NEW PARADIGM IN INSTRUMENTATION NETWORK DESIGN AND UPGRADE

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Abstract

The existing approach to instrumentation design and upgrade consists of investment cost minimization models subject to precision and error robustness constraints. In this paper, we propose to minimize the net present value of the economic value of precision and accuracy of the system as defined in recent work. Thus, we depart from the investment cost minimization models as well as the multi objective approaches that have been proposed recently.

Keywords

Instrumentation design. Process monitoring. Data reconciliation.

Introduction

One of the major obstacles in industry for the justification of instrumentation upgrade projects or the purchase/installation of software that will improve monitoring is that the benefit (in economic terms) is unclear and cannot be assessed. Bagajewicz (1997) proposed to add gross error robustness as a constraint of the design of instrumentation networks. Later Bagajewicz (2000) reviewed all techniques for instrumentation upgrade with monitoring goals.

In previous articles (Bagajewicz and Markowski, 2003, Bagajewicz et al., 2003), a statistical analysis was made to determine the economic value of precision. A formula was developed for such value based on the downside expected loss that occurs when an operator adjusts the throughput of a plant when the measurements or estimators obtained through data reconciliation suggest that the targeted production is met or surpassed. However, there is a finite probability that the measurement or estimator is above the target when in fact the real flow is below it, hence the expected financial loss calculation. The associated probability (25%) is viewed as the confidence with which these expected loss is known. For the case of low process variability (steady state), the expected financial loss is proportional to the precision (standard deviation) of the estimator, a remarkably simple formula.

To understand how biases corrupt estimators, Bagajewicz (2004a) has defined the concept of software accuracy, which is based on the notion that data reconciliation with some test statistics is used to detect biases. The software accuracy of a variable is defined as the sum of the precision (standard deviation) of the estimator plus the maximum possible undetected induced bias due to a sensor bias anywhere in the system. Based on the above concepts, Bagajewicz (2004b) studied the economic value of accuracy, that is, determined ways of calculating the downside expected financial loss when a system contains biases and these bias are (or are not) detected using heuristic methods as well as data reconciliation packages with gross error detection techniques. He focused on serial elimination and considered reliability and availability issues to determine the downside expected financial loss.

One of the difficulties of the evaluation method is that it requires complex analytical evaluations of the downside risk when there is more than two gross errors to the point that some of the integration cannot be done analytically.

In this paper, we propose one modification to the calculation methodology proposed by Bagajewicz (2004b) and we put that evaluation in the context of an instrumentation design/upgrade methodology.

Brief review of the Economic Value of Accuracy in Linear Systems

Bagajewicz and Markowski, (2003) and Bagajewicz et al. (2003) argued that a typical refinery consists of several tank units that receive the crude, several processing units, and several tanks were products are stored, summarized in three blocks as in figure 1.

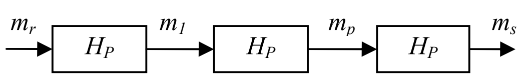

Figure 1. Material balance in a Refinery.

They argue that the probability of not meeting the targeted production is $P\{H_S(T) \le H_S^*\}$, which in turn can be rewritten as $P\{m_p(t) \le m_p^*\}$, that is, it is equal to the probability of the true value of m_p being smaller than the measurement. Let $\hat{m}_p$ be the estimate one has of the true value of m_p and consider that production is adjusted to meet the targeted value, based on the estimate. In other words, if $\hat{m}_p < m_p^*$, production is increased and vice versa, if $\hat{m}_p > m_p^*$, production is decreased. They assumed that, when $\hat{m}_p > m_p^*$, that is, the measurement indicates that the target has been met, the operator would not do any correction to the set points. They argue that the probability of being wrong is given by the conditional probability $P\{m_p \le m_p^* | \hat{m}_p \ge m_p^*\}$, for which they derive the following expression:

$$P\{\hat{m}_p \ge m_p^* \ | m_p \le m_p^*\} = \int_{-\infty}^{m_p^*} \left\{ \int_{m_p^*}^{\infty} g_M(\xi; m_p, \hat{\sigma}_p) d\xi \right\} g_P(m_p; m_p^*, \sigma_p) dm_p \quad (1)$$

where the integral is taken over all possible values of m_p below the target because of the underlying assumption for m_p that it is lower than the target.

Now, when there is a bias, induced or not, it could go undetected, which means it has an absolute value size smaller than $\hat{\delta}_{p,\max}^{i1,\ldots,in_T}$, which is the maximum induced bias (Bagajewicz and Rollins, 2004) that goes undetected by the Maximum Power Measurement test when there are n_T gross errors. As we know, this value is a function of the existing instrumentation. When there is no redundancy, this value is, theoretically, infinite, but in practical terms, when the bias reaches a certain value, say $\delta_p^{\#}$, it becomes truly apparent to the operator that there is a bias and hopefully, the instrument is calibrated. Let us assume that, when an instrument fails, which happens according to a certain probability $f_i(t)$ (a function of time), the size of the bias follows a certain distribution $h_i(\theta; \bar{\delta}_i, \rho_i)$ with mean $\bar{\delta}_i$ and variance ρ_i^2. Note that depending on the value of the measurement in the range of the instrument, the mean could be nonzero. For simplicity, we assume here that $\bar{\delta}_i = 0$. We are also assuming here that the gross error size distribution is independent of time. Thus, we now need to integrate over all possible values of the gross error and multiply by the probability of such bias to develop. Therefore, if we assume that one instrument fails at a time, then, the probability of instrument i failing and the others not is given by: $\Phi_i^1 = f_i(t) \prod_{s \ne i} [1 - f_s(t)]$. Thus, the probability of the estimate to be higher than the true value, given a bias in measurement i (Bagajewicz 2004b):

$$P\{\hat{m}_p \ge m_p^* | i\} = \Phi_i^1 \int_{-\infty}^{\infty} P\{\hat{m}_p \ge m_p^* | \theta\} h_i(\theta; \bar{\delta}_i, \rho_i) d\theta \Big\} \quad (2)$$

where $P\{\hat{m}_p \ge m_p^* | i\}$ indicates the probability being conditional to the presence of one gross error in stream *i.* Bagajewicz (2004b) also considered cases with two or more instruments at a time can fail, and finally, he derived the following expression:

$$\left. \begin{array}{l} P\{\hat{m}_p \ge m_p^* | i1,.., in_b\} = \\ \Phi_{i1,\ldots in_b}^{n_T} \int_{-\infty}^{\infty} \ldots \int_{-\infty}^{\infty} P\{\hat{m}_p \ge m_p^* | \theta_1,.., \theta_{in_b}\} \\ h_{i1}(\theta_1; \bar{\delta}_{i1}, \rho_{i1}) \ldots h_{in_b}(\theta_{in_b}; \bar{\delta}_{in_b}, \rho_{in_b}) d\theta_1 \ldots d\theta_{in_b} \end{array} \right\} \quad (3)$$

where $P\{\hat{m}_p \ge m_p^* | \theta_1,.., \theta_{in_b}\}$ is the probability of the estimate being larger that the target in the presence of several gross errors and $\Phi_{i1,i2,\ldots,in_b}^{n_T}$ the probability of these gross errors being present. He finally provides an expression for the probability of the estimator being larger than the target as a function of all the possible cases.

$$P\{\hat{m}_p \geq m_p^*\} = \Phi^0\left[\frac{1}{4}+\frac{1}{2\sqrt{\pi}}\int_0^\infty erfc\left(z\sigma_p/\hat{\sigma}_{p,m}\right)e^{-z^2}dz\right]+ \sum_{r=1}^{n} P\{\hat{m}_p \geq m_p^* | r\} \quad (4)$$

The first term is the result obtained by Bagajewicz and Markowski (2003) for linear systems in the absence of biases. He concludes that it is cumbersome to integrate the above expressions analytically, so one has to resort to a numerical scheme.

Downside Expected Financial Loss

In the absence of biases, the expected financial loss is Bagajewicz and Markowski, (2003):

$$DEFL^0(\hat{\sigma}_p,\sigma_p) = \int_{-\infty}^{m_p^*} g_p(m_p^*,\sigma_p,m_p)\left\{\begin{matrix} K_S T \\ \int_{-\infty}^{m_p^*}(m_p^*-\hat{m}_p) \\ g_M(\hat{m}_p;m_p,\hat{\sigma}_p)d\hat{m}_p \end{matrix}\right\} dm_p \quad (5)$$

which resulted in the following expression for normal distributions and negligible process variations $DEFL^0(\hat{\sigma}_p,\sigma_p)=\gamma K_S T\hat{\sigma}_p$ where $\gamma = 0.19947$ and K_S is the cost of the product sold, or the cost of storage when there is such. When there is one gross error present, the distributions are normal and for $\sigma_p/\hat{\sigma}_p \to 0$ we have

$$DEFL^1|i = DEFL^0\left[\frac{\hat{\sigma}_p^{R,i}}{\hat{\sigma}_p}\right]\left[\begin{matrix}\int_{-\infty}^{-\tilde{\delta}_i^p} h_i(\theta;\bar{\delta}_i,\rho_i)d\theta + \\ \int_{\tilde{\delta}_i^p}^{\infty} h_i(\theta;\bar{\delta}_i,\rho_i)d\theta\end{matrix}\right] + \frac{1}{2}K_S T\int_{-\tilde{\delta}_i^p}^{\tilde{\delta}_i^p}\left\{\int_{-\infty}^{m_p^*}(m_p^*-\xi)g_M(\xi;m_p^*+\hat{\delta}_p^i(\theta),\hat{\sigma}_p)d\xi\right\} h_i(\theta;\bar{\delta}_i,\rho_i)d\theta \quad (6)$$

A similar expression can be written for the case of two or more gross errors, (Bagajewicz, 2004b). Finally, we write

$$DEFL = \Psi^0 DEFL^0 + \sum_i \Psi_i^1\ DEFL^1|i + \sum_{i1,i2}\Psi_{i1,i2}^2 .DEFL^2|i1,i2 + ... \quad (7)$$

where Ψ^0 are the average fraction of time the system is in the state without biases, Ψ_i^1 the average fraction of time the system has only one undetected bias only in stream i, etc. These values are in fact equal to the probabilities of each state.

Trade off between Value and Cost

In the case of buying a data reconciliation package, one would write *NPV*= d_n {Change in $DEFL$}*–Change in Cost*, where d_n is the sum of discount factors for n years. The change in cost includes now the cost of the license and/or the cost of new instrumentation plus the increased maintenance cost. The cost of maintenance is a function of the expected number of repairs. For a given instrument, this is given by (Bagajewicz, 2000):

$$\Lambda_i(t) = \mu_i\left[\frac{1}{(1+\lambda_i)}t + \frac{1}{r_i[1+\lambda_i]^2}\left(e^{-(1+\lambda_i)r_i t}-1\right)\right] \quad (8)$$

Using this function, one can construct the net present cost of maintenance for new instrumentation. In fact, larger maintenance will reduce *DEFL* by reducing the frequency of failure.

Numerical Integration

The integrals in this model are difficult to evaluate. It is well known that the measurement test (Bagajewicz and Rollins, 2004) is not consistent in the presence of multiple errors, so it is impossible to anticipate when a serial elimination technique has been successful. This limitation does not allow an easy analytical determination of downside financial loss. An alternative, especially for many gross errors, is to evaluate the integrals numerically to save computational time. This is part of on-going work.

Design and Upgrade procedure

Bagajewicz (2000) showed that observability issues prevent the use of straightforward optimization models to design instrumentation networks aimed at data reconciliation monitoring. To design or upgrade a system, we propose now to solve the following problem

$$Max\sum_{\forall i}\sum_{k=1}^{n_i^m} NPV_{ik}\,p_{ik} \quad s.t. \quad \sum_{k=1}^{n_i^m} p_{ik} \leq m_i \quad (9)$$

where n_i^m is the number of different alternative candidates of measurement devices, $NPV_{ik}\left(k=1,...,n_i^m\right)$ is the net present value of each of these candidates. Finally, the binary variables $p_{ik}\left(k=1,...,n_i^m\right)$ determine which candidate will be used, that is, $p_{ik}=1$ if device k is used to measure variable i and $p_{ik}=0$ in otherwise. The constraint guarantees that at most m_i devices are assigned to each variable.

Therefore, to illustrate the new paradigm we propose to use a modification of the tree-based branch and bound procedure proposed by Bagajewicz (1997, 2000). This technique presents some computational challenges, but this paper does not address the computational aspect of the problem, but rather emphasizes the conceptual one.

One option consists of exploring each branch until the net present value reaches a maximum, that is, stopping exploring a branch when the addition of an instrument makes the NPV decrease. One might argue, however, that one does not know if further down the tree there isn't a sensor that would make the combination of sensors have a larger NPV. Another possibility, with the same limitations, is to modify the search to explore the levels of the tree one at a time, that is, enumerate all the different nodes with the same number of instruments and pick the one rendering the best result and continue in this fashion until one sees the NPV decrease. Thus, our procedure does not guarantee global optimality. Rather is a procedure that can render sub-optimal solutions. Alternatively some existing techniques like genetic algorithms can be tried. Since for the time being that is no better alternative than the tree enumeration, more studies on branching and bounding procedures that could guarantee optimality are needed. This is the next step in our research.

Example

Consider the example of figure 2 (Bagajewicz, 1997). The flow rates are z = {150.1,52.3,97.8,97.8}. Assume S_1 and S_4 are measured with flowmeters 3% precision.

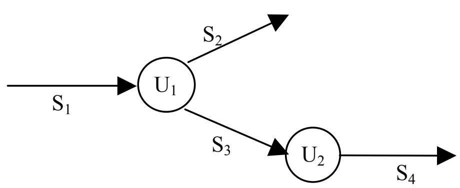

Figure 2. Example

Net Present Value of New Instrumentation

We consider adding instruments in streams S_2 and S_3. Flowmeters of precision 3%, 2% and 1% are available at costs 800, 1500 and 2500 respectively. We used a life time of 5 years, an interest rate 5%, and the following prices of products: 0.25 \$/Kg-stream S2 and 0.23 \$/Kg- stream S4. Assume λ_i=50 and equal repair rate for all instruments. In this example Ψ^0 = 0.924, Ψ^1 = 0.07355 and Ψ^2 = 0.00235, so that the downside financial loss due to two errors is not included because its contribution is small. Table 1 shows all corresponding nodes of the tree. At the first level, the addition of node (3%,1%,--,3%) renders the best answer. Proceeding with this node fixed, one identifies the best answer to be (3%,1%,1%,3%). The conjecture works in this case. However, the example is too small for any conclusions to be made.

Table 1. Solution of the Max NPV Problem

Network	NPV	Network	NPV
(3%, 3%, --,3%)	10,820	(3%,2%,3%,3%)	11,475
(3% ,2%, --,3%)	11,301	(3%,2%,2%,3%)	11,551
(3%, 1%, --,3%)	11,624	(3%,2%,1%,3%)	11,559
(3%, --, 3%,3%)	3,382	(3%,1%,3%,3%)	11,815
(3%, --, 2%,3%)	3,967	(3%,1%,2%,3%)	11,874
(3%, --, 1%,3%)	4,691	(3%,1%,1%,3%)	12,165
(3%,3%,3%,3%)	10,997		
(3%,3%,2%,3%)	11,097		
(3%,3%,1%,3%)	11,430		

Conclusions

In this paper, we present a new conceptual approach to instrumentation design and upgrade. This approach is based on recent developments on the value of accuracy (Bagajewicz, 2004b) that allow the calculation of the net present value of savings. The technique still presents some computational challenges, but this paper does not address the computational aspect of the problem, but rather emphasizes the conceptual one. More studies on branching and bounding procedures that could guarantee optimality are needed. This is the next step in our research.

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