COST-BENEFIT ANALYSIS OF INSTRUMENT MAINTENANCE POLICIES AND DATA RECONCILIATION RELATED TO PLANT DATA ACCURACY

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Abstract. Accuracy of process data is defined as the sum of the bias of the measurement plus its precision. In this paper, we overview the effect of using data reconciliation in the accuracy of data and we show the benefits of installing data reconciliation thus providing a tool to determine if a data reconciliation package is financially justified. Because new sensors improve the power of data reconciliation and gross error detection, we also discuss the effect of adding new sensors on accuracy, as well as on plant economics. Finally, instrument maintenance reduces the number of undetected gross errors, and therefore improves accuracy and plant economics. The tool we present helps determining how much a good (fast) corrective maintenance helps plant economics. In sum our methodology can help resolve the ever present dilemma of how much economic investment and operational resources should be put to strike the right balance with financial gains.

Keywords: Data Reconciliation, Instrumentation Upgrade, Economic Value of Accuracy

1. Introduction

A large amount of measurement data is available in modern chemical plants thanks to low cost and reliable sensors as well as digital signal processing systems. These data are invaluable for process operation & monitoring, process control and optimization, and production accounting. As a result, the need for more reliable and accurate measurements is unquestionable. Modern data processing techniques like data reconciliation and gross error detection appeared in the context of such demand. These techniques help improve accuracy of measurements by reducing the effect of random noise and eliminating biases above threshold values. Over the past four decades, many researches as well as industrial applications of data reconciliation and gross error detection have been reported. However, one of the main obstacles in the successful application of these data treatment techniques is that their economical benefit has been intangible to process engineers although their virtue in technical term is very well known. As known, these techniques improve accuracy of measurement. Thus, to quantify economical benefit of applying the data processing techniques, one needs to tie the accuracy of measurement to an economic value. Bagajewicz and co-workers were the first to address this problem through a series of papers. In these papers, the economical value of precision, the concept of software accuracy and the economical value of accuracy were introduced.

Bagajewicz et al. (2003, 2005) were able to obtain expressions for assessing 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 set point for the throughput of a plant when the measurements or estimators 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. Bagajewicz et al. (2003, 2005) showed that the probability of not meeting the targeted production is 0.25. They also developed an expression for expected downside financial loss associated to this probability.

In the next paper (Bagajewicz, 2005a), the software accuracy of estimators was introduced and was defined in the context that data reconciliation and gross error detection were used. If biases are too small to be detected, they smear all the estimators, including those of the variables for which the corresponding instruments have no bias, called induced bias. The software accuracy of an estimator was then given as summation of precision and induced bias rather than precision plus actual bias as in conventional definition. The concept of software accuracy was then used to develop economic value of accuracy.

Continuing the theoretical development introduced in two previous papers, (Bagajewicz, 2006) extended the concept of economic value of precision to include the effect of (induced) bias, namely the economic value of accuracy. Such economic value allows determining the economic gain when one makes use of accuracy-improving methods such as installing data reconciliation software, adding new sensors or implementing effective maintenance policy. The value of economic gain, in turn, helps to determine whether it is worthwhile to perform such investments, i.e., determine the balance between economic gain and the investment cost as represented by the net present value. In this paper, we first review briefly the concept of software accuracy, the theory of economic value of precision and economic value of accuracy. Finally, we discuss how one can use economic value of accuracy as performance measure (in economical term) of various accuracy-improving methods mentioned above.

2. Background

2.1. Software Accuracy

Accuracy was conventionally defined as precision plus the bias (Miller, 1996). However, that definition is of little practical use because bias size is generally unknown. Recently, accuracy was redefined in the context that data reconciliation and gross error detection were used to detect biases (Bagajewicz, 2005a). If biases are present somewhere in the system and they are too small to be detected, they smear all the estimators, including those of the variables for which the corresponding instruments have no bias, called induced bias. The induced bias ($\hat{\delta}$) is defined as the difference between expected values of the estimators $E[\hat{x}]$ when gross errors are present and the true value x of process variables (Bagajewicz, 2005a):

$$\hat{\delta} = E[\hat{x}] - x = [I - SW]\delta \qquad (1)$$

In this expression S is the variance covariance matrix and $W = A^T \left(ASA^T\right)^{-1} A$, A being the process incidence matrix. Then accuracy is defined as the sum of precision plus the induced bias in the estimator:

$$\hat{a}_i = \hat{\sigma}_i + \delta_i^* \tag{2}$$

where $\hat{a}_i, \hat{\sigma}_i, \delta_i^*$ are the accuracy, precision (square root of variance S_{ii}) and the undetected induced bias of the estimator, respectively.

By definition, the accuracy value relies on how one calculates the induced bias. Because the induced bias in the estimator is based on undetected biases whose sizes can be any value below the threshold detection values and their location can be anywhere in the system, the induced bias is a random number. Bagajewicz (2005a) proposed to calculate accuracy as the sum of precision and the maximum possible value of undetected induced bias. However, one can also calculate the induced bias as the expected value of all possible values. The latter is a more realistic approach. Monte Carlo simulation was recently used to determine the expected value of accuracy (Bagajewicz, 2005b, Nguyen & Bagajewicz, 2006).

2.2. Downside Expected Financial Loss

Bagajewicz et al. (2005) developed a formula for calculating economic value of precision based on the downside expected financial loss incurred by production loss. They argued that, due to biased measurement, there is a finite probability that the measurement or estimator is above the target but in fact the real flow is below it. Therefore, when the measurements or estimators suggest that the targeted production is met or surpassed, an operator did not make any correction to the production throughput. In such situation, the production output is below target and financial loss occurs. They showed that the probability of not meeting the targeted production is 0.25. They then developed an expression for expected downside financial loss associated to this probability. The general expression obtained is the following:

$$DEFL(\hat{\sigma}_p,\sigma_p) = \int_{-\infty}^{m_p^*} g_p(m_p,m_p^*,\sigma_p)\left\{K_s T\int_{-\infty}^{m_p^*}(m_p^*-\hat{m}_p)g_M(\hat{m}_p,m_p,\hat{\sigma}_p)d\hat{m}_p\right\}dm_p \qquad (3)$$

where g_M is the probability distribution of the measurements ($\hat{m}_p$) of the flowrate of the pth product stream around their mean m_p and g_p the distribution of the true value m_p around its mean m_p^* (targeted value), K_s is the cost of the product and T is the time window of analysis. Under simplified assumptions of negligible process variations (i.e., $\sigma_p/\hat{\sigma}_p << 1$) and normal distributions of the process variation and the measurements, the equation (1) reduces to $DEFL$ = 0.19947 $K_s T\hat{\sigma}_p$ (Bagajewicz et al. 2005).

One may argue that, in reality, one can remedy the production by using inventory. This is indeed the case in many industries such as those engaged in refining. In such a case, the value of K_s needs to be reassessed to reflect the cost of keeping inventory. Thus, in such the case, the theory does not change, only the value of K_s does.

Using the same concept of downside expected financial loss; Bagajewicz (2006) developed formulas for the economic value of accuracy by including the effect of (induced) bias in the economic value of precision. He assumed that, when an instrument fails, which happens with a certain probability $f_i(t)$ (a function of time), and that the size of the bias follows a certain distribution $\mathrm{h_i}(\theta_\mathrm{i},\bar{\delta}_\mathrm{i},\rho_\mathrm{i})$ with mean $\bar{\delta}_i$ and variance ρ_i^2. Thus, one needs to integrate over all possible values of the gross errors and multiply by the probability of such bias to develop. If it is assumed that one instrument fails at a time, then the probability of $\mathrm{n_b}$ instruments failing and the others not is given by: $\Phi_{i1,i2,\ldots,in_b}^{n_T} = f_{i1}(t)\ldots f_{in_b}(t)\prod_{s\neq i1,\ldots s\neq in_b}[1-f_s(t)]$. With all these assumptions, Bagajewicz (2006) obtained general expressions for the probability of missing the target, and the associated downside financial loss. Under simplified assumptions (negligible process variation and normal distributions), Bagajewicz (2006) showed general expressions for the financial loss when two or more gross errors being present in the system . He also showed that the *complete* expression for financial loss $DEFL$ is given by (Bagajewicz, 2006):

$$DEFL = \Psi^0 DEFL^0 + \sum_i \Psi_i^1 DEFL^1\Big|_i + .. \sum_{i1,i2,..,iN} \Psi_{i1,i2,..,iN}^n DEFL^N\Big|_{i1,i2,..,iN} \tag{4}$$

In equation (4), $\Psi_{i1,i2,...,iN}^n$ and $DEFL^N\Big|_{i1,i2,...,iN}$ are the average fraction of time the system is in the state containing *n* gross errors *i1, i2,..,iN* and its associated financial losses, respectively.

2.3. Procedure to Calculate Accuracy Value and Economic Value of Accuracy

Monte Carlo simulation was recently used to calculate expected value of accuracy. Firstly, Monte Carlo simulation is used to sample failure events, including failure time and bias size, of every sensor in the system. The sampling procedure is briefly described as follows (Nguyen and Bagajewicz, 2006):

- Failure times and bias sizes for every sensor in the system are sampled and recorded until the end of time horizon is reached. The sensor reliability function is used to sample sensor's failure time and the distribution function of bias is used to sample bias size of the measurement.
- The time intervals between failures in the system are obtained by combining the failure times of all sensors.
- At each failure time in the system, the MP measurement test is performed and the sensors that are detected being biased are singled out.
- If the MP measurement cannot detect any bias, no action is needed and the next time interval is then investigated. Otherwise (the MP flags the presence of biases), for each sensor with detected bias, the failure events are updated starting from that time interval. The sensor with detected bias is repaired, then it resumes work, and next a failure event is sampled (if the time is still within time horizon).

From the information obtained from the sampling procedure, the fraction of time that the system is in a specific state can be obtained. The (undetected) bias sizes are used to calculate the integrals in the expression of financial loss. Finally, the complete financial loss DEFL is calculated.

3. Cost – Benefit Analysis of Instrumentation Upgrade Using Economic Value of Accuracy

3.1. Cost - Benefit Analysis

Instrumentation upgrade improves accuracy value of measurement, which is tied to financial loss. Thus, the economical benefit of instrumentation upgrade is calculated as the difference in financial loss (*DEFL*) before and after instrumentation upgrade. The net present value of instrumentation upgrade (IU) is given by:

$$NPV = d_n \left\{ DEFL(\text{before IU}) - DEFL(\text{after IU}) \right\} - \left\{ \text{cost of IU} \right\} \quad (5)$$

where d_n is sum of discount factor for n year; the cost can be the cost of purchasing of new sensor (when adding new sensor) or the cost of license (when installing data reconciliation software). A large value of net present value of instrumentation upgrade investment may justify this type of investment.

Next, we show case studies of the cost-benefit analysis using the following example process, which is a crude distillation unit (CDU):

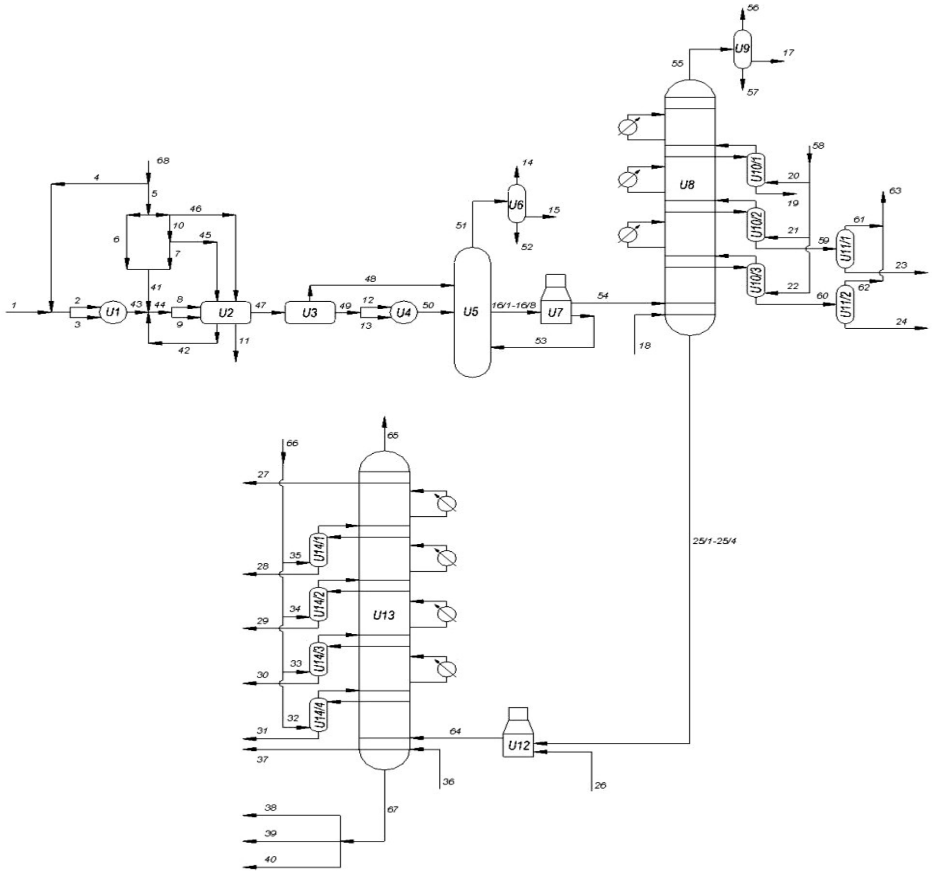

Figure 1. Example 1: crude distillation unit

Stream data for this example process is given table 1. The cost of product is given in table 2. Standard deviations of sensors are 1.5%. The following case studies are extracted from published papers (Bagajewicz et al., 2005 and Bagajewicz, 2006).

3.2. Case studies

Case a: net present value of installing data reconciliation software using value of precision.

For this case study, the cost of crude oil is 30 $/bbl, the economic value of precision (i.e. not considering effect of biases) is used in the calculation of the financial loss (equation 3). The downside financial loss for the existing instrumentation without the aid of data reconciliation is around $7.36 million, whereas after applying data reconciliation it decreases to $7.12 million. This renders a net present value (over only 5 years) of $236,817.

Case b: net present value of installing data reconciliation software using value of accuracy.

Table 1. Stream data for crude distillation unit

Stream Number	Measured Flow Rate (kg/h)	Mass Flow Rate from Balance (kg/h)	Standard Deviation (kg/h)	Flow Rate after DR* (kg/h)	Standard Deviation after DR (kg/h)	Stream Number	Measured Flow Rate (kg/h)	Mass Flow Rate from Balance (kg/h)	Standard Deviation (kg/h)	Flow Rate after DR (kg/h)	Standard Deviation after DR (kg/h)
1	418839		6283	413336	1259	31	18187		273	18196	191
2	212050		3181	209310	2339	32	312		5	314	4.87
3	213020		3195	210256	2341	33	338		5	340	4.87
4	6231		93	6231	91	34	325		5	327	4.87
5	20352		305	20327	244	35	311		5	313	4.87
6	7174		108	7174	108	36	3226		48	3225	48
7	7256		109	7256	109	37	18097		271	18106	190
8	230650		3460	230650	3460	38	15141		227	15154	224
9	229870		3448	229870	3448	39	20245		304	20268	297
10	10188		153	10188	153	40	12650		190	12659	188
11	26180		393	26243	391	41		14430			192
12	209170		3138	206932	2296	42		26523			5048
13	208950		3134	206718	2295	43		419566			1256
14	5122		77	5124	54	44		460520			4886
15	21434		322	21467	227	45		2932			192
16/1	62562		938	61562	938	46		2966			288
16/2	60985		915	60985	915	47		413651			1186
16/3	61253		919	61253	919	48		0			NA*
16/4	61490		922	61490	922	49		413651			1191
16/5	61009		915	61109	915	50		413651			1200
16/6	60796		912	60796	912	51		27068			192
16/7	62012		930	62012	930	52	478		7	478	7
16/8	60413		906	60413	906	53		103938			2849
17	45680		685	45829	478	54		386582			1171
18	4275		64	4272	64	55		57169			494
19	26084		391	26133	275	56	7130		107	7137	107
20	155		2	156	1.98	57	4200		63	4202	63
21	256		4	260	3.83	58	795		12	759	5.85
22	337		5	343	4.65	59		73900			752
23	73319		1100	73704	753	60		50852			538
24	50533		758	50716	528	61	196		3	196	3
25/1	45721		686	45902	615	62	136		2	136	2
25/2	45698		685	45878	615	63		332			3.6
25/3	45747		686	45928	615	64		185593			721
25/4	45671		685	45851	615	65	4512		68	4513	68
26	2035		31	2035	31	66	1322		20	1293	9
27	38515		578	38557	392	67		48081			245
28	18921		284	18931	198	68	26583		399	26559	249
29	19835		298	19846	208						
30	23864		358	23880	249						

NA: not applicable, DR: data reconciliation.

A time horizon of 5 years was used. In the complete expression of financial loss (Eq. 4), we calculate only the terms corresponding to the two cases: no bias is present and one bias is present (i.e., the first two terms in the equation). This simplification is justified if flowmeters are well-maintained such that the probability of two failures at the same time is very small, which is the case for this example (that probability is smaller than 2.5%). Therefore, we obtain a lower bound for the financial loss. When there is no data reconciliation, the financial loss was calculated to be 23.82 million. If data reconciliation is used, the financial loss is 7.38 million. Thus, the net present value of data reconciliation is 16.44 million. This proves that in plants of this size, the financial loss due to biases is far larger than the one due to precision. More detail can be found in Bagajewicz, 2006.

Case c: net present value of adding new sensors using economic value of precision.

The economic value of precision was used in the calculation of financial loss (equation 3). We do not explore here any strategy to optimize the addition of new instrumentation. Rather, we illustrate the effect of adding an instrument of 1.5% standard deviation to some streams. The results are shown in Table 3. The first column of this table indicates which instruments have been added. The second column indicates the net present value of the project, assuming no data reconciliation package has been installed, whereas the third column indicates the net present value for the case where the plant already has data reconciliation installed and in use.

Table 2. Stream values for crude distillation unit

Stream	Ks ($ / kg)	Stream	Ks ($ / kg)
14–15	0.13	28	0.13
17	0.14	29	0.12
19	0.25	30	0.11
23	0.24	31	0.1
24	0.23	37	0.08
27	0.15	38–39–40	0.06

Table 3. Effect of new flowmeters on savings

Location of New Sensors	NPV Without Originally Installed Data Reconciliation	NPV With Originally Installed Data Reconciliation
14, 15, 17, 19, 23, 24, 27, 28, 29, 30, 31, 37, 38, 39, 40	$2,088,108	$1,851,290
14, 15, 17, 19, 23, 24, 27, 28, 29, 30, 31, 37, 38, 39	$2,098,762	$1,862,945
14, 15, 17, 19, 23, 24, 27,28, 29, 30, 31, 37, 38	$2,071,202	$1,834,384
14, 15, 17, 19, 23, 24, 27, 28, 29, 30, 31, 37	$2,052,908	$1,816,091

4. Cost – Benefit Analysis of Maintenance Policies Using Economic Value of Accuracy

4.1. Maintenance Policies

It has been shown that the financial loss without bias $DEFL^0$ is less than financial loss in the presence of biases $DEFL^1\big|_i, DEFL^2\big|_{i1,i2}, \ldots$ (Nguyen et al., 2005). Looking at the complete expression for financial loss (Eq. 4), it is obvious that if one is to reduce financial loss, one can either directly reduce the individual financial loss (i.e., $DEFL^0, DEFL^1\big|_i, DEFL^2\big|_{i1,i2} \ldots$) by instrumentation upgrade, or one can increase the fraction of time that the system is in the state containing no biases Ψ^0 (as the result, the fractions of time that the system is in the sate containing biases $\Psi_i^1, \Psi_{i1,i2}^2, \ldots$ are reduced). This is where maintenance policies come into play because different maintenance schemes of sensor system affect the mentioned fraction of time. We discuss here the effect of corrective maintenance only. Preventive maintenance is left for future work.

Reactive (corrective) maintenance only

Reactive maintenance is a kind of maintenance performed whenever an equipment failure is recognized and is aimed at correcting the failure and restoring the equipment function. This kind of maintenance policy is unplanned and demand-based; it represents the “Run-to-Failure” or “if it isn’t broken, don’t fix it” maintenance philosophy that used to prevail in manufacturing plants. Plant managers used to think that, since maintenance doesn't add value to plant’s products, the less spent on it, the better. The expenses of this wrong maintenance management are: high machine downtime, low production availability, high spare parts inventory cost, high overtime labor costs (Mobley, 2004).

Recently, maintenance management philosophy in manufacturing plants has shifted from “Run-to-Failure” mode to preventive or proactive mode (Mobley, 2004). Now the ultimate objective of maintenance program is to preserve equipments function to keep them running rather than to correct equipment failures. However, the corrective maintenance is still the basic element in modern maintenance programs in chemical plants because any recognized sensor failure needs to be corrected in time by corrective maintenance.

Because different maintenance schemes render different financial losses of the system, we use economic value of accuracy as performance measure (in economic term) of a specific maintenance program. Here we assume that corrective maintenance is the basic element in any maintenance program (because fault sensor needs to be repaired when failure is recognized). Also, because no purchasing of software and equipment involved is assumed, we use the net benefit “benefit minus cost” directly as objective function (to be maximized).

4.2. Example

Consider the example process given in figure 2. The process consists of 24 streams. The total flowrates are variables of interest. Assume that all streams are measured and the flowrates are given in Table 4:

Parameters of sensors are given below:

- Precision = 2.5 % (for all sensors).
- Failure rate: r_i = 0.01 (1/day), i = 1, 3, 5,..., 23 and r_i = 0.02 (1/day), i = 2, 4, 6,…,24.

- Repair time R_i = 1 day, i = 1, 3, 5,…, 23 and R_i = 2 day, i = 2, 4, 6,…, 24.
- Measurement biases are assumed to follow normal distribution with zero mean and standard deviation of 4.0 (for all sensors).
- A time horizon of one year is used.

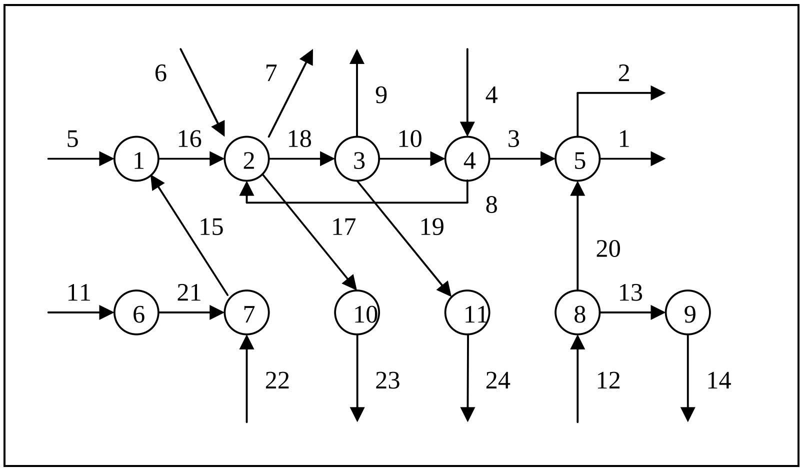

Figure 2. Flowsheet of example 2

Table 4. Flowrates of example 2

Stream	Flow	Stream	Flow	Stream	Flow
S_1	140	S_9	10	S_{17}	5
S_2	20	S_{10}	100	S_{18}	135
S_3	130	S_{11}	80	S_{19}	45
S_4	40	S_{12}	40	S_{20}	30
S_5	10	S_{13}	10	S_{21}	80
S_6	45	S_{14}	10	S_{22}	10
S_7	15	S_{15}	90	S_{23}	5
S_8	10	S_{16}	100	S_{24}	45

The following parameters are used in the calculation (the exact values for the parameters are not available, so they are estimated):

- The time window of analysis T in the calculation of financial loss is 30 days (this is based on the argument that, by mean of production accounting calculation every month, one can detect the loss in production that has been covered by biased measurement).
- The cost of product (or cost of inventory) K_s per day is $10000.

The product stream for which financial loss is calculated is stream 1.

4.3. **Results**

When there is data reconciliation, biases above threshold values are detected and the fault sensors are repaired under corrective maintenance program. However, when there is no data reconciliation, biases can not be detected using data treatment technique. They can only be detected when the fault sensor is inspected under preventive maintenance program or the sensor failure is so obvious that the operator can detect sensor failure. Here we assume that, when there is no data reconciliation and no preventive maintenance (i.e., corrective maintenance only), biases are not detected. One may notice that, without data reconciliation, corrective maintenance is of no use for the fault sensor because sensor failure is not detected; hence the fault sensor is not repaired under corrective maintenance program. The calculation results for accuracy value of the product stream (S_1) and the financial loss are shown in table 5.

Table 5. Accuracy value and financial loss for example 2

	Corrective maintenance only With data reconciliation	Corrective maintenance only Without data reconciliation
Accuracy of measurement of stream S_1	2.8109	4.1696
Financial loss DEFL	$ 169,380	$ 288,900

The result shows that the accuracy value and financial loss in the case no data reconciliation is used is more than the corresponding values when data reconciliation is used. The economical benefit of using data reconciliation is 119,520 $.

5. Conclusions

The economic value of accuracy can be used to calculate economical benefit of various instrumentation upgrade investments such as installing data reconciliation, adding new sensors. The cost-benefit analysis using economic value of accuracy for different maintenance schemes also allows one to determine the best maintenance scheme that renders highest net benefit among many candidates under investigation. The calculation results show that accuracy-improving methods such as instrumentation upgrade and maintenance are worth implementing when one considers their benefit both in technical term (accuracy value is improved) and in economic term (large net present value or net profit).

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