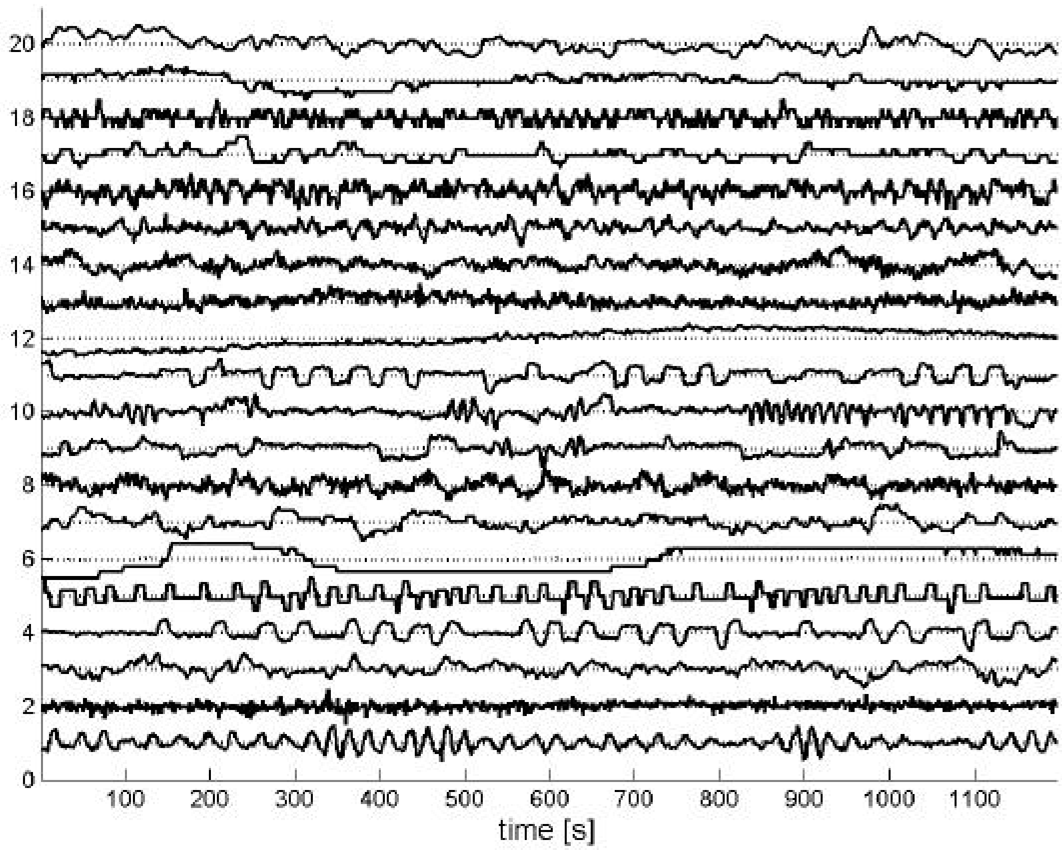

Figure 1: Example data (SP and PV respectively) for 20 loops from one data collection occasion. The signals are scaled such that they have equal standard deviation and are plotted on top of each other.

The data collection was done automatically, once per day for more than a year resulting in 424 data sets.

3 PERFORMANCE INDICES

Quite a number of performance measures for assessing controller performance have been proposed in the literature, especially during the last decade. Most of them targeted to be computed from normal operating data only. It is the constraint of not allowing experiments that outperforms the computation of similar performance measures that are typically used in controller design (e.g. the loop overshoot or rise time).

3.1 Simple statistics

The term 'simple indices' refers to indices that can be evaluated with a modest amount of computations and that do not require any non-trivial a priori knowledge. Table 1 shows the simple performance indices that were evaluated in this study.

The control error mean should of course be centered around zero with no offset and a sufficiently small standard deviation. Long or excessive deviation can easily be identified (see loops no. 2, 12, 15 and 20 in Figure 2.

Index	Description
CE mean [%]	mean of control error
CE std [%]	standard dev. of control err.
OP std [%]	st. dev. of controller output
CE skewness	skewness of control error
CE kurtosis	kurtosis of control error
std ratio	ratio of std of control error and controller output
maximum bic	max. bicoherence
correlation coefficient	correlation coefficient between control error and controller output

Table 1: Simple performance indices that were evaluated for all data sets. The units [%] refer to the operating ranges of OP and PV.

The (normalised) standard deviation of the control error can also give considerable insight into loop behaviour, see Figure 3. It can be clearly seen that loop No. 8 has a problem with increased variability between logs no. 250 and 300. At this time, the loop had a strong oscillatory behaviour.

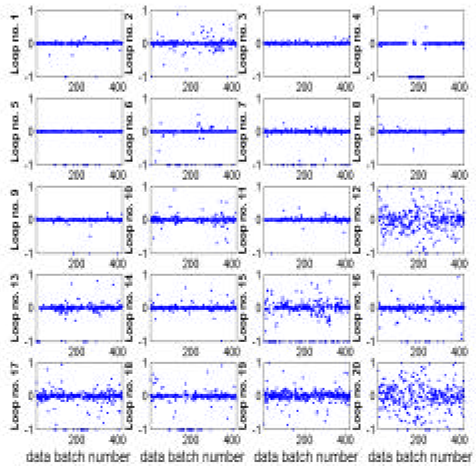

Figure 2: Trend of loop standard deviation.

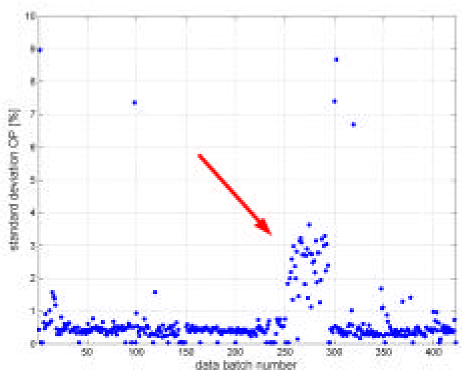

Figure 3: Standard deviation of control error (loop No. 8).

Another interesting statistics is the control error skewness. Skew data often indicate problems of nonlinear character. As an example see Figure 4 where it can be seen that for many data sets, the skewness is rather large, indicating regular problems of nonlinear source. As a matter of fact, this loop exhibits stiction regularly resulting in the presented non-symmetrical data distribution.

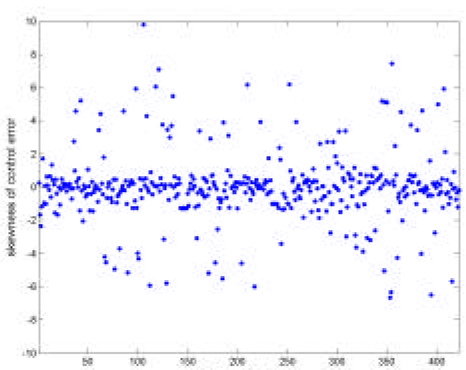

Figure 4: Skewness trend of control error for loop No. 2.

Consider another example in Figure 5 where the control error kurtosis for loop No. 12 is shown. For Gaussian signals, the kurtosis should be centered around zero. In this case, it is clearly around –1 instead, indicating rather non-Gaussian signals. The reason in this case is a slow periodic behaviour with a cycle time of around one hour. The data batches are too short for a detection algorithm to detect this oscillation.

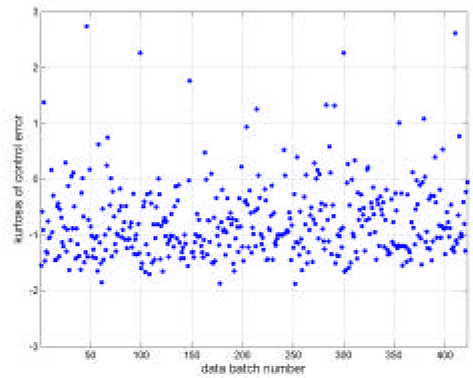

Figure 5: Control error kurtosis trend for loop 12.

In Figure 6, two trends of the ratio of the standard deviations of control error and controller output are shown

$$R = \frac{s_{SP-PV}}{s_{OP}}.$$

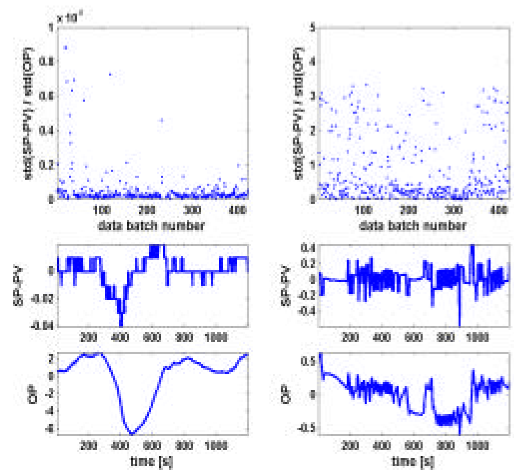

Figure 6: Example for ratio of standard deviations of control error and controller output. Left: case with not moving process output, loop No.6; Right:loop with normal behaviour, loop No.5.

It can be seen that the value is 5 orders of magnitude smaller in the left example than in the right one. The reason is that the process variable in the left loop (No. 6) does not move much more than the quantisation level, whereas the loop on the right (No. 5) moves reasonably much. In loop No. 6, either the sensor signal is corrupt or the loop actuator does hardly move.

For a last example consider Figure 7 where the maximum bicoherence of the control error is plotted for all loops. In [Choudhury et al., 2004] it is shown that the bicoherence plot can be used to assess signal nonlinearity. Single evaluations may tend to contradict this hypothesis but when considering many data sets, it turns out that such a measure may be able to detect loops that exhibit nonlinearity problems (in this case loops No. 1, 2, 5, 6, 9, 10 and 11). This is in line with the knowledge about these loops.

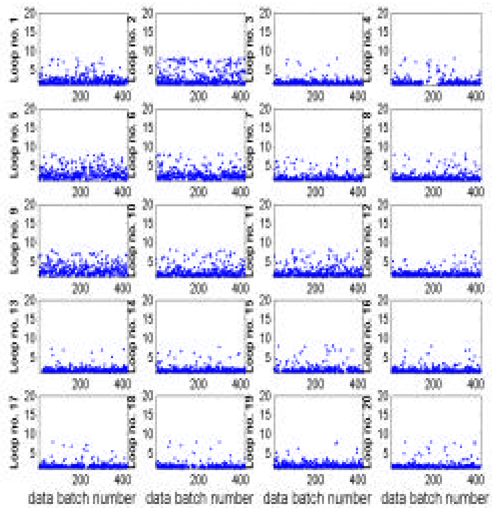

Figure 7: Trend of maximum bicoherence over all loops.

3.2 More advanced indices

Another group of indices involves more complex computations and eventually more prior knowledge. As already mentioned, the most prominent of these indices is the Harris index that compares actual loop variability to minimum-variance variability leading to an index between 0 and 1 where 1 equals minimum-variance performance,

$$I = \frac{s^2_{\text{min var}}}{s^2_{SP-PV}}.$$

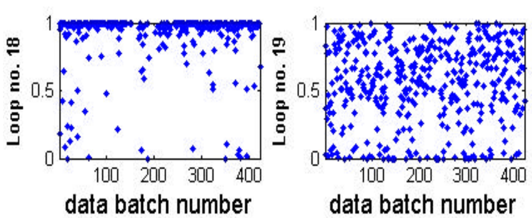

Figure 8: Example of trends for the Harris index.

The example in Figure 8 shows the need for interpreting the Harris index with a grain of salt. The left loop shows a good behaviour, however, for some batches the index is very low. The right loop on the other side offers the complete range of index values, indicating that the performance (or its assessment) is very different at different days. To rely on a few or a single data set only can be misleading when dealing with the Harris index.

Badly performing loops often exhibit oscillatory behaviour. Therefore, oscillation indices for oscillation detection and assessment are the most important quantity that should be monitored. More and more industrial applications start focussing on periodic disturbances in addition to the Harris index, which was mostly discussed in the mid-90s.

Oscillation detection can be done in various ways, see [Hägglund, 1995], [Forsman and Stattin, 1999] or [Seborg and Miao, 1999].

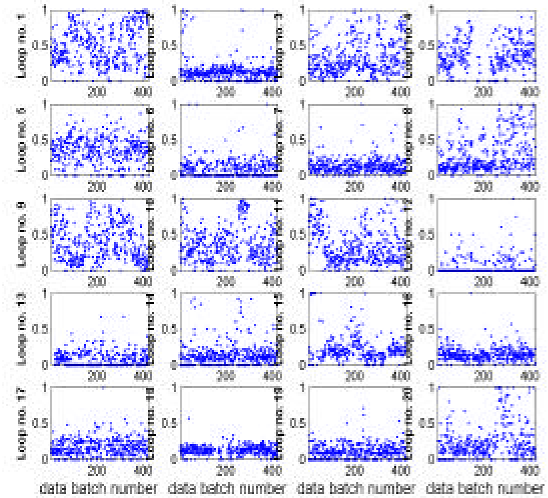

Figure 9: Oscillation index for all loops.

In Figure 9, trends of the oscillation index [Forsman and Stattin, 1999] are plotted. It can easily be seen that loops No. 1, 3, 4, 5, 8, 9, 10, and 11 exhibit regular oscillatory behaviour. The human eye recognises an oscillation when the index is larger than about 0.3.

3.3 Combination of indices

Performance indices provide a good means of analysing plant behaviour. However, it is often the *combination* of indices that gives significant insight into bad plant performance.

A very compact assessment would be the test if certain control loops exhibit bad behaviour simultaneously. Hence, a correlation of a specific index for different loops would be a valuable source of information.

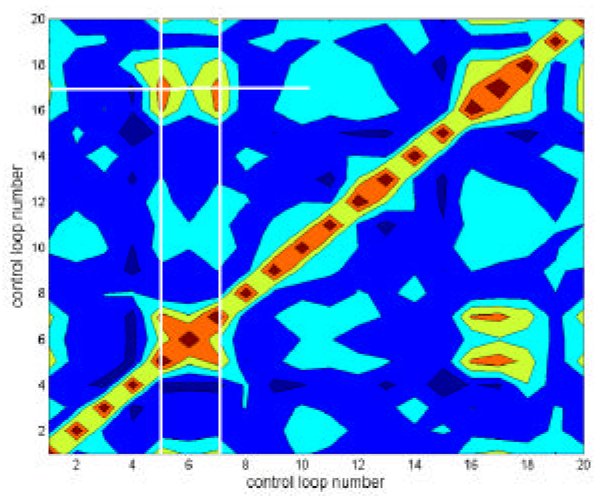

Figure 10: Correlation coefficients for oscillation indices over all loops.

Consider Figure 10 where oscillation indices are correlated for each loop. Such a plot indicates which loops typically oscillate simultaneously. The plot reveals a common oscillatory behaviour between loops no. 5, 7 and 17; see Figure 11. Note that the equality of frequency is of no importance for the correlation of the oscillation indices.

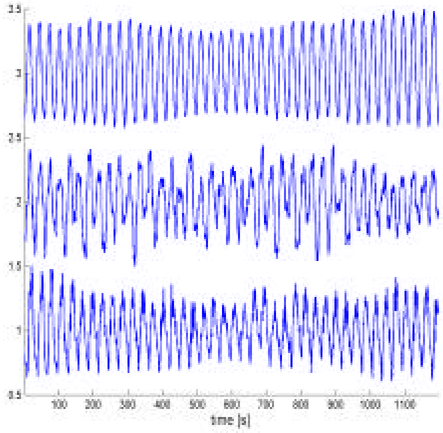

Figure 11: Three oscillating signals (with normalised variance) as indicated by correlation of their oscillation indices.

4 INFORMATION FROM MANY DATA SETS

As mentioned in the introduction, the step beyond storing indices for single data batches is to collect and combine assessment information from single evaluations for future use. Examples for such applications are:

- Creation of static input – output maps
- Indication of data sets suitable for model identification

A static input output map is often of importance when control loop tuning is performed. Many commercial tuning tools offer ways to analyse experimental data where the process input is changed stepwise. The automatic generation of static y-u-maps can avoid costly experiments and thus enable faster controller tuning without disturbing current production.

If the data within a data batch is sufficiently stationary, then an algorithm can extract stationary values of OP and PV and store them. Figure 12 shows examples of static maps for all control loops analysed. For loops where sufficiently many different operating points have been found, a quadratic function has been fit to the data using a least-squares method.

For most data sets, a linear function would be sufficient to describe the static input output relationship well. Loops where the quadratic function fits the map better are No. 1, 2 and 8. However, the nonlinearity does not seem to be too severe, such that it could also be neglected.

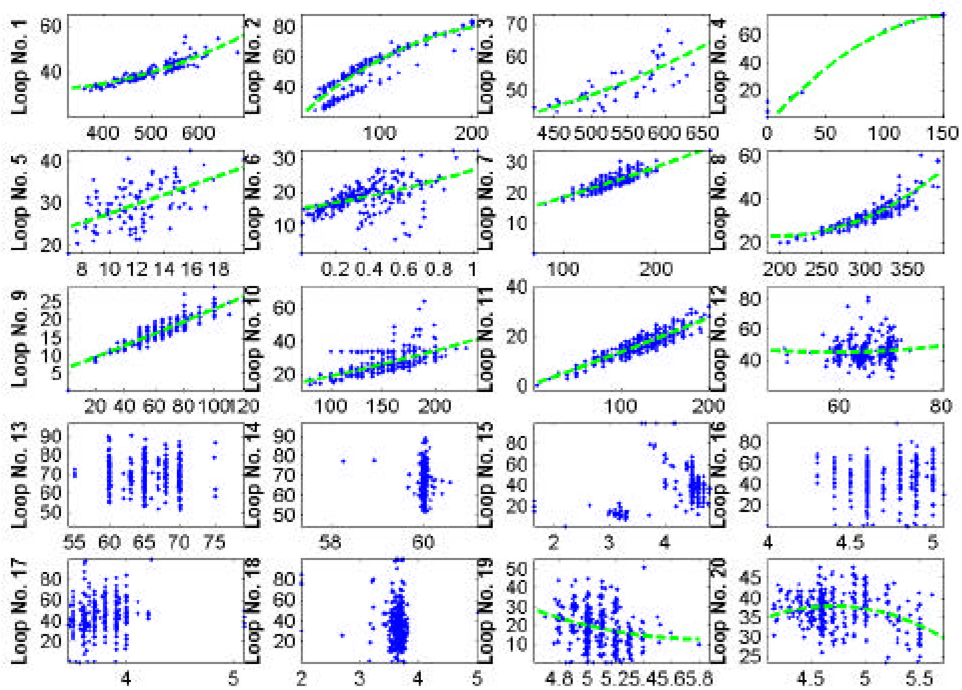

Figure 12: Static maps for all 20 control loops. The fitted curve is quadratic. Vertical axis is the controller output and horizontal axis is the process variable.

It was mentioned that static maps provide useful insight into the process model when dealing with controller tuning. A natural question is then: Could the regular analysis of normal operating data be used to detect data sets that are suitable for model identification? This would be data sets where (a) the setpoint is changed abruptly by a significant amount or, (b) the loop is in manual mode and the operator changes the process input stepwise. For both cases, a regular analysis of data could raise and store a flag if suitable identification data is available.

Since it may not be sufficient to flag for setpoint changes (or input changes in manual loop mode) only, it was chosen to use a flag that indicates if an estimated dynamic model for the process has sufficiently good quality. The quality is measured by goodness of fit test as they are used in standard system identification packages. Figure 13 shows an example of a data set that typically would flag for being suitable for system identification.

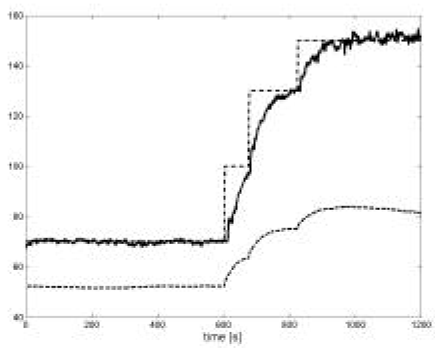

Figure 13: Data set suitable for model identification and controller tuning.

Clearly, some loops would never generate these flags since setpoints may never be changed or the loops are never taken into manual mode. Note that disturbances alone never qualify data to be useful for process model identification. In these cases, only the controller can be identified.

Using both static maps and the described model fit flags, it is hence possible – at least for some loops – to generate the information that is usually required for controller tuning without being forced to perform experiments.

Yet another flag that is useful to store for later use in controller tuning is whether the loop exhibited stiction behaviour [Horch, 1999]. Such information should be available when tuning loops.

5 IMPLICATIONS FOR INDUSTRIAL TOOLS

From the above results, some implications for the controller performance tools shall be stated. A practically useful tool should …

- … enable analysis of performance indices such as plot combinations, correlation, trend plots etc.;
- … enable application-dependent selection /discarding of indices;
- … offer an index database for search queries;
- … help to retrieve data collection dates and – if possible – specific data sets.

6 CONCLUSIONS

The usefulness of performance indices for automatic controller performance assessment is an accepted fact in the process industry. A question that has received little attention so far is which indices to use and what kind of information can be deduced from each of them.

The focus in this paper was to show the strengths of some selected indices when a large amount of data batches is available. From the analyses, some general conclusions shall be drawn:

- Simple statistics are most useful for fast and overview-like scans of large amounts of data.
- More advanced indices are very useful when averages over many data sets are available. Single evaluations may be misleading.
- Combination (e.g. correlation) of indices is useful and gives insight into the plant dynamics
- Storage of results for later usage is very helpful, especially for tuning (linearity, stiction).
- Trending of indices presents an extreme data and information compression for comfortable reporting.

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