CONFIDENCE BASED ESTIMATION AND DETERIORATION INDICATION OF ON-LINE MEASUREMENT

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Abstract: In an industrial process, the accuracy and reliability of process creates basics for control system and ultimately to product uniformity. Measurement results, whether from fast on-line sensors or from sample-based laboratory analyses, is the key for selecting the method for process control and analysis. Intelligent and advanced control methods, exploiting measurements, are of no benefit if the measurements cannot be trusted. This paper presents an estimation method for combining real-time redundant signals, consisting of sensor data, and analytical measurements. The validation of on-line measurement uses less frequently updated but more accurate information to validate frequently updated but less accurate on-line measurements. An estimate of the measured variable is obtained as a weighted average of the on-line measurements and laboratory analyses. The weighting coefficients are recursively updated in real time when new analysis and measurement results are available. The calculation of optimal estimate can be used in several industrial applications for more precise process control. In addition, pre-processed data is used to calculate a "need for maintenance indicator" to warn the operator for sensor breakdowns, wearing or deterioration and detect calibration needs. The operator's workload is reduced in problematic situations where measurement and validation signals are not convergent, by offering calculated best estimation.

1 INTRODUCTION

The validation means the verification of the measurement with other information or measurements. The practical problem is to validate a continuous measurement using its previous values or a corresponding laboratory analysis as a reference. Laboratory analyses are commonly used in process industry, but the purpose of the use and criticality of analyses vary. Normally, analyses are used either to monitor the process, or to validate on-line measurements. If based solely on laboratory analysis, process control becomes inefficient because of the infrequency of analyses. Several factors make it difficult to validate sensor data and to calculate confidence levels. The difference between slight sensor failures and noisy sensor readings is not easy to verify if the process and time delay in reference analysis is not known. On the other hand, laboratory analysis improves control when it is used to validate and correct on-line measurements. The calculation of the optimal estimate has three parts: pre-processing, confidence level estimation and the calculation of the estimate (Figure 1).

Applied maximum and minimum limits are defined by process dynamics, not by analyzers maximum measuring range. In this way, the accepted area of the operation becomes more realistic. Fuzzy limits are used for softening change between reliable and non-reliable values. Example data consists redundant sensor data from electrolytic zinc production process, where analyzer measures Fe^{2+} content in the dissolution reactor. Deterioration of the measurement device causes drifting and occasional breakdowns. Measured value is used for process monitoring, not for control and if working properly, it gives useful information about process condition.

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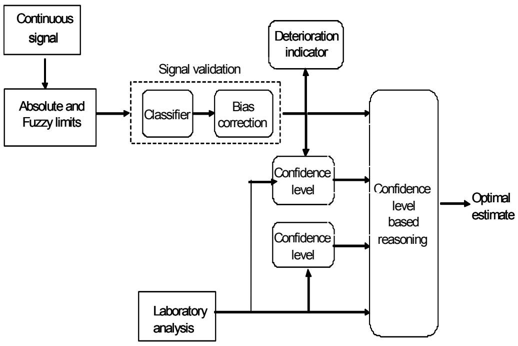

Figure 1: Different steps in the signal processing to the optimal estimate

The confidence levels are estimated for both the measurement and laboratory analysis. The measurement's confidence level is determined by two criteria: change between measurements and the deviation from the laboratory analysis. The confidence level of the laboratory analysis depends only on time since the analysis has been done. The optimal estimate is calculated according to an algorithm by using the pre-processed measurement, laboratory analysis and the confidence levels.

Various control methods can be effective in dealing with uncertain measurements, but measurement noise and errors effect on their performance. Outliers constitute a challenging problem and detecting them is much easier for human than for a computer. The self-validating (SEVA) approach provides tools for the single sensor signal validation (Henry, 1993). The approach utilizes sensor fault detection and uncertainty estimation to produce advanced information about the measurement. Multi-sensor data fusion can be used, when multiple sensors are used to measure the same variable (Luo et al., 2002). Thus a measurement is validated with other sensor data.

In redundancy-based approaches, duplicate measurements or a process model is used to generate a residual vector by comparing the measurements from multiple sensors or output of the process model and actual measurements. The residuals can be examined with many methods to make a decision about the sensor malfunctioning. Such methods include multi-sensor data fusion, voting systems, expert systems, artificial intelligence, fuzzy logic and neural network approaches (Amadi-Echendu, 1996). Model based fault detection and identification (FDI) methods are thoroughly discussed in survey papers by Isermann (1984) and Frank (1990). Voting systems require three or more measurements of same variable (Willsky, 1976). The deviating opinion (measurement) is neglected as the decision is made based on the majority of similar measurements. The voting system may include advanced characteristics as the differentiation between process upsets and sensor failures may be included in the reasoning (Stork & Cowalski, 1999).

2 OPTIMAL ESTIMATE

In this paper, the measurement validation problem is converted into the calculation of an optimal estimate of the measured variable based on the confidence levels of the actual and reference measurements. The calculation of the optimal estimate is divided into signal validation, confidence level estimation and calculation of the estimate.

2.1 Absolute and fuzzy limits

Absolute limits define the scale, where process parameter can vary under normal process conditions. The upper limit gives the maximum reliable value. If measurement device gives larger values than this, they should be ignored and replaced with other process information. Similarly, smaller values than minimum should be replaced. The limits can be defined manually by experts, but they can be also defined automatically from process data.

Fuzzy limits are used to narrow the area limited by absolute limits and for softening change between reliable and non-reliable measurement. Efficient use of fuzzy limits, combined to the absolute limits and reference measurement creates basics to the reliable calculation of "optimal" signal (Figure 2).

2.2 Signal validation

After the definition of the absolute and fuzzy limits, the classifier (Figure 1) detects the outliers and deviating values and replaces them with an estimate. If the measured value is inside the fuzzy limits, the classifier considers it valid. In this case, the weight of the measurement is 1. In the case of an outlier, (measured value is beyond the absolute limits) the weight of the measurement is 0 and the output of the classifier is either the previous measured value or the latest reference analysis. If the measurement is inside the fuzzy zones, the output from the classifier is a weighted average of the actual measured value and the reference value. In this fuzzy zone, the weight of the measurement decreases from 1 to 0.

In the case of a gradual degradation (e.g., a sensor drift), the faulty signal is not immediately abandoned but its influence on measurement estimation is diminished as a function of change and deviation from the laboratory analysis. This is achieved by decreasing the relative weight of the degraded signal. When the degradation strengthens, monotonic function diminishes its relative weigh.

2.3 Confidence levels and calculated estimate

As earlier described, the pre-processing provides practical signal for actual processing. The confidence levels are calculated for analyzer and laboratory analysis signals (Figure 2). The optimal estimate is then calculated using the pre-processed signals and confidence levels.

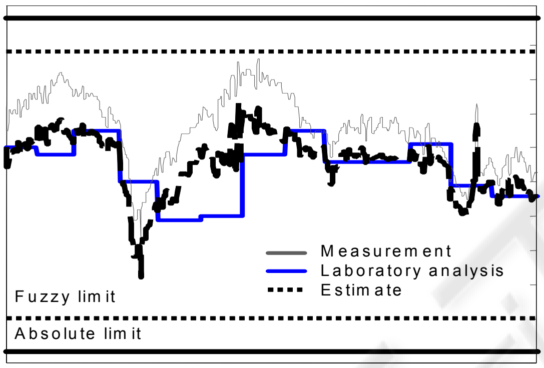

Figure 2: Limits, on-line measurement, laboratory analysis and calculated estimate

The confidence level of the measurement is determined by two criteria: the deviation of the measurement from the laboratory analysis and the change between consecutive measurements. The confidence level of laboratory analysis depends only on time. When a new result is available, its confidence level is 1. The aging of the analysis decreases the confidence level closer to 0. However, the laboratory analysis must be trusted (at least a little) always and therefore its confidence level never decreases to 0.

In the calculation of an estimate, the pre-processed signal, laboratory analysis and calculated confidence levels are used. Estimate is trusted always when its confidence level is relatively high (the confidence level of the laboratory analysis is decreased by a coefficient $(1 - C_m)$). The estimate (X_e) is calculated:

$$X_e = \frac{C_m X_c + (1 - C_m) C_l X_l}{C_m + (1 - C_m) C_l}$$, where

C_m is confidence level of the measurement
C_l is confidence level of the laboratory analysis,
X_c is validated measurement and
X_l is laboratory analysis.

3 DETERIORATION INDICATOR

Information produced in the calculation of the optimal estimate is used also for calculation of on-line deterioration (need for maintenance) indicator. Pre-processed data sets are combined in the validation block, where difference between on-line measurement and laboratory analysis is calculated and changes in the bias error are turned to the on-line deterioration indicator. In these cases, drift in the indicator value shows on-going deterioration in the measuring device (Figure 3).

A more sophisticated way to estimate changes in the deterioration indicator is to calculate changes in the measurements standard deviation (Figure 4). As long as a measuring device works properly, standard deviation should stay nearly constant.

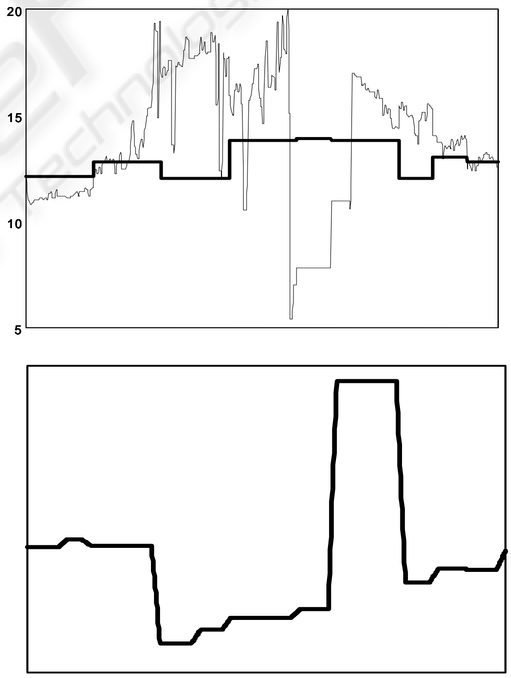

Figure 3: Bias error- based deterioration indicator, calculated from on-line measurement and laboratory analysis showing deterioration and breakdown. Data set represents one week time period from real process

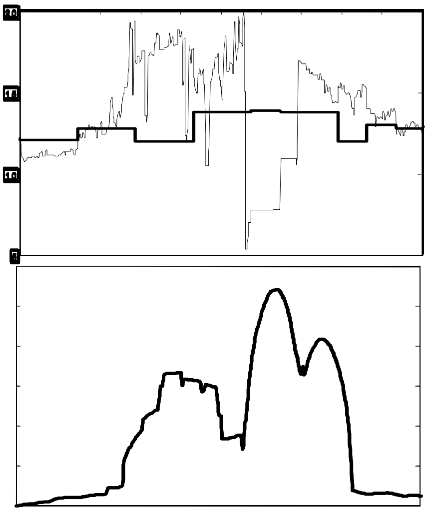

Figure 4: Standard deviation- based deterioration indicator to the same data as in Figure 3

Results from the indicator fall into two categories: need for calibration and warning for breakdown — depending on how the application is adjusted. Beginning deterioration is compensated in the pre-processing and in the calculation of the estimate, but after a certain point confidence values and confidence of the estimate descends. Warnings may contain information about problems in the measuring device (on-line analysis is not reliable and estimate is based mainly to the laboratory analysis).

4 CONCLUSIONS

Used data validation and estimation combines information from laboratory analyses and measurement device to calculate the optimal estimate of the actual process variable. This reconstructed data is then brought forward to operators or used by the controller (the estimate can be applied as a part of advisory or direct control strategy depending on the target process).

Used limits in data validation are proven to be critical, since too strict limits give laboratory analyses unnecessarily big weight and lose fast and short-time changes in the process. On the other hand, limits too wide allow faulty measurement device readings to be accepted and utilized in further process control (malfunctions of the measurement device are not differentiated from process upsets). If a faulty measurement device is detected (measurement device readings change more rapidly than process dynamics will allow or signal is not inside the area of operation) estimation algorithm tends to follow laboratory analysis and only when possible takes advantage from the measurement device data.

Output of the classifier (weighted estimate of the measured variable) is generated in the real time and the admissible range is adjusted as a function of process conditions. The effects of the failures and measurements oscillation are taken into account by diminishing their relative weight. Real data sets have been collected from an operating plant.

A model of the physical process or expert knowledge is not needed for successful calculation of the estimate. Only prominent data period of measurement device data and analytical measurements are needed for basis of the process parameters estimation. The pre-processing manipulates measurements that are beyond the fuzzy limits of the variable's dynamic range and corrects the static error between measurement device data and laboratory readings.

The confidence level of the measurement is determined by the deviation of the measurement from the laboratory analysis and by change between individual measurements. Respectively the confidence level of laboratory analysis is only time-dependent. The weight coefficients of the on-line signal and laboratory measurements are adaptively updated.

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