On the impact of sensor maintenance policies on stochastic-based accuracy

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ABSTRACT

The concept of stochastic-based accuracy and its calculation procedure for the case of corrective maintenance in data reconciliation-based systems were recently presented [Bagajewicz, M. (2005b). On a new definition of a stochastic-based accuracy concept of data reconciliation-based estimators. In: *Proceedings of the 15th European symposium on computer-aided process engineering*; Bagajewicz, M., & Nguyen, D. (2008). Stochastic-based accuracy of data reconciliation estimators for linear systems. *Computers and Chemical Engineering, 32*(6), 1257–1269]. This paper discusses the effect of preventive maintenance policies in chemical plants on stochastic-based accuracy. We show and evaluate a few practical solutions to the problem. The extent to which an effective maintenance policy helps to improve accuracy is shown and the economic justification is provided. Two examples are provided.

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1. Introduction

Modern chemical plants make extensive use of process data for process monitoring, process control, process optimization and production accounting purposes. Thus, the performance of chemical processes and chemical plants relies on the availability of accurate plant data. As a result, the need for more reliable and accurate measurements and consequently variable estimators 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 estimators by reducing the effect of random noise and eliminating biases above threshold values. Although methods to improve accuracy exist, as discussed next, the economic justification for improving it had not been developed until recently.

Software accuracy of estimators was defined in the context of the use of data reconciliation in conjunction with some sort of gross error detection: It is the sum of precision and induced bias (Bagajewicz, 2005a) rather than precision plus actual bias as in the conventional definition (Miller, 1996). Induced bias is the bias resulting from undetected gross errors somewhere in the system affecting the variable under analysis through the smearing effect of data reconciliation. The first definition made use of the maximum induced bias (Bagajewicz, 2005a) and it represents the worst case scenario. To ameliorate the shortcoming and obtain some sort of averaged value, not an extreme one, a Monte Carlo simulation-based approach was proposed to calculate the expected value of accuracy (Bagajewicz, 2005b; Bagajewicz & Nguyen, 2008).

The accuracy value of a measurement, however, is of little practical use unless its economical benefit can be quantified. To address this, Bagajewicz and Markowski (2003) and Bagajewicz, Markowski, and Budek (2005) were able to obtain expressions for assessing the economic value of precision. Finally, Bagajewicz (2006) extended the concept of economic value of precision to include the effect of (induced) bias, that is, he obtained the economic value of accuracy. Such economic value allows one to determine the economical gain when one makes use of accuracy-improving methods such as installing data reconciliation software, performing instrumentation upgrade or implementing better (more effective) maintenance. The value of economic gain, in turn, helps one determine whether it is worthwhile to perform such investments, i.e., determine the balance between economical gain and the investment cost. Bagajewicz et al. (2005) and Bagajewicz (2006) provided examples on the economic value of performing data reconciliation and on the economic value of instrumentation upgrade.

Prior research works on the effect of maintenance on plant instrumentation performance are rare. Lai, Chang, Ko, and Chen (2003) proposed a mathematical programming model optimizing a hardware-redundant sensor network used in a corrective maintenance program. Sanchez and Bagajewicz (2000) investigated the impact of corrective maintenance in the design of sensor network. In both works, the impact of corrective maintenance is studied from a technical viewpoint rather than an economic one: system reliability/availability, which is dependent on a corrective maintenance program, is used as an objective function or a constraint in the sensor network design problem. On the other hand, the problem of optimization of preventive maintenance has been extensively studied, mainly by people in the field of industrial engineering and operation research. An extensive review of maintenance optimization models was given in Wang and Pham

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(2006); the most commonly used problem formulation is to minimize maintenance cost rate (cost per unit time) subjected to constraint on availability/reliability of the system. A few works on maintenance optimization in chemical process plants have also been published. Dedopoulos and Shah (1995) proposed a simple MILP model to optimize preventive maintenance policy for multipurpose plant equipment. Tan and Kramer (1997) presented a general framework for maintenance optimization in chemical process plants using Monte Carlo simulation as modeling tool and Genetic Algorithm. Vassiliadis and Pistikopoulos (2001) optimized preventive maintenance policies under uncertainty using a MINLP model. Goel, Grievink, and Weijnen (2003) presented a MILP model that optimally selects initial reliability of equipment along with the selection of process configuration, production and maintenance planning for multipurpose process plants at the design stage. Liang and Chang (2008) simultaneously generated the design specifications and the corresponding maintenance policies for protective systems (the systems of sensors and valves that perform two basic functions: alarm and shutdown) using integer programs. Process plant equipments in general were considered in the mentioned works on maintenance optimization except Liang and Chang's work while this work specifically considers the sensor systems for process monitoring purpose.

This paper discusses different commonly used maintenance policies in process plants and their effect on the expected accuracy value as well as on the economic value of accuracy. Different maintenance strategies dictate how maintenance personnel monitor sensor faults and keep sensors functioning so they have direct effect on the accuracy value of measurement, which is in turn coherently tied to economic value of accuracy. Thus, we focus on investigating the economical effect of maintenance on process plant instrumentation performance. Optimization of instrumentation and/or maintenance policy based on the results obtained in this work is not addressed.

The paper is organized as follows: the concepts of software accuracy, the theories of economic value of precision and the economic value of accuracy are first briefly introduced. Next, the Monte Carlo simulation-based procedure to determine the expected value of accuracy and the economic value of accuracy is described. Then, we discuss how one can use economic value of accuracy as an economical performance measure of various maintenance schemes. Finally, the procedure to obtain the best maintenance scheme that renders the highest economical benefit is introduced. Two examples are finally provided.

2. Background

2.1. Software accuracy

Accuracy was conventionally defined as precision plus bias (Miller, 1996). However, the definition is of little practical use because bias size is generally unknown. Recently, Bagajewicz (2005a) introduced the concept of software accuracy in the context of data reconciliation and gross error detection being used to detect biases. In such context, accuracy was defined as sum of precision and induced bias instead of the actual bias. The induced bias and the software accuracy are shown next (Bagajewicz, 2005a):

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

$$\hat{a}_i = \hat{\sigma}_i + \delta_i^* \qquad (2)$$

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

By definition, the accuracy value relies on how one calculates the induced bias. Bagajewicz (2005a) proposed to calculate the induced

bias as the maximum possible value and recently, Bagajewicz (2005b) and Bagajewicz and Nguyen (2008) proposed to calculate the induced bias as the expected value of all possible values, which is more realistic, and used a Monte Carlo simulation-based procedure to obtain such expected value.

2.2. Downside expected financial loss

Bagajewicz et al. (2005) presented the theory of economic value of precision and developed formulas for assessing downside financial loss incurred by production loss. They argued that, due to inaccuracy (caused by random errors) of the estimator of a product stream flowrate, there is a finite probability that the estimator is above the target but in fact the real flow is below it. In such situation and under the assumption that the operators did not make any correction to the production throughput set point when the estimator suggested that the targeted production has been met or surpassed, the production output will be below the target and financial loss occurs. The financial loss under simplified assumptions of negligible process variations and normal distributions of the process variation and the measurements was found to be $DEFL = 0.19947 K_s T \hat{\sigma}_p$ where K_s is the cost of the product (or the cost of inventory) and T is the time window of analysis (Bagajewicz et al., 2005).

Using the same concept of downside financial loss, Bagajewicz (2006) extended the theory of economic value of precision to include the effect of (induced) bias, namely the economic value of accuracy. The expression for financial loss $DEFL$ considering bias is given by (Bagajewicz, 2006):

$$DEFL = \Psi^0 DEFL^0 + \sum_i \Psi_i^1 DEFL^1|_i + \sum_{i_1,i_2} \Psi_{i_1,i_2}^2 DEFL^2|_{i_1,i_2} + \cdots$$

$$+ \sum_{i_1,i_2,\ldots,i_N} \Psi_{i_1,i_2,\ldots,i_N}^n DEFL^N|_{i_1,i_2,\ldots,i_N} \qquad (3)$$

In this equation, $\Psi_{i_1,i_2,\ldots,i_N}^n$ and $DEFL^N|_{i_1,i_2,\ldots,i_N}$ are the average fraction of time the system is in the state containing n gross errors $i_1, i_2, \ldots, i_N$ and its associated financial losses, respectively. Detail expression and procedure to calculate the financial loss for system containing n biases $i_1, i_2, \ldots, i_N$ can be found in Nguyen Thanh, Siemanond, and Bagajewicz (2006).

Applications of the theory of economic value of precision/accuracy for the determination of economical benefit of instrumentation upgrade were shown by Bagajewicz et al. (2005) and Bagajewicz (2006). The economical benefit of an instrumentation upgrade was calculated as the difference in downside financial loss ($DEFL$) before and after such upgrade. The net present value of instrumentation upgrade (IU) was then given by:

$$NPV = d_n \{DEFL(before\ IU) - DEFL(after\ IU) - \cos t\ of\ \text{IU}\} \qquad (4)$$

where d_n is sum of discount factor for n years. The cost can be the cost of purchasing of new sensor (when adding new sensors) or the cost of license (when installing data reconciliation software). A large value of the net present value of instrumentation upgrade may justify this type of investment. Case studies on the value of performing data reconciliation as well as savings of adding new sensors at selected locations to the sensor network of a crude distillation unit were provided by Bagajewicz et al. (2005) and Bagajewicz (2006).

It has been also shown that the financial loss without bias $DEFL^0$ is smaller than financial loss in the presence of biases $DEFL^1|_i$, $DEFL^2|_{i_1,i_2}$, ... (Nguyen Thanh et al., 2006). Looking at the complete expression for financial loss (Eq. (3)), it is obvious that if one is to reduce financial loss, one can either directly reduce the individual financial loss (i.e., $DEFL^0$, $DEFL^1|_i$, $DEFL^2|_{i_1,i_2}$, ...) by instrumentation upgrade, or one can increase the fraction of time

that the system is in the state containing no biases Ψ^0 (as a result, the fractions of time that the system is in the state containing biases Ψ_i^1, Ψ_{i_1,i_2}^2, ... are reduced). This is where maintenance policies come into play because different maintenance schemes of sensor system affect the aforementioned fractions of time.

2.3. Procedure to calculate accuracy and economic value of accuracy

Monte Carlo simulation was recently used to calculate the expected value of accuracy. The sampling procedure is as follows (Bagajewicz & Nguyen, 2008):

- 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 failure times of each sensor and the density distribution function of bias (assumed to be normal distribution with zero mean) is used to sample the corresponding bias size.
- 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 maximum power measurement test (MPMT) is performed and the sensors that are detected being biased are singled out.
- If the MPMT does not detect any bias, no action is needed and the next time interval is then investigated. Otherwise, if the MPMT flags the presence of biases, each sensor with detected bias is assumed to be repaired and then resumed work. Next, all subsequent originally sampled failure events are erased and the new failure events are sampled (if the time is still within the time horizon).

From the information obtained from the sampling procedure, the fraction of time that the system is in a specific state $\Psi_{i_1,i_2,...,i_N}^n$ can be obtained. Following the procedure described in Nguyen Thanh et al. (2006), the financial loss in a specific state $DEFL^N|_{i_1,i_2,...,i_N}$ (which are integrals with discontinuous integrand function) can also be calculated based on information about (undetected) bias sizes provided by Monte Carlo simulation. The final result is then calculated by Eq. (3).

3. Effect of maintenance on accuracy and financial loss

Today's industrial and manufacturing plants would be unable to operate competitively and profitably without an effective maintenance program. Machine and equipment failures are to be minimized in order to minimize production loss and downtime. Different kinds of maintenance policies are discussed next.

3.1. Corrective maintenance

Corrective maintenance (CM) is a kind of maintenance performed whenever an equipment failure is recognized. It is done to correct the failure and restore the equipment normal 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 (Mobley, 2004).

3.2. Preventive maintenance

Preventive maintenance (PM) is a preplanned (scheduled) inspection/repair performed at specific points in time to prevent/mitigate equipment failure, detect any hidden failure and retain equipment function. The preventive maintenance (PM) task takes many forms: inspection, lubrication, calibration. As a result of a PM program, failed sensors that are inducing undetected biases are fixed at the time when PM is performed, while CM takes care of the repair when biases are detected.

The implementation of a PM program can vary in frequency and schedule, depending on the available resource in process plant or the strategy of the organization.

4. Optimal maintenance planning maximizing economical benefit

To help in the task of planning/scheduling preventive maintenance, we propose to use the economical benefit as the performance measure of various candidate PM schemes to be contrasted with the associated cost to determine which plan renders maximum economical benefit (or, specifically, maximum net present value). The economical benefit of performing a certain schedule of PM is calculated as the difference in financial loss with PM and without PM (i.e., usually with CM only).

We introduce now a general optimization model to find the best maintenance scheme that renders maximum economical benefit. Let ψ be the set of selected sensors subjected to PM, T be the vector of scheduled maintenance times for the selected sensors. The first element of this vector gives the maintenance time of the first sensor in ψ and so on. We assume that the maintenance is cyclical. The optimization model is:

$$\left.\begin{array}{l} \underset{\psi,T}{Max}\{[DEFL^0 - DEFL(\psi,T)] - Cost(\psi,T\} \\ s.t. \\ N(\psi,T) \le AN \\ LH(\psi,T) \le ALH \end{array}\right\} \qquad (5)$$

The objective maximizes the benefit (financial loss before $DEFL^0$ minus the financial loss after the PM program is put in place) minus the cost. The constraints reflect limitations on resources: N is the number of sensors that are inspected/calibrated *at the same time* and LH is the required labor hours to perform PM. In turn, AN and ALH are the number of available maintenance personnel and available maintenance labor hours within the time horizon under consideration, respectively.

Because the objective value is evaluated stochastically using Monte Carlo simulation, the model cannot be solved using mathematical programming technique. We consider two solution procedures:

- Devising practical maintenance schemes for plant instrumentations taking into account resource limitation in the plant and following maintenance planning guidelines from literature. The benefit (the objective value) for each devised maintenance plan is evaluated and the best one among these candidates is identified. This approach is the approximate approach based on enumeration of a limited number of practical solutions. Because the enumeration is limited, the best found solution is not guaranteed optimal; however it is still useful because only practical solutions (determined manually by the user) are evaluated.
- Using stochastic search method (e.g. Genetic Algorithms or similar techniques) to optimize the model.

In this work, we use the first approach. We show commonly used maintenance planning schemes and their economical impact; the results provide perspectives on the benefit of different maintenance strategies in process plant.
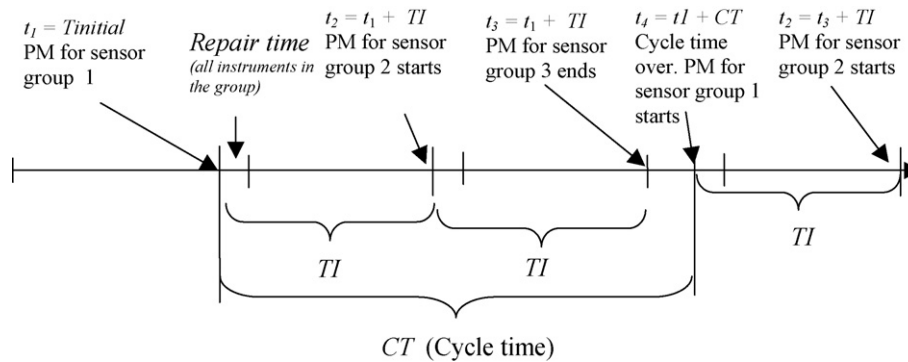
Fig. 1. Allocation of preventive maintenance times for different sensor groups.

5. Approximate models

In view of the numerical difficulties and the impracticality of many feasible solutions, various practical options (situations) can be defined as follows:

(1) *All* instruments are considered equally important, are subjected to PM and are inspected at the same time. This is usually the case if PM is performed periodically by a third party contractor. We call this strategy: "Periodic-All instruments at once".

(2) *All* instruments are subjected to PM program, which is performed by available maintenance personnel at the plant. However, due to limited maintenance human resource, it is required to appropriately schedule maintenance activities so that all instruments are preventively maintained at least once during the time horizon. This is achieved by associating sensors to different groups, which are to be maintained at different scheduled times. We call this strategy: "Periodic-All instruments in sequential groups". The size of each group would be commensurate with the number of available employees.

(3) *Only some sensors* are subjected to PM, because the human resource in the plant is limited. Usually, sensors that measure important variables for production accounting, critical control loops are selected for PM. We call this strategy "Periodic-Some instruments at once" or "Periodic-Some instruments in sequential groups", depending on the resource limitations.

Thus, to complement the above choices, the following decision variables are needed:

- Selection of important sensors that are subjected to preventive maintenance.
- Cycle (periodic) time interval (*CT*) to perform PM.

- Scheduling (group choices and sequential ord*er*) *of PM of* important sensors.

To simplify the scheduling task we propose to:

(i) Choose the cycle (periodic) time interval (*CT*) and use it as a parameter.

(ii) Group important sensors into *n* groups. The number of groups of sensors (*n*) is chosen a-priori and all groups have, if possible, the same number of sensors.

- The maximum number of selected sensors is calculated as the available maintenance labor hours within the duration of the time horizon divided by the average labor hours for inspecting a sensor.
- The selection of sensors to be included in each group is done in such a way that sensors with high failure rate or operate under harsh conditions (i.e. they are more likely to fail than the others) should be inspected first. Thus sensors are sorted in descending order of degree of urgent need for PM (e.g. descending order of failure rate), and kept adding sensors to the different groups until all candidates are chosen.
- In the extreme cases where observability is lost (e.g. when sensor fails and data reconciliation is not used), we assume that the estimation of the variable during sensor's repair time is possible by using historical data. We assume a precision of three times the historical precision observed.
- We first decide on the time interval between PM actions (*TI*) of two groups of sensors (illustrated in Fig. 1).
- We assume that at the beginning (*t* = 0), all sensors are as good as new. The first time at which PM is performed (*Tinitial*) is a parameter in the model. We illustrate the scheduling in Fig. 1 where the allocation of different times for PM of two different sensor groups (1 and 2) is shown for the "Periodic-All instruments at once" option. Note that the cycle time needs not be
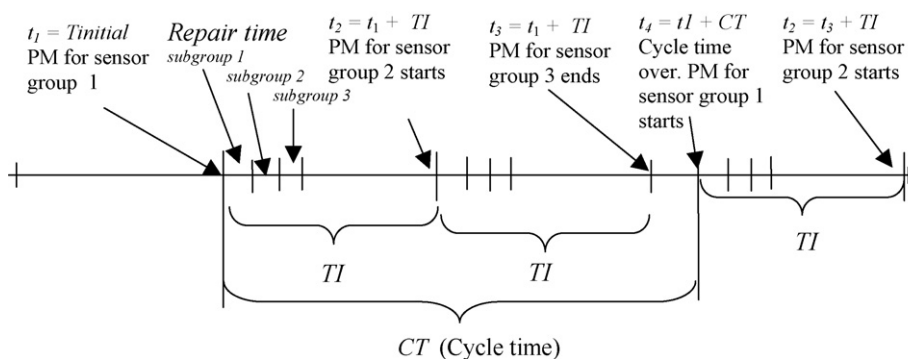

Fig. 2. Allocation of preventive maintenance times for resource limitations.
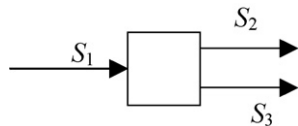
Fig. 3. Flowsheet for example 1.

the same as the sum of the time intervals, that is, $nTI \leq CT$. In turn, Fig. 2 shows the "Periodic-All instruments in sequential groups" option. When only some instruments are maintained the figures are conceptually equivalent.

(iii) In calculating the maintenance cost, we consider only the labor cost and the material costs (e.g. cost of spare parts).

(iv) Sensors can be inspected, calibrated online without interfering with production.

6. Sampling procedure

In the first step of sampling procedure, the bias size is sampled and is left in the measurement until the time horizon is reached or the instrument is repaired. Then, the maximum power measurement test (MPMT) is used to decide whether that bias is undetected (in which case it will stay that way until the end of the time horizon or until PM is performed) or detected. In the latter case, if repair is performed, the sensor is off line for a small period of time, within which the residual precision is assumed, the sensor is then added in line as brand new one. A new sampling is then performed starting from the time the repaired sensor resumes service. In the case that there is no data reconciliation, there is no MPMT test to detect biases and hence the biases will be present in the measurement until the end of the time horizon or when PM is performed.

When there is data reconciliation but no repair, if the bias is detected, we assume that one can simply remove the measurement. If that time (the time that PM is performed) is still within time horizon, we sample new failure events for the sensor starting from that time.

7. Examples

7.1. Example 1

This small example was discussed by Bagajewicz and Nguyen (2008) (Fig. 3). We follow up with new results to highlight the effect of the different decision making, especially PM related ones. We focus on accuracy, leaving financial losses and optimality to be discussed in the next example.

The sensor data is as follows (Bagajewicz, 2005b): sensor precision $\sigma_i^2 = 1, 2, 3$; failure rate: 0.025, 0.015, 0.005 (1/day) and repair time: 0.5, 2 and 1 (day), respectively. It is also assumed that biases follow a normal distribution with zero mean and standard deviations $\rho_k = 2, 4$ and 6, respectively. The accuracy of the estimator for product stream flowrate S_3 is calculated. The calculation procedure is implemented in FORTRAN running on a 2.8 GHz Intel Pentium, 1024 MB RAM PC.

When any two out of the three sensors fail at the time and are removed for repair, the measurements associated with those fault sensors become unobservable. If historical data is recorded, it can be used to estimate the variable during repair time. The residual precision (during the repair time) is assumed to be 3 times the precision.

The following situations are considered:

- *Case 1*: Neither data reconciliation (DR) nor any kind of maintenance is used; the bias in measurements is therefore not detected.
- *Case 2*: There is no data reconciliation but PM is used; hence, sensor failures can be detected by sensor inspection only, which take place every 365 days.
- *Case 3*: Data reconciliation is used without any kind of maintenance. It is assumed that when a bias is detected due to sensor failure, the measurement is simply ignored.
- *Case 4*: Data reconciliation is used together with CM; hence, when a bias is detected through software detection techniques, the sensor is repaired and resumes service afterward. No PM is used.
- *Case 5*: Data reconciliation is used together with CM & PM; hence, sensor failures can be detected either by data treatment techniques or by sensor inspection under a PM program. For this case, considering the three PM schemes as follows:
  - All three sensors are inspected every 180 days.
  - All three sensors are inspected every 365 days.
  - Only the sensor measuring the product stream is inspected every 180 days.

The number of Monte Carlo sampling is 10^5. The results are shown in Table 1. The computation time varies from less than 5 s when neither data reconciliation nor maintenance is used to about 8 min when data reconciliation and PM are used. This computation time reduces if fewer samples are taken.

Although cases 1 and 3 are unrealistic (at least some basic types of maintenance policies are implemented in the plant), they are included for comparison. The results show how much the use of maintenance and data reconciliation improves accuracy and how much more the use of preventive maintenance improves accuracy. Moreover, they also assess the impact of frequency. Data reconciliation (together with gross error detection) improves accuracy by reducing the effect of random noises and detecting biases above threshold values. The effect of the maintenance policy is better explained when one looks at the behavior of accuracy value with time. We show in Fig. 4 the accuracy value as function of time for the cases 1, 2, 3 and 5b.

Case 4 (data reconciliation and CM are used) was already shown by Bagajewicz and Nguyen (2008) and it has the same trend as the one shown in Fig. 4A and C (for case 1 and case 3), that is, the accuracy value increases progressively with time. When PM is used (case 2 and case 5b), at the time sensors are inspected, undetected biases (when no data reconciliation is used or they are too small to be detected) are eliminated because the sensors are repaired. The results of using PM are:

Table 1
Calculation results for example 1.

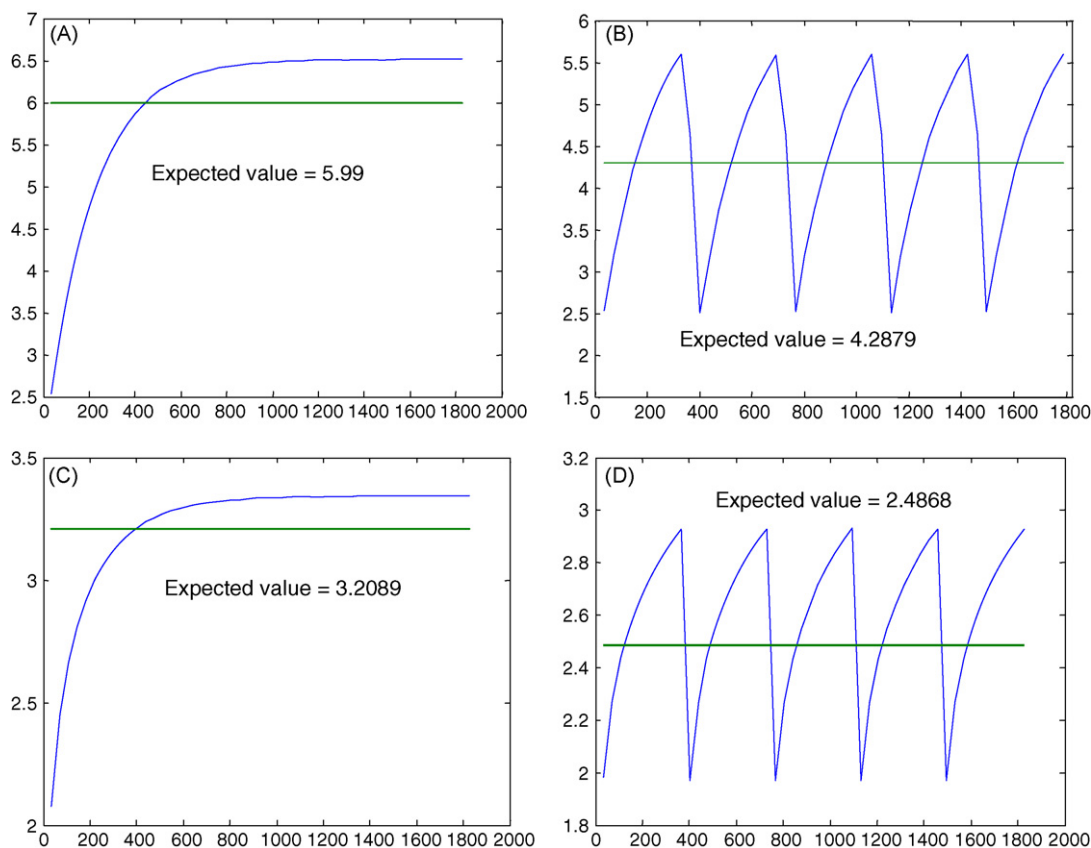| Cases	Data management	Maintenance management	Accuracy
1	No data reconciliation	No maintenance	5.9905
2		PM every 365 days	4.2879
3	Using data reconciliation	No maintenance	3.2089
4		Only CM	3.0752
5a		CM & PM every 180 days for all sensors, all at once	2.0668
5b		CM & PM every 365 days for all sensors, all at once	2.4868
5c		CM & PM every 180 days only for sensor S_3	2.2694

Fig. 4. Accuracy at specific points in time when preventive maintenance is used. (A) Case 1, (B) Case 2, (C) Case 3, and (D) Case 5b.

(i) Accuracy improves (e.g. accuracy in case two is less than in case one).

(ii) Accuracy increases with time, but it will be improved (back to the level of "as good as new" if the maintenance is perfect) at the scheduled PM times. Obviously, the larger the frequency of maintenance, the shorter the cycles and therefore the accuracy is smaller.

We now focus on the effect of maintenance polices on financial loss by considering another example, a larger scale process. This example is used to demonstrate the use of expected financial loss in the planning/scheduling of preventive maintenance.

7.2. Example 2

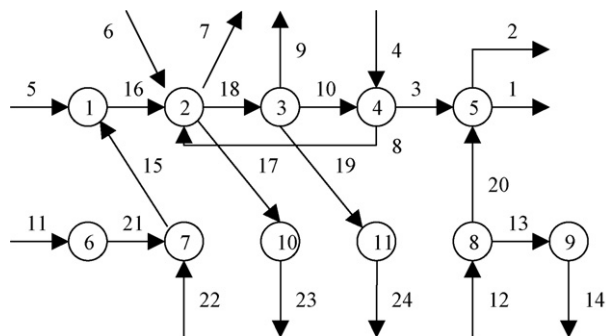Consider the process depicted in Fig. 5.

Fig. 5. Example 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 2.

Parameters in the example are given below:

- Sensor precision = 2.5% (for all sensors).
- Sensor failure rate: $\lambda_i = 0.01$ (1/day), $i = 1, 3, 5, \ldots, 23$ and $\lambda_i = 0.02$ (1/day), $i = 2, 4, 6, \ldots, 24$. Sensor repair time $R_i = 1$ day, $i = 1, 3, 5, \ldots, 23$ and $R_i = 2$ day, $i = 2, 4, 6, \ldots, 24$.
- A time horizon of 2 years is used.
- The first PM time ($T_{initial}$) is half of the cycle time (CT).
- The economical benefit of using PM is calculated using the difference of downside financial losses: $DEFL$ (with PM) $- DEFL$ (without PM).
- The average hours for inspecting/calibrating a sensor is 2 h.
- Cost of PM and CM includes labor cost and material cost.
- If PM is performed by a contractor, the PM labor cost (including traveling cost to the site, other costs) is 50 $/h. The PM cost (per month basis) is calculated as follows: 50 ($/labor hours) × 2 (labor hours/sensor) × 24 sensors × (number of PM cycles in a year)/12 (months).

Table 2
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

Table 3
Results for example 2 – strategy: "Periodic-All instruments at once".

Data management	Maintenance management	Accuracy S_1	Financial loss ($DEFL$)	Gross benefit	Total cost	Net benefit
No data reconciliation	No maintenance	4.46	150,750	0	0	0
	CM & PM every 180 days, all sensors	3.59	130,935	19,815	6,890	12,925
	CM & PM every 90 days, all sensors	3.21	122,235	28,515	8,506	20,009
With data reconciliation	No maintenance	3.86	123,030	27,720	2,000	25,720
	CM only	2.55	90,495	60,255	6,927	53,328
	CM plus PM every 180 days, all sensors	2.14	43,455	107,295	9,938	97,357
	CM plus PM every 90 days, all sensors	1.97	32,715	118,035	11,476	106,559

- Maintenance labor cost (for CM & PM) in the plant is calculated as the number of employees × 4000 ($/person/month).
- The materials cost for CM (e.g. cost of part replacement) is estimated to be 75% of the price of the brand new sensor, the materials cost for PM (e.g. cost of lubricating oil, calibrating agents) is estimated to be 5% of the price of the brand new sensor. Prices of sensors are 1000 for sensors 1, 2, 5, 6, 7, 11, 12, 22, 23, 24; 800 for sensors 3, 4, 8, 9, 10, 13, 14; 600 for 15, 16, 17, 18, 19, 20, 21.
- The time window of analysis T in the calculation of financial loss is 30 days (this is based on the argument that, by mean of production accounting calculation every month, one can detect the loss in production that has been covered by biased measurement).
- The cost of product (or cost of inventory) (K_s) per day is 5000$.
- Cost of license for data reconciliation (per month basis) is 2000$.

The product stream for which the financial loss is calculated is stream S_1. The following assumptions are made:

(i) No resource limitation for corrective maintenance is included, that is, *all* recognized fault sensor will be repaired in time, right after the failures are identified. If this assumption is relaxed, in the situation that there are too many failed sensors at the time, the repair of some sensors would have to be delayed.

(ii) Resource limitations on PM are taken care of by choosing the different options of grouping the sensors. For example when the sensors are arranged in groups of three it is assumed that there are resources to inspect three sensors at a time.

The number of Monte Carlo samplings used is 1.10^4. We used a 2.8 GHz Intel Pentium, 1028 MB RAM PC for this example. The computation time varies from about 45 min when neither data reconciliation nor maintenance is used to about 4 h when data reconciliation and PM are used. Reducing the number of Monte Carlo samplings to reduce computation time is at the expense of less accuracy of results, a well known trade-off in Monte Carlo simulation. It is recommended that the number of Monte Carlo samplings is not lower than 10^4 to obtain reasonably accurate results.

For completion and comparison, we will discuss all PM strategies and compare them with the use of CM only or no maintenance at all.

- Periodic Maintenance of all instruments at once:
  Table 3 summarizes all gross benefits as compared to the case of no maintenance and no data reconciliation (first row). It is assumed that, if maintenance (CM & PM) is used, there is one employee providing fast-response CM in the plant while PM is provided by third party contract. The total cost includes material cost of CM (determined from simulation), labor cost for CM (one employee), material and labor cost for PM (dependent on PM schedule) and the license fee for data reconciliation. All the cost results are shown in per month basis. All the assumptions stated in example 1 are also applied in this example.

  Table 3 shows clearly the benefit of using data reconciliation (to detect biases) and preventive maintenance (to detect hidden failures and preserve sensor condition): both of them significantly improve accuracy and reduce financial loss. The best result (lowest financial loss) is obtained when both data reconciliation and PM are used.

- Periodic Maintenance of all instruments in sequential groups:
  For this maintenance strategy, CM & PM are provided by available maintenance employees and the cost is calculated correspondingly. We consider two cases related to the number of maintenance employees available: case **a**: 3 people and case **b**: 1 person. Grouping of sensors (case **a**) is done in numerical order (from 1 to 24): three sensors are included at a time. For case **b**, sensors are sorted according to their failure rate. The sorted sensor list is: sensors 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23 (failure rate = 0.01) then sensors 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24. The PM schedule described by the cycle time (CT), PM starting time ($Tinitial$) and time interval (TI) between groups of sensors (or between individual sensor as in case **b**) together with calculated results are shown in Table 4. The gross benefit is calculated against the case of no data reconciliation, no maintenance.

  Case **b** renders much better benefit than case **a** because case **b** achieves the same job (preventively maintaining all sensors in a 90 days cycle), hence essentially the same financial loss, at a much lower labor cost (1 employee vs. 3 employees in case **a**). The results show that the financial loss depends mainly on the cycle time (i.e. PM frequency) and is relatively insensitive to the sequence at which the sensors are preventively maintained. The results also suggest that one employee is enough for this 24-sensor system.

- Periodic Maintenance of some instruments in sequential groups:
  We now explore the case where only some sensors are of concern and need PM and the rest is subjected to CM only. This is the case when maintenance resources (labor, tools, budget, etc.) are limited and PM for all instruments is impossible. Assuming that there is one employee responsible for both the process and the utilities system (hence labor resource is limited), then prioritization of PM duties is needed in this case. We assume that only 12 out of 24 sensors are preventively maintained and choose a cycle time of 6 months. We consider two cases: **c** (sensors 1–12 are selected) and **d** (sensors 13–14 are selected). Description of the two cases and the calculated results are shown in Table 5.

Table 4
Results for example 2 – strategy: "Periodic Maintenance of all instruments in sequential groups".

Case	Maintenance management	Accuracy S_1	Financial loss ($DEFL$)	Gross benefit	Cost	Net benefit
a	CM plus PM, 3 sensors in a group, CT = 90 days, TI = 10 days, $Tinitial$ = 15 days.	2.02	33,948	116,802	31,691	86,111
b	CM plus PM, One group, CT = 90 days, TI = 3 days, $Tinitial$ = 15 days.	2.01	33,255	117,495	14,719	102,776

Table 5
Results for example 2 – strategy: "Periodic Maintenance of some instruments sequentially".

Case	Maintenance management	Accuracy S_1	Financial loss (*DEFL*)	Gross benefit	Cost	Net benefit
c	CM plus PM, sensor 1–12 are selected, *CT* = 180 days, *TI* = 15 days, *Tinitial* = 10 days.	2.25	43,575	107,175	12,531	94,644
d	CM plus PM, sensor 13–24 are selected, *CT* = 180 days, *TI* = 15 days, *Tinitial* = 10 days.	2.44	72,645	78,105	12,118	65,987

For case **c**, the financial loss is lower than in case **d**. This is expected because the product stream is stream S_1 and therefore, if sensors measuring product stream flowrate and the streams that are redundant with it (directly connected to stream S_1 through data reconciliation) are selected for PM, the accuracy value and also the financial loss is lower than the case they are not measured (case **d**).

7.2.1. Resource limitations in corrective maintenance

We have used the assumption that there is no resource limitation for CM, that is, all recognized fault sensors will be repaired immediately. If this assumption is relaxed, the number of fault sensors that can be repaired at a time is equal to the number of available maintenance employees; hence it is probable that the repair of some fault sensors has to be delayed until the maintenance team finishes their current work. During the waiting time (for fault sensors to be repaired), the biased measurements are removed and hence the accuracy and financial loss will increase. We tested this case and the results show that the accuracy value and the financial loss increase insignificantly for the examples shown (less than 1%). This is because the frequency that multiple sensors fail in the same day is very low: during the simulated time horizon of 720 days, there are totally 3–18 days (depending on the preventive maintenance scheme) at which at least two sensors fail at a time. Moreover, relaxing this assumption requires about 10% more computational time. Thus, this simplified assumption is justified when computational time is of concern.

8. Conclusions

We presented some practical strategies for a preventive maintenance program and proposed the use of the economic value of accuracy as the performance measure for evaluating different candidate maintenance schemes. The best maintenance scheme (among many candidates) is the one that renders maximum economical benefit at the same time satisfies constraints on resource limitation and any applicable a-priori criterion. The results point out the importance of using data reconciliation and preventive maintenance in process plants because their costs are reasonable and their benefits (reduction of expected financial loss) are significant.

Finally, if no data reconciliation is used, to maximize economical benefit one should focus the maintenance effort on the *most important* sensor, which is the product flowrate-measuring sensor (but from the process operation point of view, focusing only on that sensor is not enough).

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