Optimal Quality Limits for On-line Measurements

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ABSTRACT

Paper mills make use of hundreds of on-line measurements to monitor and control the process. These measurements are key to rational decision making. Operators possess vast amount of process knowledge, partly tacit knowledge – this is huge partly unexploited resource. This paper tackles the problem of optimal quality limits for on-line measurement and introduces traffic light application as a combination of process (tacit) knowledge, measurement knowledge and data analysis.

INTRODUCTION

The process industries make use of hundreds of on-line and laboratory measurements to monitor and control the process. Information systems are designed with the aim of supporting the daily decision making about the process and product quality by operators and engineers so that the best practice of operation can be achieved continuously. Measurements, soft sensors and process simulators form the basis for such decision support by reducing the uncertainty about the present state of the process and about its future evolution. This sets requirements on how much uncertainty may be tolerated in the quality estimate.

Every quality parameter has its acceptance limits ("quality pipe") set by the product specification. Quality parameters are typically statistically dependent and thus measuring a subset of them provides information about the others. This can be exploited either by measurement scheduling where number of costly measurements is minimized and resources are targeted more efficiently or by understanding measurements as information channels and trying to maximize the collected information by combination of actual measurements, *a priori* and mutual information from other measurements. This paper concerns the latter case in the case of on-line measurements which are usually made rapidly and the making the measurement itself is cheap but the cost of making the measurement available is much higher. All this is meaning that we want to maximize information content of the measurements within reasonable costs.

Motivation

Can we achieve more with the exploitation of measurement information and tacit knowledge? Can the measurement resources be focused more efficiently to get current information more accurately and cost effectively or to get more information and gain better control over the process? This paper tackles this problem by applying optimal quality limits for on-line measurements with a combination of measurement knowledge, data analysis and tacit knowledge. Every measurement has its own maximum range or largest allowable uncertainty, that is, we can form quality pipe dependent on grade and scenario.

This paper is organised as follows. First we discuss about measurement policy and strategy including tacit knowledge with aspects of uncertainty handling and risk behaviour. Then measurability and information channels are addressed. Next chapter deals with Statistical Process Control (SPC), how the quality pipe is formed and how it is used in monitoring. Then traffic light application is presented and paper ends with conclusions.

MEASUREMENT POLICY AND STRATEGY

This chapter discusses about measurement policy and strategy with tacit knowledge and how to obtain it in this context. Also uncertainty handling and risk behavior is discussed.

Industrial operational decision support systems are based on measurement data and on pre-existing process knowledge. However, the uncertainty in the measurements and pre-existing knowledge is not provided by process information system, and thus, uncertainty is rather unfamiliar concept to process operators. This leads to one interesting point of the measurement strategy – decision making is based on the uncertain measurements but decision makers are not so familiar with the concept of uncertainty. Therefore the decision making should be supported with systems such that the uncertainties are described explicitly and consistently, allowing systematic combination of information from several sources. This information derived from the process is used in many ways, but it is poorly known, how and if the operators exploit all the information available. Therefore there has not been systematic work on optimizing the measurement activities. This may lead to situation where some measurements are carried out without purpose, only by habit, and the common practice continues to be to measure all quality parameters at regular time intervals. Obviously this is costly and rigid and may limit possibilities to measure those quality parameters that would be most important for overall quality management and thus for decision support.

However, if end user information requirements and constraints on uncertainty of the measurements are made explicit, the optimal arrangement of the measurements and decision support system can be determined. Figure 1 shows the chain from the process via measurements to data and via data processing to information and finally to decisions. The other direction is feedback from user requirements (decision making) to data (pre-) processing and to measurements, this meaning that decisions we are making should guide the data (pre-) processing and the measurements. This other direction is often overlooked and forgotten but it is as important as the other one - use of information, control and other decisions, defines processing of data and measurements [1,2]. This leads to our definition about measurement strategy that is optimizing of which and when measurements should be done to get information worth the costs of obtaining it.

Tacit knowledge

Tacit knowledge and reasoning means empirical and non-documented information about the process itself and interaction of process and operator, that is, in broad sense process knowledge of the operator. This is huge uncharted resource for mill to exploit and organizations are beginning to understand its value. With tacit knowledge, people are not often aware of the knowledge they possess or how it can be valuable to others. Knowledge of this kind is difficult to track and capture. It's important to understand the two types of knowledge: explicit and tacit. Explicit knowledge is written down but the concept of tacit knowledge refers to a knowledge which is only known by an individual and that is difficult to communicate to the rest of an organization. Tacit knowledge is the relevant information that resides in an individual's head. It's not written down, but is simply the knowledge someone has gathered from experience.

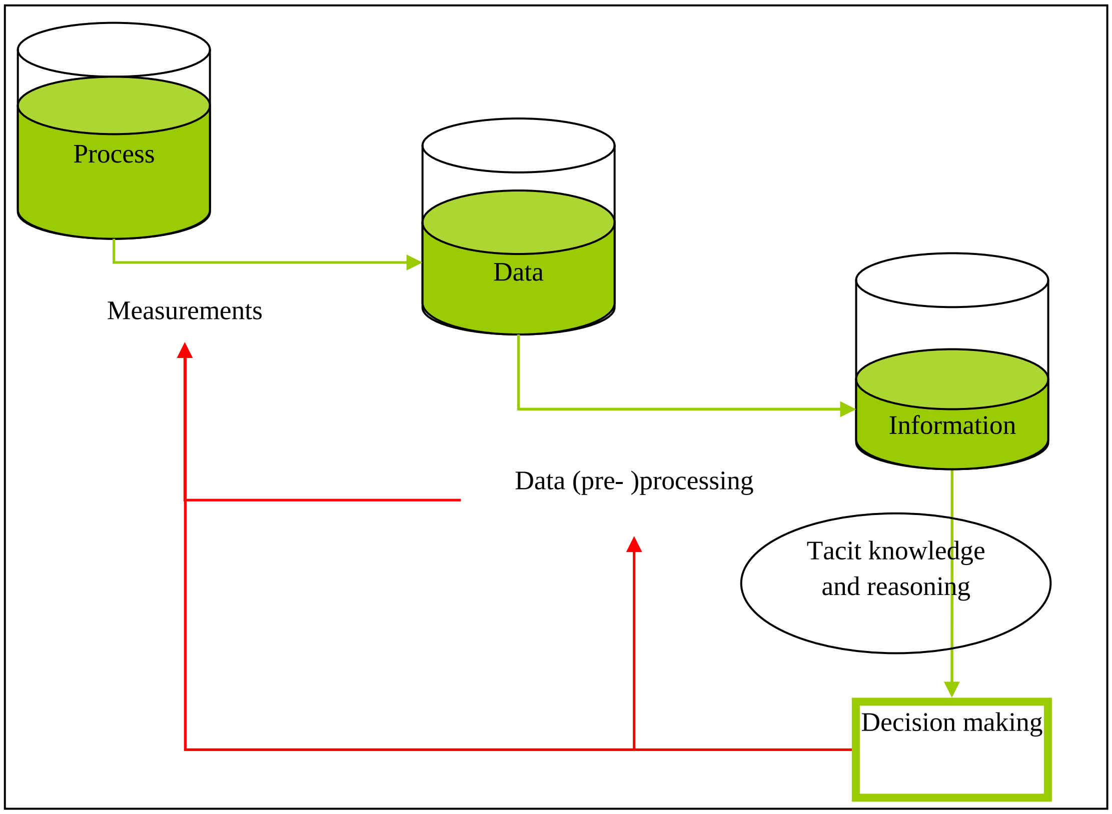

Figure 1. Tacit knowledge combined with reasoning produces the knowledge for decisions.

Process of evaluating maximum allowed uncertainty

Collecting tacit knowledge, process knowledge of mill staff is in the key role when building up these kinds of applications. From that knowledge can be induced what are the important measurements for each grade, decision and scenario and with combination of data analysis the walls of quality pipe for different situations can be acquired. However, the amount of value generated depends on the goal set by the decision maker, including the decision maker's attitude towards risk. Process operators and engineers are rather unfamiliar with the concept of uncertainty and hence uncertainty of consequences is dealt with rather implicitly when making decisions. Therefore the set limits for uncertainties have to be considered carefully before implementing the represented methods in practice, although the process of finding these limits can be very informative and useful.

There is uncertainty in every measurement we observe and thus every decision and action is based on uncertain information. Consequently, uncertainty in state information and about predictions should be made explicit for the decision maker. This is highly challenging for two quite different reasons – the present IT infrastructure does not support propagating uncertainty metadata along with the data, and operations personnel is not accustomed to dealing with uncertainties. However, if uncertainties are neglected, a main factor affecting complex decisions is lost and the resulting performance of decisions and hence that of operations is severely hampered. Uncertainty is described exactly only by probability densities, which in the most general case is computationally intensive and consumes storage capacity. When uncertainties can be approximated with Gaussian distributions, the description reduces to covariance matrices or variances that are computationally simple and can be readily applied in optimization.

Operators risk behavior can vary from gambler to very safe – question remains should this be choice of operator or strategy parameter. If decisions are made at the same risk level then the prediction of consequences are more constant.

MEASURABILITY AND INFORMATION CHANNEL

This chapter represents short theory of measurability and formulation of information channel. As stated in [3] all measurements can be thought as information channels, but not every information channel is a measurement in the strict sense, see also [4, 5].

Let us assume here measurements as information channels so that every on-line measurement in fact contains *a priori* information and information from other measurements via covariance matrix in addition to actual measurement information. *A priori* information is a combination of information from previous measurements and tacit knowledge process operators has obtained. Based on probabilistic, Bayesian, approach, presented by Rossi [5] we can form joint probability distribution from variables with normal distributions, see equations 1 – 3.

$$f\left(x_{true}\middle|x_1,\dots,x_j\right) = \frac{f(x_j|x_{true})\dots f(x_1|x_{true})f_{ap}(x_{true})}{f(x_j)\dots f(x_1)}, \qquad (1)$$

Where $x_1, \dots, x_j$ is a measurement and $f_{ap}(x_{true})$ is our *a priori* information about true state of the variable x_{true}.

Then we can calculate estimate value for information channel.

$$\hat{x}_{ic\_new} = \frac{\sum \frac{x_i}{\sigma_i^2}}{\sum \frac{1}{\sigma_i^2}} \qquad (2)$$

And estimate of the variance (uncertainty) of information channel is

$$\hat{\sigma}^2_{ic\_new} = \frac{1}{\sum \frac{1}{\sigma_i^2}} \qquad (3)$$

Where x_i is the measurement or *a priori* information and σ^2_i is corresponding variance (uncertainty) [6, 7].

Basically we need measurement value and its uncertainty from each measurement, model or information source associated to one information channel.

Usually on-line measurements are made simultaneously and as fast as possible. Then we can include information from other measurements by exploiting covariance matrix calculated from previously collected data. We form quality model by regression analysis for every information channel. This quality model can be constructed using stepwise regression, which chooses between regression models with an automated sequence of F-tests. A forward selection which will be applied here starts with no variables in the model, tries out the variables one by one, and includes those in order of statistically significant [8]. Information from quality model may be utilized in sensor malfunction detection and perception of subtle process changes and disturbances.

As time evolves it is self-evident that the uncertainties of estimates of quality model increase. We assume random walk [9], with diffusion constant *D*. That is, in the case of normal distribution the expectation value of signal is constant but variance (uncertainty) increases as time passes, see equation 4.

$$\sigma^2(t_n) = \sigma^2(t_{n-1}) + D\Delta t \qquad (4)$$

Where *D* is the diffusion constant.

SPC AND MONITORING

SPC is an optimization philosophy concerned with continuous process improvements, using a collection of (statistical) tools for data and process analysis, making inferences about process behavior and decision making. SPC can be used in monitoring that allows us to see which quality pipe or pipes are in good condition. We form quality pipes for every information channel output. Quality pipe has double walls, inner for estimate value of information channel and outer wall to its uncertainty, see figure 2.

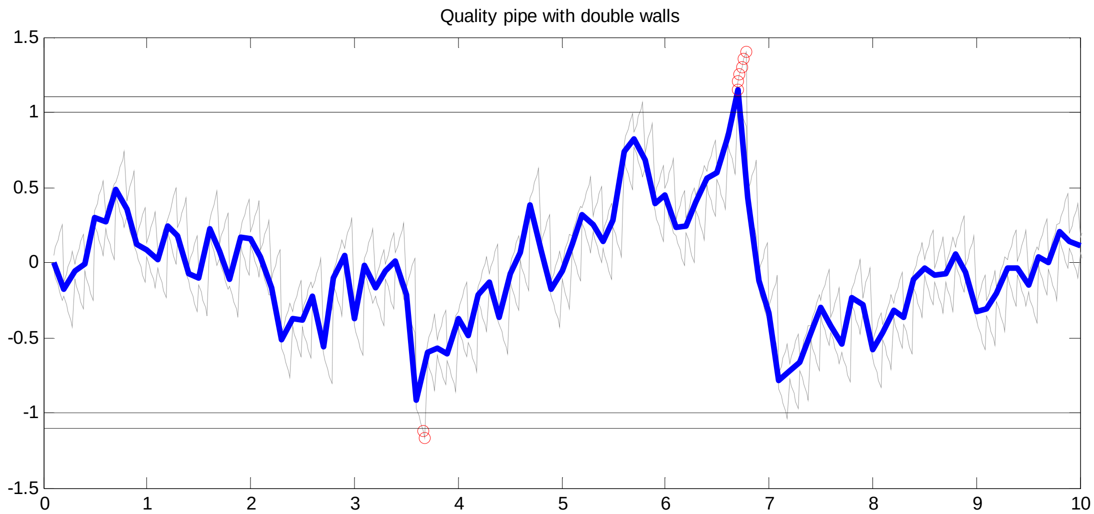

Figure 2. Quality pipe with double walls. Actual signal is exceeding inner wall about time 6.7 and uncertainty of the signal is exceeding outer wall about time 3.7 and time 6.8.

These quality pipes can easily be formed for every interesting signal. When monitoring the process every time either of these walls has been breached warning is produced for inspection. Then based on this monitoring various traffic lights can be generated for different scenarios, for example, grade change or web feeding. Metadata collected through this process benefits our knowledge about the behaviour of process in various situations.

Future work includes different ways to detect possible breach, different Shewhart tests, EWMA and CuSum can be tested for their ability to predict when some kind of problem might occur.

TRAFFIC LIGHT APPLICATION

As in [10] we have formed case based knowledge database and visualization system. Paper discussed about the concept of process intelligence and tacit knowledge – how to improve operational efficiency by learning from collective experience. Objective was to make information and data more comprehensible and use process knowledge more effectively. Resulting decision support tool can effectively aid process personnel for their daily decision making routines. As collection of cases is automatic, with comments and conclusions from process personnel, the work load of operators is not increasing. Rather the opposite due the decision support.

Traffic light application described here can be an additional feature for this previously presented tool but can act also as a standalone tool. These traffic lights serve for example in web feeding as a notification when machine is ready for feeding. Usually operators don’t want to use check list or similar tool and these traffic lights act as a automated check list and try to minimize human errors. Figure 3 presents phases needed when building up this traffic light application.

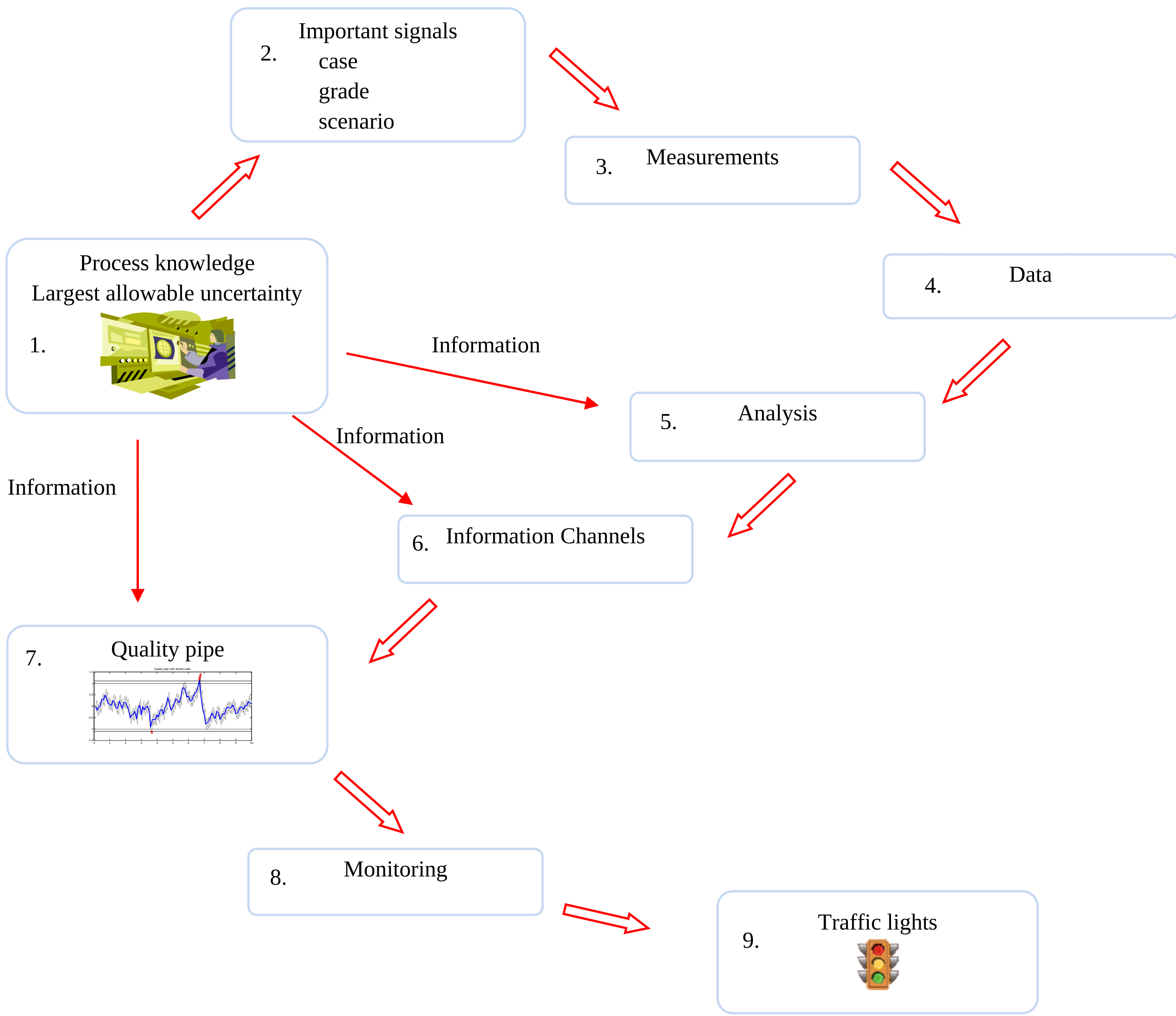

Figure 3. Phases in the path from process knowledge to traffic light application.

1. Operator - This task involves the collection of process (partly tacit) knowledge of operators to database. From here is direct link to parts analysis and quality pipe. This is base block for whole system and the information derived from the process knowledge affects the functionality of this system.

2. Signals - Based on information derived on former block signals to be measured and observed are chosen. Important signals depend on the purpose and target of this application. We can limit or group the analysis by grade, case or scenario.

3. - 4. Measurement and data - In these tasks the measurements are made and uncertainty is handled. After that some preprocessing are made and measurement data is formed.

5. Statistical analysis - This task involves data analysis and processing such as statistical analysis of quality pipe and information channel blocks.

6. Information channels - This task involves exploiting the measurement knowledge and forming of information channels from several sources of information. Uncertainty information comes from former analysis block and from first task (process knowledge).

7. Quality pipe - This task involves forming of quality pipe with the information (walls) from analysis block and from the first task (process knowledge).

8. Monitoring - When quality pipes are in order the monitoring task can be started. Different warning limits and rules are based on first task (process knowledge) and analysis block.

9. Traffic light - In this task traffic lights application is formed with the information from all previous tasks.

Of course iteration is crucial part of this process so that information flows to both directions. It should also be remembered as in any SPC application that if number of tests and number of signals under test are increasing then the probability of false alarm is increasing

CONCLUSIONS

This paper has been discussing quality limits for on-line measurements based on process and measurement knowledge and data analysis. Process knowledge of operators gives us basis of this application in the form of what measurements are important in different scenarios and what is the maximum allowed uncertainty. Based on measurement knowledge we can form information channels and maximize available information. With combination of statistical analysis we can form quality pipes and traffic light application.

The traffic light application was introduced as an additional feature to decision support tool based on process intelligence concept [10] or as a standalone tool for operators to monitor the process. Application is presented stage by stage and what information and knowledge is needed in which stage.

Future work includes implementation of this application.

ACKNOWLEDGMENTS

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