State dependent optimization of measurement policy

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Abstract. Measurements are the key to rational decision making. Measurement information generates value, when it is applied in the decision making. An investment cost and maintenance costs are associated with each component of the measurement system. Clearly, there is – under a given set of scenarios – a measurement setup that is optimal in expected (discounted) utility. This paper deals how the measurement policy optimization is affected by different system states and how this problem can be tackled.

1. Introduction

Measurements support daily decision making about production systems. Decision making is affected by available data, but also uncertainty of data. Meaning how well available data (both measurements and a priori) represents the state of reality (X at figure 3.). It follows then that from requirements for performance of decision making raises the requirements for accuracy of measurement of the state of reality (i.e. maximum allowed uncertainty). The optimal measurement system is such that it maximizes the value of information generated, under a given set of scenarios on external effects to the process. System usually has several states which would need different measurement policy and measurement model for decision making. System state also affects a priori information of process personnel and use tacit knowledge and reasoning is more accurate when system state is known.

There is always a cost of operation involved in measuring and also investment cost so the measurement is available. Usually different quality parameters correlate strongly and some parameters might be calculated accurately enough from measured parameters. As considered in papers [11 - 13], the measurement policy about what and when to measure can be applied to real processes. But some problems appear when system has at least two or more different states, for example different paper grades. Also some disturbance can affect to system so that it drifts to another state.

Different system states have different limits for maximum allowed uncertainties, quality pipe [14]. In figure 1 is an example of this kind of quality pipe where system has changed state and this variable should be known more accurately. This is a problem that should be addressed so to support decision making of operators and simplify measurements and measurement models. This paper presents one solution to this problem.
This paper is organized as follows, after introduction the next chapter discusses measurement policy with uncertainty and risk handling. After that statistical decision theory with decision making are discussed as it is the framework within which we analyzed value generated. Furthermore state estimation method is discussed. An example of how state affects measurement policy is given and paper ends with the conclusions.

2. Measurement policy

This chapter discusses about measurement policy, meanings and strategy with uncertainty and risk handling. 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. In some cases uncertainty is hard to estimate even roughly, and some upper estimates based on domain knowledge or general considerations must be applied. It is of particular importance that model predictions about consequence actions may strongly depend both on present state estimates (data) and on the action considered.
Operators uncertainty and risk handling, although are strategic parameters, are affected by a priori information and tacit knowledge. Figure 2 shows the chain from the process via data and information to decision and vice versa. This other direction is often overlooked and forgotten but it should be taken into consideration. Use of information, control and other decisions, defines (pre-) processing of data and measurements [1, 2]. This leads to our definition about measurement policy that is optimizing of which and when measurements should be done to get information worth the costs of obtaining it.

3. Statistical Decision Theory

Statistical Decision Theory (SDT) is a mathematical theory on how to make rational decisions when there is uncertainty in consequences of potential actions and such uncertainties may vary greatly from action to action. Fully structured SDT is a deterministic optimization problem with the objective, constraints, and system and observation models. Decisions are based on available information about the target system – current measurements, a priori information in form of models and tacit knowledge.

The formal statistical decision making problem consists of the following elements: a priori information about the state of the system, models of measurements, model for predicting the consequences of decision alternatives, and the expectation value of utility of the consequences. To define these elements, the system state ($x$), the set of consequences ($c$) and the set of allowable decisions (actions, $a$) must be described. Figure 3 presents the decision making task: given the measurement value $x^{(obs)}$, and the probabilistic models what is the action that yields maximal expected utility for decision maker (DM) [3,4].

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**Figure 2** From process to decisions and back.

**Figure 3** The key descriptors of the decision making problem and their relationship.
3.1. Making the decision

Decision maker knows the state of the system, $x$, only probabilistically through uncertain measurements and *a priori* information. The consequence $c$ of the action $a$, given that system state is $x$, is known probabilistically as *a priori* information. DM evaluates the system performance in terms of consequences. The utilities of consequences $c$, if the consequences were certain, are given as $u(c)$ [5]. Then the best action $a^*$ is the one with highest expected utility. The utility is a description of both DM’s preference order and attitude towards risk. If utility exists, DM is guaranteed rational in the sense that he does not have circular preferences in pair wise comparisons of decision alternatives. Formally, the elements of a priori information, measurement models and prediction models are then, respectively, the probability density functions:

$$f_X^{(ap)}(x)$$

$$f_{(x|\text{obs})}^{(meas)}(x|\text{obs})|x\right]$$

$$f_{(c|a,x)}^{(pred)}(c|a,x)$$

Here $x^{(\text{obs})}$ refers to the measured value of $x$. The probability density function of consequence $c$, given that $x^{(\text{obs})}$ has been measured and DM would decide $a$ is then according to Bayes formula [6,7]

$$f_{(c|a,x)}^{(pred)}(c|a,x) = N \times \int_{\text{domain}(x)} f_{(c|a,x)}^{(pred)}(c|a,x)f_{(x|\text{obs})}^{(meas)}(x|\text{obs})|x\right] f_X^{(ap)}(x)dx^n x$$

(2)

where $N$ is a normalization factor and $n$ is the dimensionality of system state space description.

We want to minimize the cost of decision (including cost of information retrieval, that is, measurements) and maximize utility – meaning how good the decision was or what was the value of consequence to decision maker and other mill personnel.

Decision making is based on measurements (model) and *a priori* which are dependent on system state. If system state is known it is then easier to choose correct measure model and DM has more accurate *a priori* information about the system.

3.2. State estimation method

Requisite for the state recognition system is any model (non-linear or linear, with enough inputs) with outputs and comparable reference measurements such as laboratory analysis. System takes outputs of any (non-)linear model, for example soft sensor, and corresponding reference measurements as inputs for dynamic verification block.

Then formulate simple linear identity model between outputs of (non-)linear model and reference measurements. It could be one model per variable (SISO) or combined model with all variables (MIMO). This paper concentrates SISO system and model (SISO) is the form of $y = ax + b$, where $x$ is the output of soft sensor and $y$ is corresponding laboratory reference measurement.

In optimal situation where output of soft sensor equates to reference value, the parameter $a$ is 1 and $b$ is 0. When difference of $a$ and $b$ from their original values is significant (based on Mahalanobis distance [8]) state of system is suspected to have been change [9, 10]. Then it is important to recognize
correct state, this can be done analyzing history data and maybe using several soft sensor applications which observe the system [9]. After the correct system state is acquired the measurement policy can be applied more accurately.

4. Measurement policy and state of the system

This chapter present an example of how measurement policy changes when state of the system drifts to another one. Here is one soft sensor measurement which has also regular (but not frequent as soft sensor measurement) reference measurement. Figure 4 shows data and on the right figure variation of measurements 1 and 5 has increased and variation of measurement 3 has decreased. Soft sensor is not detecting this decrease because of it is working correctly in one state.

Figure 5 shows how state change is detected at time 1000. Upper figure has all the measurements; soft sensor, dynamically validated soft sensor and reference measurement. Second figure consists of these parameters $a$ and $b$ (in normal situation (close to) 1 and 0). Third figure present uncertainty of parameters $a$ and $b$. Lower figure presents the abnormality signal based on Mahalanobis distance. Figure 6 shows then two different measurement policies at two different states system can have.

Figure 4 Data from the system. Measurement 3 acts as a soft sensor, which has two different models depending on the state of the system.
Figure 5 Detection of state change. Upper figure has all the measurements; soft sensor, dynamically validated soft sensor and reference measurement. Second figure consists of these parameters $a$ and $b$ (in normal situation (close to) 1 and 0). Third figure present uncertainty of parameter $a$ and $b$. Lower figure presents the abnormality signal based on Mahalanobis distance.
5. Conclusion

Optimized measurement policy, meaning what to measure and how often, should be used in every system. Process of acquiring measurement policy increases knowledge about the process and decreases costs so that resources can be targeted more efficiently.

This paper has been discussing state dependency of measurement policy optimization and proposed on solution to observe system so that it states can be detected. This state recognition system simplifies the analysis of decision support as measurement model can be reduced to cover only one state of system. An example of how this system works is also presented. Using this simple tool detection of need for a calibration (remodeling) of single soft sensor is also possible.

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