INTEGRATED PROCESS SENSOR NETWORK DESIGN

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Abstract

Hitherto, instrumentation network design methodologies have been based solely upon sensor capital costs. Within this framework the cost of new instrumentation is minimized subject to constraints indicating the desired level of performance. While, these formulations account for the cost of a network, they do not reflect the potential benefit of adding sensors. To capture this potential profit, we have developed a new formulation of the instrumentation design and upgrade problem based on the expected trade off between value and cost (for additional details concerning material accounting see Bagajewicz et al. (2004), for control systems see Peng and Chmielewski (2004b) and for fault detection see Narasimhan and Rengaswamy (2004)). In this work, we aim to combine the three, profit based sensor network design formulations into a single integrated sensor network design.

1. Introduction

The state of a process can be inferred only through the window of measured process variables. This inferred knowledge is used to meet three primary process management objectives: (i) optimizing process operation for maximizing productivity, (ii) controlling the process for enhancing product quality (iii) monitoring and fault diagnosis for maintaining safety. The number and type of variables that are measured, the sensors used and their location, together determine how accurately the process state can be inferred and, therefore, have a direct bearing on how well the above three objectives can be satisfied. The problem of sensor network design deals with the optimal selection of variables to be measured to meet the three process management objectives. In a majority of previous instrumentation network design formulations, each task was considered independently. Bagajewicz (2000), in his book, reviews mostly state estimation and material accounting. Reviews of the hardware selection literature for controlled systems can be found in Chmielewski and Peng (2004), Padula and Kincaid (1999) and Kubrusly and Malebranche (1985). Sensor network design for fault diagnosis based on cost, reliability and resolution has been discussed in Bhushan and Rengaswamy (2000, 2002a, 2002b).

In this paper, we show how these three operational objectives should be considered, all at the same time, to determine the optimal sensor network design using the quantification of profit/savings and the network costs in a Maximum Network Value formulation. This short paper is organized as follows: We first discuss how a value of a network is obtained from the aforementioned three perspectives. Then we show how an integrated design methodology can be put together.
2. Economic Value

2.1 Economic Value in Material Accounting

In previous articles (Bagajewicz and Markowski, 2003, Bagajewicz et al., 2004), a statistical analysis was made to determine the economic value of precision. The connection between precision and economic value for material accounting is obtained by calculating the downside expected production loss. Conceptually, precision is related to inventory levels, or to expected production not met, in the case of low inventory capacity. More specifically, the operator has a targeted production and if this is surpassed according to the measurements, then we assume for simplicity that he/she makes no corrective action. Alternatively, one may see estimates above the target, when the true values are below (false positive). Then, the expected loss can be calculated as follows. Consider a target production \( m^* \). Let \( \hat{m} \) be the average of measurements of production and let \( g(\xi, \hat{\sigma}_{p,m}) \) be a distribution of measurements for flowrate \( p \). Then the downside expected production loss is (Bagajewicz et al., 2004):

\[
DEPL(\hat{\sigma}_{p,m}) = T \int_{-\infty}^{\infty} (m^* - \xi) g(\xi, \hat{\sigma}_{p,m}) \, d\xi = 0.2T\hat{\sigma}_{p,m}
\]

where \( \hat{\sigma}_{p,m} \) is the standard deviation of the estimator, which could be that of the real measurement or one smaller obtained through data reconciliation. Therefore, there is a certain chance that the target production is not met. Now consider a new and smaller value of \( \hat{\sigma}_{p,m} \), say \( \tilde{\sigma}_{p,m} \) obtained from performing data reconciliation using new instrumentation. Then the economic value is given by the difference of downside financial losses.

\[
V(\hat{\sigma}_{p,m}, \tilde{\sigma}_{p,m}) = K_S \{ DEPL(\hat{\sigma}_{p,m}) - DEPL(\tilde{\sigma}_{p,m}) \} = K_S \gamma_{\Delta S}(\hat{\sigma}_{p,m} - \tilde{\sigma}_{p,m})
\]

where \( K_S \) is cost of keeping inventory, or the cost of product (if inventory is not kept).

2.2 Economic Value in Control Systems

Without the notion of profit, the sensor network design problem for closed-loop systems is formulated as follows: Measured but noisy outputs, \( y \), are used by a Kalman filter to generate an estimate, \( \hat{x} \), of the true system state, \( x \). This estimator is then used by the controller to coerce the various performance outputs into being close to zero (in deviation variables). A primary goal of the controller, is to achieve small standard deviations for the state (or output) variables, \( x \), as well as the manipulated variables \( u \). To capture these notions one can define a set of performance inequalities: \( \sigma_x^2 < \bar{x}_i^2 \) and \( \sigma_u^2 < \bar{u}_i^2 \), where \( \bar{x}_i \) and \( \bar{u}_i \) are the maximum acceptable standard deviations.

The trade-off concept of this formulation is that while the addition of a sensor will increase the system’s capital cost it will also increase the controller’s ability to satisfy the performance inequalities. Details of this formulation can be found in Chmielewski et al. (2002) and Peng and Chmielewski (2004a).

In recent decades, Model Predictive Control (MPC) has become a major vehicle for increasing process profitability, and thus will play a major role our new profit based problem formulation. Traditional controller designs were guided by a fear of constraints, resulting in operating points being placed near the center of a constraint polytope, rather than near the more profitable regions along the edges (see figure 1). The most profitable operating point, the Optimal Steady State Operating Point (OSSOP), is typically determined by a steady-state focused real-time optimizer. While operation at
this point is desired, it typically cannot be achieved while simultaneously observing all constraints, due to the influence of external disturbances. To deal with this, the use of a backed-off operating point was proposed (Narraway et al., 1991 and Loeblein and Perkins, 1999). Chmielewski and Manthanwar (2004) and Peng et al. (2004) have recently proposed a new Minimally Backed-off Operating Point (MBOP) selection problem. Starting from this MBOP selection problem, it is clear that the addition of sensors (i.e., better information to the controller) will allow for ever smaller MBOPs, and thus increased profit. The trade-off question is: When does the cost of adding sensors surpass the expected increase in profit? Details of this formulation can be found in Chmielewski and Peng (2004b).

2.3 Economic Value of Fault Detection

So far an optimal sensor network for fault diagnosis has been considered as the one that minimizes the cost of sensor network that detect and diagnose certain faults (Bhushan and Rengaswamy, 2000). We consider now that an optimal sensor network for fault diagnosis is the one that maximizes the difference between a benefit function that represents the ability of the sensor network to detect and diagnose faults and the cost of the instrumentation (Narasimhan and Rengaswamy, 2004). We start with the assumption that a fault occurring in the system affects some (or all) of the process variables, some of which are measured using the given sensor network. The Signed DiGraph (SDG) is a powerful technique that can be used to perform fault diagnosis based on limited quantitative information from the process. It assumes that it is possible to model the cause-effect behavior of the system. Thus, corresponding to each fault, one has a fault set of sensors that are affected by the fault and the direction in which the corresponding variable is affected. The observability problem is to pick a set of sensors \( \{S_i\} \) such that each sensor in this set occurs in at least one set of sensors affected by fault \( i \). But observability does not guarantee that one can know which fault(s) have taken place, only states that their effect has been observed. Resolution can be guaranteed by solving an augmented observability problem (Raghuraj et al., 1999).

Before determining the value of a sensor network, it will be necessary to quantify the value of detecting a particular fault. Faults in a process can be classified as structural, parametric or sensor faults (Venkatasubramanian et al., 2003). Structural faults, in general, lead to shut-down, and the value of a network that can diagnose structural faults can be calculated by the loss incurred during downtime. The value of detecting faults in controlled sensors can be calculated by quantifying unnecessary control effort that leads to loss in utility and the loss incurred from the products being off-spec (see section on the economic value of control). Biases in non-control variables are related to loss incurred through loss of precision (see section on economic value of accuracy). Gross errors in sensor faults can lead to loss of resolution property of the corresponding sensor network. The value of
detecting this fault can be quantified through the loss that one will incur due to the loss in resolution property. This would relate to the economic value in detecting the other parametric faults. A detailed discussion on the approach for calculating the value of various sensor networks can be found in Narasimhan and Rengaswamy (2004).

2.4 CSTR Example from the 3 Perspectives

Consider the CSTR system depicted in figure 2 which we assume we want to upgrade. This system is described elsewhere (Bhushan and Rengaswamy, 2000). We assume that the system currently has 6 sensors in place (C_A, C_Ai, T, V, F and P), all with a precision of 2%. Next we assume that 1% precision sensors can be place at any location, however if a 2% sensor already exists at that location then it must be removed before adding the 1% sensor. The annualized cost of adding a 1% sensor is $1000 even if it is replacing an old sensor. This annualized cost includes purchase, installation, maintenance and replacement costs (replacements being at periods equal to the average lifespan of the sensor). If an existing sensor is unchanged then the cost is $0. Next we define a profit function:

\[
p(C_A, F, F_c, F_{vg}) = M_{an} \left[ \alpha_1 (C_A - C_A) F - \alpha_2 F_c - \alpha_3 F_{vg} \right]
\]  

(5)

where \( \alpha_1 = \$0.375/\text{mole B} \), \( \alpha_2 = \$0.015/\text{ft}^3 \) of cooling water, \( \alpha_3 = \$0.00225/\text{ft}^3 \) of vapor pumped and \( M_{an} = 8760 \text{ hr/yr} \).

**Optimal solution from the Material Accounting perspective:** Production is given by \( P_B = F(C_{Ai} - C_A) \) and therefore \( \tilde{\sigma}_p = F(\tilde{\sigma}_{C_{Ai}} + \tilde{\sigma}_{C_A}) + (C_{Ai} - C_A)\bar{\sigma}_F \). Table 1 shows a few solutions for only one sensor added and one for all sensors. From the accounting point of view, it does not make sense to upgrade this CSTR system.

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C_Ai</td>
<td>131.5</td>
<td>1000</td>
<td>-868.5</td>
</tr>
<tr>
<td>2</td>
<td>F_{vg}</td>
<td>127.5</td>
<td>1000</td>
<td>-872.5</td>
</tr>
<tr>
<td>3</td>
<td>F_2</td>
<td>77.4</td>
<td>1000</td>
<td>-922.6</td>
</tr>
<tr>
<td>4</td>
<td>All sensors</td>
<td>355.8</td>
<td>13000</td>
<td>-12644.2</td>
</tr>
</tbody>
</table>

**Optimal solution from the Control perspective:** We start by linearizing the nonlinear dynamic model around the nominal operating point. The resulting linear model, \( \dot{x} = Ax + Bu + Gw \), has 5 states and 5 inputs (3 manipulated and 2 disturbance) \( x^T = [C_A \ T \ T_c \ V \ P]^T \), \( u = [F_c \ F \ F_{vg}]^T \), \( w = [F_i \ C_{Ai}]^T \). From this model we determine the set of possible steady-state operating points defined by the equalities, \( Ax + Bu + Gw = 0 \). Combining this with a set of upper and lower inequality bounds on each variable we define the set of feasible steady-state operating points. The profit function is then linearized around the nominal operating point. This along with the set of feasible steady-state operating points is used to define a steady-state optimizing LP. The solution to this LP (the OSSOP) has a profit of $4737/yr. This solution represents the amount of profit one would yield if zero cost perfect sensors were available and no disturbances acted on the system. Returning to the system dynamics, we start by assuming the disturbance inputs \( F_i \) and \( C_{Ai} \) will have standard deviations of 0.1 and 0.01,
respectively. Then if we solve the MBOP problem using the existing network we find the expected profit to be $2897/yr. If we now define an objective function as “controller based profit minus sensor costs” and apply the global search scheme, described in Peng and Chmielewski (2004b), we find that configuration 1 (of table 2) maximizes this function. The value column of table 2 simply illustrates the profit improvements over the existing sensor network, case 10.

Table 2: Value from the Control System Perspective

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C_A, P</td>
<td>7,060</td>
<td>2,000</td>
<td>5,060</td>
</tr>
<tr>
<td>2</td>
<td>C_A, T_c, P</td>
<td>7,630</td>
<td>3,000</td>
<td>4,630</td>
</tr>
<tr>
<td>3</td>
<td>C_A, T, P</td>
<td>7,610</td>
<td>3,000</td>
<td>4,620</td>
</tr>
<tr>
<td>4</td>
<td>C_A, V, P</td>
<td>7,090</td>
<td>3,000</td>
<td>4,080</td>
</tr>
<tr>
<td>5</td>
<td>C_A</td>
<td>4,870</td>
<td>1,000</td>
<td>3,870</td>
</tr>
<tr>
<td>6</td>
<td>P</td>
<td>4,500</td>
<td>1,000</td>
<td>3,500</td>
</tr>
<tr>
<td>7</td>
<td>T, P</td>
<td>5,420</td>
<td>2,000</td>
<td>3,420</td>
</tr>
<tr>
<td>8</td>
<td>C_A, T, T_c, V, P</td>
<td>8,090</td>
<td>5,000</td>
<td>3,080</td>
</tr>
<tr>
<td>9</td>
<td>T, T_c, V, P</td>
<td>6,150</td>
<td>4,000</td>
<td>2,140</td>
</tr>
<tr>
<td>10</td>
<td>none</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Optimal solution from the Fault Diagnosis perspective: The following faults are considered: \(C_{ai}^+, \ C_{ai}^-, \ F_i^+, \ F_i^-, \ C_d^-, \ U^-, \ T_i^+, \ T_i^-\), \(T_c^+, \ T_c^-\), which correspond to faults (positive or negative deviations as indicated by the signs) in inlet concentration of A, inlet flow rate, catalyst deactivation (as measured by catalyst activity), heat exchanger fouling (reduction in overall heat transfer coefficient or a fouling factor), inlet temperature of A and cooling water respectively. The value for each network, the resolution properties of the chosen networks etc. are discussed in detail by Narasimhan and Rengaswamy (2004). The best value-sensor cost from diagnosis perspective is configuration 1 (Table 3). A few other typical networks and their values are reported in Table 3.

Table 3: Value from the Diagnosis Perspective

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>T_c, T_i</td>
<td>7,810</td>
<td>2,000</td>
<td>5,810</td>
</tr>
<tr>
<td>2</td>
<td>F_c, T_c, T_i</td>
<td>7,810</td>
<td>3,000</td>
<td>4,810</td>
</tr>
<tr>
<td>3</td>
<td>T_c, T_c</td>
<td>4,720</td>
<td>2,000</td>
<td>2,720</td>
</tr>
<tr>
<td>4</td>
<td>F_c, T_c</td>
<td>4,720</td>
<td>2,000</td>
<td>2,720</td>
</tr>
</tbody>
</table>
3. Integrated Sensor Network Design

Addressing the integrated case, we first define the notion of integrated value. This is simply the sum of the individual values for a given network configuration. Next we define integrated profit increase as the integrated value minus sensor costs for the given configuration. Then the integrated design objective is to maximize the integrated profit increase. For this example, this can be identified as follows: It is clear that no upgrade would be done solely from the material accounting perspective. Consider now the union of the two best solutions from the control and fault perspectives: \([C_A, P, T_{ci}, T_i]\) (we list only the new sensors). The value from the accounting point of view is $61.6/yr. Therefore the integrated value for this upgrade is $14930/yr and the sensor cost is $4,000/yr. Then the integrated incremental profit is $10,930/yr. If one looks at all network combinations from the above tables, this configuration is found to be the best. However, one might notice that the union of the second best networks shown in the table from control and fault perspectives, that is: \([C_A, P, F_c, T_c, T_i]\), has an overall value $10,525/yr and is better than the union of the best configuration from the control point of view shown in Table 2 and any of the configurations from the fault point of view shown in Table 3. Since we have not conducted an exhaustive search, we cannot say this is the second best solution. Nevertheless, the discussion illustrates the synergism of the three perspectives and a need for a procedure to find the integrated solution.

Conclusions

In this paper, we present a new integrated approach to instrumentation design and upgrade. We first review the idea that a proper framework is given by that of maximizing Value-Cost, and not the prevalent one of minimizing costs. We then illustrate how this can be achieved for three different objectives (material accounting, control, and fault diagnosis), and we finally show how this concept can be used as the enabler for achieving an integrated design scheme.

We expect this technique to be implemented in a systematic way for larger flowsheets where simple enumeration of nodes cannot be performed. The small example shown in this paper has around 8000 candidate solutions to evaluate, so the need for an efficient solution procedure is clear. Some options are available. One can explore genetic algorithms, or see if one can modify the procedure of tree enumeration with bounding proposed by Bagajewicz (1997), which does not apply here in the form it was proposed. In addition, the cases of material accounting and control have not fully considered the effect of sensor biases. Further, the value of detecting sensor faults, which is coupled to gross error detection schemes, has to be investigated further. These are the next steps in our research.

Acknowledgments

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References


