# *AN UNCONSTRAINED APPROACH FOR INSTRUMENTATION NETWORK DESIGN AND UPGRADE*

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**Abstract.** This paper proposes an unconstrained optimization approach to the design and upgrade of sensor networks. The proposition is motivated by the fact that current methods require threshold values for different instrumentation network attributes, which are in turn very difficult to determine. In fact, these attributes are, after all, related to the process economics and therefore should not be arbitrarily constrained. The methodology replaces a recent trend in viewing the problem as a multi-objective one. In this sense, the unconstrained objective can be considered as the proper utility function of the multi-objective problem.

**Keywords:** Instrumentation network design. Instrumentation Upgrade.

## Introduction

Instrumentation is needed in process plants to obtain data that is essential to perform several activities. Among the most important are control of plants, assessment of the quality of products, production accounting (sometimes called yield accounting) and detection of failures related to safety. In addition, certain parameters that cannot be measured directly, like heat exchanger fouling or column efficiencies, are of interest. Finally, new techniques such as on-line optimization require computer models for which the estimation of process parameters is essential.

The problem of instrumentation network design and upgrade consists of determining the optimal set of measured variables and selecting the accuracy and reliability of the corresponding instruments. The goal is to obtain sufficiently accurate and reliable estimates of variables of interest while at the same time, be able to filter bad data due to possible instrument malfunction, all this at minimum cost. Filtering of bad data is related to gross error detectability while robustness of performance is related to residual precision (precision in key variables that is left after gross errors are detected and eliminated) and resilience (low impact of undetected gross errors (Bagajewicz, 1997, 2000). In addition one can consider maintenance costs as part of the total cost and require fault detection capabilities in addition to precision. Thus, the simplest minimum cost model is:

$$\textbf{(P1)} = \text{Minimize } \{\textit{Total Cost}\}$$
$$\text{s.t.} \quad \begin{cases} \textit{Desired level of Precision of Key Variables} \\ \textit{Desired level of Reliability of Key Variables} \\ \textit{Desired level of Gross-Error Robustness} \end{cases}$$

where the total cost includes the maintenance cost, which regulates the availability of variables, a concept that substitutes reliability when the system is repairable.

Several authors proposed methodologies to solve this problem. Almost all are described in detail by Bagajewicz (2000). Recent work includes multiobjective optimization and two dimensional pareto optimal graphs were developed (Bagajewicz and Cabrera, 2001b). This shows a departure from other multiobjective approaches (Viswanath and Narasimhan, 2001; Carnero *et al.,* 2001). An MILP procedure to design sensor networks was recently submitted (Bagajewicz and Cabrera, 2001a). This compares well with the alternative approach by Chmielewski (2001). Finally, the first attempt to unify the design of sensor networks for monitoring with sensor networks for fault detection and resolution has been recently submitted (Bagajewicz and Fuxman, 2001).

One of the difficulties of the present approach is that the model is based on thresholds of different instrumentation features (residual precision, gross error detectability, resilience, etc), which are not transparent to the process engineer. In other words, the process engineer has no feeling for what values to request in a particular design and upgrade. In addition, maintenance has been taken into account through a cost representation, but other features (availability of personnel, etc) were not considered. Thus, the present formulation based on minimizing cost subject to threshold constraints on precision, reliability and network robustness is clearly insufficient. Multicriteria approaches to the problem (Viswanath A. and S. Narasimhan, 2001; Cabrera and Bagajewicz, 2001) address these problems to a certain extent. Indeed, the cost-optimal formulation is nothing else than both a parametric decomposition and a value function approach to obtain a multidimensional pareto-optimal solution of a multiobjective problem in which all the network features are alternative objectives together with the cost. While exploring pareto optimal surfaces is useful and can provide an idea of what value is obtained at different costs, this still leaves the practitioner with a vague notion about the value obtained. For example, a practitioner may inquire about the cost benefit relationship of increasing error detectability by one non-dimensional unit.

To ameliorate these difficulties, we propose to relate all sensor network properties (precision, residual precision, error detectability, reliability and resilience) to lost/increased revenue functions converting the problem into an unconstrained one based on cost or cost-benefit only.

This paper is aimed at introducing the concepts related to this technique but not to address its numerical difficulties. The unconstrained formulation is first explained, some examples follow and finally, a discussion on the incorporation of other network attributes in the objective function is performed.

## Unconstrained Formulation

Consider the simple problem with only precision constraints:

**(P2)** = Minimize {*Investment Cost*}
s.t.
*Desired level of Precision of Key Variables*

We propose to introduce the value added of reliability and solve the following problem:

**(P3)** = Maximize {*Net Present Value*}

In this problem, one computes the net value as the present monetary value of the project, which is normally obtained by discounting over time the value added of precision and subtracting from it the investment. In more complete formulations one would also discount the maintenance costs. One can, of course, continue with obtaining the net present value of reliability and other network properties.

We now turn to calculating the value added of precision. There is a variety of ways that precision can be related to revenues. We will consider here that the value added because of precision is a function of better product quality. Other definitions can be used, like for example the reduction of lost revenue due to better assessment of product flows.

Let $\sigma_i$ be the precision of the estimator of variable *i*, which in turn is obtained from redundant measurements through data reconciliation. Therefore $\sigma_i$ is directly calculated using the variance of the instruments that are selected for installation. If one assumes that the estimators are normally distributed N($\mu_i$ $\sigma_i$), where $\mu_i$ is the estimator. Assume also that the measured variable is normally distributed.

For simplicity we consider a process with low variability (due to control and possibly other factors), and with such variability being lower than the one that could be measured by the candidate instruments or eventually by the best estimator that can be obtained by placing a large amount of instruments in the systems. Such relation is depicted in Figure 1 where the both distributions are depicted.

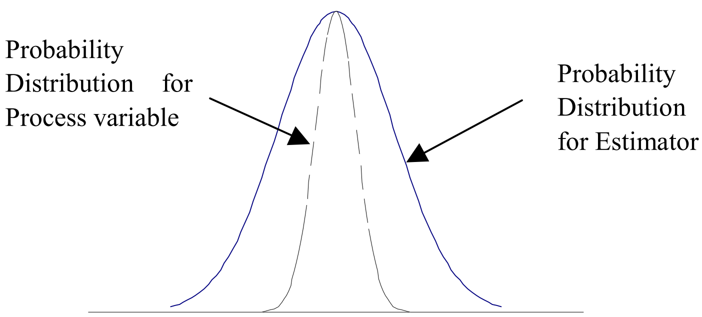


**Fig. 1**.

The case where process variability is of the same magnitude or larger than the variance of the estimator is left for future work. Now the next step is to relate the variance of the estimator to product loss associated with rejection of production due to bad quality. Indeed, assume the simplest scenario in which the financial loss is *K* units for any product with deviation ±Δ from the specified value. Thus, for an estimator with variance $\sigma_i$, the expected financial loss per unit of production is

$$L_{\sigma,i} = 2\,K\int_{\mu_i+\Delta}^{\infty} N(\mu_i,\sigma_i;\xi)d\xi \tag{1}$$

where it was assumed that the estimators probability distribution is normal. Indeed, rejection due to poor quality comes when an estimator is larger than $\mu_i$ +Δ or smaller than $\mu_i$ -Δ. Thus the probabilities of such events are equal and are given by the integral shown in (1). The next simplification is to make this financial loss constant throughout time. Therefore for each period in the future obtains the following loss due to bad instrument predictions

$$D_{\sigma,i,k} = F_i L_{\sigma,i} T_k \tag{2}$$

In this expression, $F_i$ is the flowrate of product *j* rejected because of out of range property *i* and $T_k$ is the length of the time period *k*. Since these are future losses, one should discount them appropriately. Thus,

$$NPV = \sum_k d_k \sum_i \left\{ D_{\sigma_i^0,i,k} - D_{\sigma_i,i,k} \right\} - \sum_i c_i (q_i - q_i^0) \tag{3}$$

where $d_k$ is the discount factor. The net present value is composed of two parts. The first term is composed of the difference of the expected loss between the case where there the estimator has a nominal a-priori chosen variance ($\sigma_i^0$) and the case where the variance is eventually smaller ($\sigma_i$). Since we are considering adding instrumentation, the former is larger than the latter. This is illustrated in Figure 2.

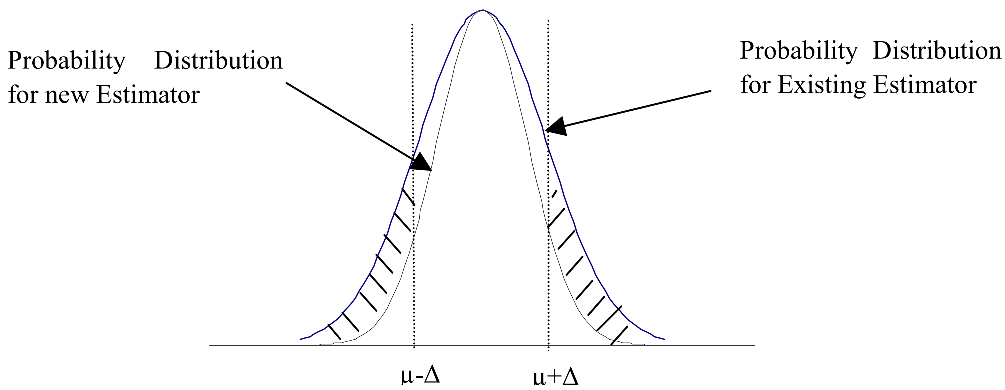


**Fig. 2**.

The shaded region corresponds to the difference of integrals in the first term. In retrofit cases, $\sigma_i^0$ corresponds to the current estimator variance, but in grassroots designs, one should consider using variance of the cheapest instrument available to measure variable *i*. The second term is the extra investment cost. Thus when no instrumentation is added, the investment is zero and the shaded area is zero (both distributions coincide) and therefore, *NPV*=0, but when instrumentation is added, both the investment cost and the value added increase. In the extreme, when all possible instrumentation has been added, the shaded region in Figure 2 is the largest possible, but the additional investment cost may become too large. We therefore recognize that there is a trade off and at some intermediate point the maximum of *NPV* is reached.

## Example

Consider the process of figure 3 (Bagajewicz, 1997). The flowrates are $F$ = (151.1, 52.3, 97.8, 97.8). Flowmeters of precision 3%, 2% and 1% are available at costs 800, 1500 and 2500, respectively. The set of variables of interest is $\{S_4\}$. When $\Delta$ =2%, the interest rate used to calculate the discount factors over 5 years is 5% and K=20, only four solutions have positive NPV. They are depicted in Table 1.

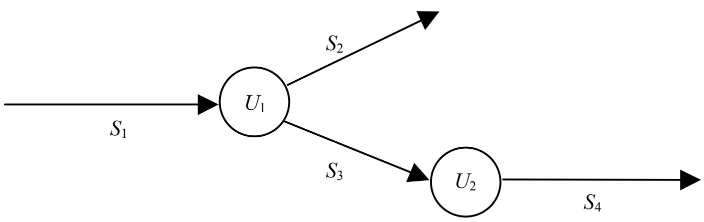

**Fig. 3.** Flow sheet for the Example

**Table 1.** Feasible solutions with Positive NPV (K=20, Δ =2%)

| NPV | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|
| 289.33 | -- | -- | -- | 1% |
| 289.33 | -- | -- | 1% | -- |
| 112.53 | -- | -- | -- | 2% |
| 112.53 | -- | -- | 2% | -- |

The solution, clearly states that instead of the minimum investment of installing a sensor of minimum value (800) in $S_4$ one can install one of 1% in $S_3$ or $S_4$ (they are equivalent). As *K* is increased, the solutions are shown in table 2.

**Table 2.** Selected Optimal solutions with Positive NPV (Δ =2%)

| *K* | *NPV* | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|---|
| 0 – 17.091 | 0 | -- | -- | -- | 3% |
| 17.091-66.084 | 0 – 4,873.18 | -- | -- | -- | 1% |
| > 66.084 | >4,873.18 | 1% | 1% | 1% | 1% |

As one can observe, as K increases above 17.091, a direct jump to a 1% sensor is more profitable than a transition to a 2% sensor. Similar direct jumps to higher precision and redundancy take place at K=66.084. When Δ is smaller, then sometimes a less expensive network can be chosen for similar ranges of *K,* but some other times a more expensive one is required. This behavior is shown in Table 3. Indeed, for *K* in the range 17.091-21.456, a less expensive network is needed for Δ=0.8%, compared to the one needed for Δ=2%. Conversely, for *K* in the range 45.969-66.084 a more expensive network is needed when Δ=0.8%.

**Table 3.** Selected Feasible solutions with Positive NPV (Δ =0.8%)

| *K* | *NPV* | $S_1$ | $S_2$ | $S_3$ | $S_4$ |
|---|---|---|---|---|---|
| 0 – 21.456 | 0 | -- | -- | -- | 3% |
| 21.456 – 45.969 | 0 – 1,942.39 | -- | -- | -- | 1% |
| > 45.969 | > 1,942.39 | 1% | 1% | 1% | 1% |

## Discussion

Many formulations can be added or used alternatively for determining the value added of instrumentation. For example, in the case of material balances, one accounting issue is the lost revenue for underestimating sales and overestimating raw material purchases. In theory, if the probability distribution is symmetric, these are the same, that is, one should overestimate as much as one underestimate. However, in practice, one could be interested in assigning value to smaller overestimation of products, but zero value to smaller underestimations. Conversely, one could assign value to smaller underestimation of raw material flows and zero to overestimations. The issue is also valid for gross error detectability capabilities of the network.

Maintenance cost should be factored in negatively in the NPV. Maintenance cost, however, is related to reliability of instruments, or more precisely to rate of failure. In addition, it is related to the preventive maintenance policies. Failure of instrumentation reduces precision, and therefore reduces value added.

## Conclusion

In this paper, the basic principle for the design and upgrade of instrumentation networks using unconstrained optimization (cost) has been presented. The concept was illustrated for the case of the value added of instrument precision and a brief discussion was made in relation to other ways of relating instrument properties to value added.

## Nomenclature

| | |
|---|---|
| $K$ | Cost of rejection of production. |
| $NPV$ | Net present value |
| $d_k$: | Discount factor for year $k$. |
| $c_i$: | Cost of sensor $i$. |
| $q_i$: | Binary variable. $q_i$ =1 ➔A sensor is located in variable i. |
| $L_{\sigma,i}$: | Expected financial loss per unit of production. |
| $D_{\sigma,i}$:: | Total expected financial loss |

*Greek Letters:*

| | |
|---|---|
| $\sigma_i^0$ | Original or minimum possible precision of variable $i$. |
| $\sigma_i$ | Precision of variable $i$. |
| $\mu_i$: | Mean value of variable $i$. |
| $\Delta$: | Threshold deviation for quality assurance. |

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