

PROCESS FLOW RATES RECONCILIATION AND DATA ANALYSIS

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1. Abstract

For plant control improvement, coherency of information supplied by instrument lines and sensors must first be ensured. Because of the presence of random and possibly gross errors, the model equations of the process are not generally satisfied. The problem of how to reconcile the measurements so that they satisfy the model constraints and how to use the reconciled values to detect faulty measurements (often called gross errors) are considered in this article. The authors strive to summarise various aspects of data reconciliation with the double aim of presenting the state of the art and bringing out the major difficulties encountered in the field. For that, the different steps of the methodology are presented in the following order : data reconciliation techniques, gross errors detection and gross errors localisation.

2. Introduction

The safety of processes can be greatly enhanced through the detection and isolation of the changes indicative of modifications in the process performances. If the models describing the process are accurate, the problem of fault detection may be solved by observer-type filters. These filters generate the so-called residuals computed from the inputs and the outputs of the process. This residual generation is the first stage in the problem of fault detection and identification (FDI). For them to be useful in FDI, the residuals must be insensitive to modelling errors and highly sensitive to the failures under consideration. In that regard, the residuals are designed so that the effects of possible failures are enhanced which in turn increases their detectability. The residuals must also respond quickly. The second stage of FDI is concerned with residuals analysis and decision making; the residuals are examined for detecting the presence of failures. The use of simple decision rules such as threshold tests or more sophisticated approaches using pattern recognition, sequential probability ratio test or sensitivity analysis is very helpful at this stage. Various FDI methods have been reported in the literature, notably in the excellent survey papers of Willsky (1976), Iserman (1984), Frank (1990), Gertler (1991). Among the classical books on the subject are those of Pau (1981), Basseville (1986a), Patton (1989b), Dubuisson (1990).

It should be noted that in the field of chemical and mineral processing industry, data reconciliation using material balance steady-state models has been extensively studied and applied. The particular point of view of data reconciliation and gross error detection is addressed in the book of Ragot (1990a). In the last two decades, the problem of detecting and

identifying gross errors in measurements due to biases in the measuring instruments has been well studied. Several statistical tests for this purpose have been developed, such as for example, the constraint test (Mah and al., 1976), the measurement test (Mah and Tamhane, 1982), the iterative measurement test method, the screen combinatorial method (Serth, 1986), the dynamic measurement test (Rosenberg, 1987), the generalised likelihood ratio test (Narasimhan, 1987) or the maximum power test (Crowe, 1989). There are different ways to identify a large error : with a theoretical analysis of all effects leading to this error, with hardware redundancy by measuring a given process variable with different sensors, by checking the consistency of the raw data. This third alternative is selected here ; it is based on analytical redundancy by using the model equations of the process.

The general procedure of error detection is classically divided into two main parts : firstly the generation of so-called residuals, which are functions of measurements that are accentuated by the errors, secondly the detection, the isolation and the estimation of the error. These two points will be presented in this paper and an example is provided in order to illustrate the gross error detection technique.

3. Static redundancy equations

Historically speaking, likely due to measurement availability, static redundancy equations have first been utilised in the mineral processing and chemical industries as well as for electrical distribution networks. The first studies (Ripps 1962, Vaclavek 1969) were concerned with data reconciliation using the now classical technique of equilibration of production's balances. In the following stages this data reconciliation principle has been generalised to processes which are described by algebraic equations either linear (Crowe 1983) or non linear (Sood 1979, Crowe 1986). At the same time, data reconciliation went into use for more general applications than establishing statistically coherent balances.

3.1. Principles of redundancy generation

The linear relationship between the measurements Y and the actual values X of a process variables vector is given in a simple matrix form as:

$$Y = CX + e \quad (1)$$

where Y is the (c.1) data vector whose entries are obtained from either sensors or analytic relationships, C the (c.m) measurement matrix, X is the (m.1) actual values of the process variable vector and e the (c.1) noise vector associated to the data. It is assumed that the noise is zero mean and characterised by a known variance matrix V (which is diagonal if the measurement errors are independent).

For obtaining the vector X , a minimum m , out of the c measurements, is needed. Therefore, redundancy in measurements generally (sufficient condition) appears when the inequality $c > m$ holds.

Data inconsistency can be easily pointed out by eliminating the unknown variables X from equation (1) when e is null. This yields $(c - m)$ linearly independent equations known as parity equations. Potter and Suman (1977) have established a general formulation of this problem when the covariance matrix of the measurement errors is equal to unity. When the covariance matrix is not equal to unity, let us define the $((c - m).c)$ projection matrix W so that it fulfils several conditions among them :

$$WV^{-1/2}C = 0 \quad (2)$$

Under these conditions, the redundancy equations can be written under the following form:

$$WV^{-1/2}Y = 0 \quad (3)$$

When the hypotheses about measurement noises are not valid, different situations can appear. In the case of errors whose mean values are not equal to zero, because of a systematic error of a sensor, the problem can easily be solved. Indeed, this systematic error can be statistically estimated which allows a correction of the measurements. For this estimation to be performed, the faulty measurement has first to be localised and identified. Many authors have studied this difficult localisation problem in the case of static redundancy equations. The main localisation methods will be presented in the third section of this chapter.

3. 2. The constrained case. A systematic decomposition

Let us now consider the system described by a linear constraint and a measurement equation:

$$AX = 0 \quad (4a)$$

$$Y = CX + e \quad (4b)$$

X is a v -dimensional state vector, Y is a m -dimensional vector of measured outputs, A and C are known matrices of appropriate dimensions.

Using simple transformations this equation can be reduced to those used for the unconstrained case. Linear systems, in which redundancy is present, can be written under various forms depending on the structure of the constraint and measure equations. However, through a few simple transformations they can be reduced to a unique representation defined by equations (4) or under an equivalent form:

$$\begin{pmatrix} I \\ 0 \end{pmatrix} Y = \begin{pmatrix} C \\ A \end{pmatrix} X + \begin{pmatrix} I \\ 0 \end{pmatrix} e \quad (5)$$

Then after a slight rearrangement, we can consider the same case that one given by (1) and therefore the generation of redundancy equations may be performed by the same way.

3.3. Example

The procedure can be illustrated using the following simplistic example. In this case the system is described by the measurement equation (1) without measurement errors. It is a priori redundant as there are 4 observations of only 2 variables.

$$Y = \begin{pmatrix} 1 & 2 \\ 1 & 0 \\ 1 & 1 \\ 2 & 0 \end{pmatrix} X$$

It is easy to solve (2) with V reduced to an identity matrix. Here, with regard to the simplicity of the measurement equation, a direct elimination procedure can also be applied. Then, the redundancy equations are expressed :

$$\begin{pmatrix} 1 & 1 & -2 & 0 \\ 0 & 4 & 0 & -2 \end{pmatrix} Y = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \quad (6)$$

When the measurements are affected by faults, the redundancy equations are not fulfilled and this may be enhanced by defining the residuals :

$$\begin{cases} r_1 = y_1 + y_2 - 2y_3 \\ r_2 = 4y_2 - 2y_4 \end{cases} \quad (7a)$$

If the main goal is to detect measurement faults, these residuals are compared to threshold values. Examination of the residual structure shows that faults on y_1 and y_3 are detectable but non isolable while they belong to the same residual equation. More generally, detectability and isolability mainly depend on the structure of the equations and on the occurrences of the variables in each of them. This may be analysed more deeper by considering all the redundancy equations ; for example, from (6), it is possible to eliminate the common variable y_2 which gives a third residual :

$$r_3 = -4y_1 + 8y_3 - 2y_4 \quad (7b)$$

Thus, considering (7) show that each residual depends on a certain number of variables and therefore specific signature of gross errors may be generated according to the occurrence of the variables.

4. Dynamic redundancy equations

The different concepts that have so far been introduced for studying the observability of linear systems can also be perfectly applicable to the case of dynamic systems. In particular the previously defined classification of variables according to their deducibility and redundancy can be generalised. The only difficulty lies in the increase in dimension of the vector of variables

which is a function of the dimension of the observation time-window. Because of this similarity between the static and dynamic case, fault detection (sensors and actuators) can be achieved using the principles defined in the case of static redundancy equations. In a practical sense, it is possible to generate redundancy equations from state equations either in time or frequency domain. These two approaches are totally equivalent (Lou, 1982) if some conditions of duration of the observation time-window are satisfied. Whatever the approach, the basic principle is the same: the unknown variables are eliminated so that only known or measured variables appear in the equations.

4. 1. Presentation

Consider the following deterministic model (8) where x is the n -dimensional state vector, A is a $n.n$ matrix, B a $n.p$ matrix, C a $m.p.n$ matrix. The vectors u and y correspond to the known inputs and outputs of the process. In all the following treatments, without loss of generality, the measurement y depends only on the state x and do not include the input u .

$$x(k+1) = Ax(k) + Bu(k) \quad (8a)$$

$$y(k) = Cx(k) \quad (8b)$$

Direct redundancy may exist among sensors whose outputs are algebraically dependent; this corresponds to the situation where the variable measured by one sensor can be determined instantaneously by other sensor measures. This direct redundancy is very useful for sensor failure detection but is not applicable for the detection of actuator failures. In this situation, the temporal redundancy which links sensor outputs and sensor inputs must be established. When integrated on $[k, k+r]$ window, the system (8) is expressed as:

$$Y(k,r) - G(r)U(k,r) = H(r)x(k) \quad (9)$$

where Y is the $m(r+1)$ vector of the outputs $y(k)$ to $y(k+r)$, U is the pr vector of the inputs $u(k)$ to $u(k+r)$, G a $m(r+1).(pr)$ matrix and H a $m(r+1).n$ matrix; $H(r)$ is called the r -order observability matrix of the process. Thus, it is clear that the structure of (9) is the same that those of equation (1).

4. 2. Example

Let us consider an example taken from Massoumnia (1988) with state matrices:

$$A = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{pmatrix} \quad C = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Direct calculation of the output system on the window $[k, k+2]$ according to (8) and elimination of the state yields the two redundancy equations:

$$\begin{aligned} 2y_1(k+1) - y_1(k+2) - 2u_1(k) + u_1(k+1) + u_2(k+1) &= 0 \\ -y_2(k+1) + y_2(k) + u_1(k) + u_2(k) &= 0 \end{aligned}$$

Assuming that the actuators are fully reliable, the first equation is sensitive to the failure of the first sensor, and the second one is sensitive to the failure of the second sensor. Hence these two equations can be used to identify any sensor failure. By aggregation of the two equations, considering u_1 or u_2 as common variables, we obtain:

$$\begin{aligned} y_1(k+2) - 2y_1(k+1) - y_2(k+2) + 2y_2(k+1) + u_1(k) &= 0 \quad (10a) \\ -y_1(k+2) + 2y_1(k+1) + y_2(k+2) - 3y_2(k+1) + 2y_2(k) + 2u_2(k) + u_2(k+1) &= 0 \quad (10b) \end{aligned}$$

Assuming that the sensors are fully reliable, the first equation is sensitive to the failure of the first actuator and the second equation is sensitive to the failure of the second actuator. Hence these two equations can be used to identify any actuator failure.

5. Residuals analysis

The first two sections were devoted to the generation of redundancy equations for linear static and dynamic systems. As already mentioned, the second stage of FDI concerns the so-called residuals evaluation i.e. the forming of diagnostic decision on the basis of the residuals. To limit the length of the present paper, all the aspects of this stage will not be covered in this section. We will especially focus on the methods issued from static systems analysis and which can be extended to dynamic systems (Maquin, 1991b). As indicated by Gertler (1990), the decision making stage usually implies statistical testing. There is a close relationship between statistical testing and residual generation. Residuals are variables that are zero under ideal circumstances; they become nonzero as a result of failures, noise and modelling errors. To account for the presence of noise, statistical testing is applied to the residuals. Then, a logical pattern is generated showing which residuals can be considered normal and which ones indicate faults. Such a pattern is called the signature of the failure. The final step of the procedure is the analysis of the logical patterns obtained from the residuals. The aim is to isolate the failures. Such analysis may be performed by comparison to a set of signature each of them representing a given failure.

5.1. Presentation of the process model

In this section, residuals generated either from static or dynamic systems are in a unified framework. A linear system can be described, in the fault-free case, by the following model and measurement relations:

$$MX = 0 \quad (11a)$$

$$Z = HX + e \quad (11b)$$

where X is the v -dimensional vector of process variables, Z the m -dimensional vector of measurements, M the $n.v$ matrix of model equations (without loss of generality, it is supposed of full row rank), H the $m.v$ measurement selection matrix and e is a vector of random errors characterised by its variance matrix.

For dynamic processes, the model, which relates the state vector $x(k)$ to the actual input vector $u(k)$ and the output vector $y(k)$, described in state space discrete form, may be written as :

$$x(k+1) = Ax(k) + Bu(k) \quad (12a)$$

$$y(k) = Cx(k) \quad (12b)$$

where $u(k)$ and $y(k)$ denote the actual values of the input and output of the system. Defining, on a time-window of length N , the mixed vector of inputs and states and the corresponding constraints matrix:

$$X = (x(0) \ u(0) \ x(1) \ u(1) \ \dots \ u(N) \ x(N+1))^T \quad (13)$$

$$M = \begin{pmatrix} A & B & -I & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & A & B & -I & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & A & B & -I \end{pmatrix} \quad (14)$$

the constraint equation and the measurement equations (11) may be condensed into the form:

$$MX = 0 \quad (15a)$$

$$Z = HX + e \quad (15b)$$

As the inputs and only a part of the state (15b) are measured, the selection matrix H is defined by:

$$H = \begin{pmatrix} C & 0 \\ 0 & I & 0 \\ 0 & 0 & C \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & C \end{pmatrix} \quad (16)$$

As equations (15a) and (15b) are strictly identical to (11a) and (11b), static and dynamic systems can be analysed in a unified framework.

5. 2. State estimation

The methods for fault detection and isolation are often divided into two groups: those which apply a priori, without carrying out the full data reconciliation (estimation of process

variables), by directly testing the residuals issued from redundancy equations and those which apply a posteriori on the residuals generated by calculating the differences between the raw measurements and their estimations. In practice, both methods are used together in order to improve the robustness of the procedure of fault detection and isolation.

The estimation or data reconciliation problem of system (11) involves finding a set of adjustments such that the adjusted values verify the model equation (11a). With the classical assumption that the measurement errors e are normally distributed with zero mean and known variance matrix V , this optimisation problem can be stated as maximising the probability density function (Ragot, 1990a):

$$P(Z) = \frac{1}{(2\pi)^{m/2} |V|^{1/2}} \exp\left(-\frac{1}{2} (Z - HX)^T V^{-1} (Z - HX)\right) \quad (17)$$

subject to $MX = 0$

Using the Lagrange multipliers technique leads to the classical unbiased estimator:

$$\hat{X} = (G^{-1} - G^{-1} M^T (M G^{-1} M^T)^{-1} M G^{-1}) H^T V^{-1} Z \quad (18a)$$

$$G = H^T V^{-1} H + M^T M \quad (18b)$$

Due to space limitation, the following analyses focus on the case corresponding of the measurement of all process variables, i.e. H is equal to an identity matrix. This situation is reducing but it allows the main ideas of the analyses to be presented. For a complete description of the proposed methods, the reader is referred to (Ragot et al., 1990). In this simplified case, the previous estimator may be written under the form:

$$\hat{X} = (I - VM^T (MVM^T)^{-1} M) Z \quad (18c)$$

The vector E of adjustments (or residuals) and the residual criterion ϕ_R are then obtained by direct substitution:

$$E = Z - \hat{X} = VM^T (MVM^T)^{-1} MZ \quad (19a)$$

$$\phi_R = E^T V^{-1} E \quad (19b)$$

Both the vector of adjustments E (19) and the direct imbalances vector of redundancy equations R defined by :

$$R = MZ \quad (20)$$

can be considered and processed as residuals. However, it should be noticed, that these residuals cannot be analysed in the same way as each entry of R is associated with an equation and each entry of E with a specific variable.

5. 3. Residual criterion analysis

A first approach to testing the residuals is to introduce a single scalar statistic like, for example, the residual criterion (19). As was first pointed out by Reilly (1963), the residual criterion ϕ_R has a chi-square distribution with a number of degrees of freedom equal to the rank of M. Furthermore, it is also useful to note that the calculation of ϕ_R does not require the estimation stage. It is easy to show that the residual criterion can be expressed as a function of R :

$$\phi_R = R^T (MVM^T)^{-1} R \quad (21)$$

Thus the residuals can be globally tested against tabulated values of chi-square. In the fault-free case, the function ϕ_R is below the threshold for the chi-square with the appropriate confidence level and number of degrees of freedom. Unfortunately, if the chi-square test is satisfied, it does not prove that there are no faults in the measurements set since a fault may exist among a large set of measurements. It is then preferable to use further specific tests to diagnose the measurements.

A difficulty with this global test is that, while it indicates well the presence of fault it is not able to identify the source of these errors. The use of a sequential procedure allows the location of the fault (see section 6).

5. 4. Imbalances or adjustments vectors analysis

Another approach is the direct parallel testing of the residuals. With the assumption of a Gaussian distribution of the measurement errors, the vector R also follows a normal distribution with zero mean and covariance V_R :

$$V_R = MVM^T \quad (22)$$

In order to compare the elements of the R vector, let us define a standardised imbalance vector R_N :

$$R_N = \text{diag}(V_R)^{-1/2} R \quad (23)$$

Each entry $R_N(i)$ follows a normal distribution with zero mean and unity variance. A simple statistical two tailed test can therefore be used: we may conclude that equation i is a "bad" equation if:

$$|R_N(i)| > t \quad (24)$$

Classically, one may choose the critical constant t to control the familywise Type I error rate at some pre-assigned level α . Even if we assume the presence of only one gross error, the relationship between the "bad" equation(s) and the suspect measurement is not

straightforward. It depends on the structure of the equations and the location of the faults. In some cases, we are not able to suspect one measurement only.

For solving this case (Mah, 1976) proposed to apply the preceding test to each equation and also to the aggregates of two or more equations (also known as pseudo-equations). The main assumption underlying this method is that faults do not cancel each other.

This latter approach can also be applied to the adjustments vector E . The variance matrix of this vector is expressed as:

$$V_E = VM^T(MVM^T)^{-1}MV \quad (25)$$

As for the imbalance residuals vector, we define the standardised adjustments vector:

$$E_N = \text{diag}(V_E)^{-1/2} E \quad (26)$$

Each $E_N(i)$ is compared with a critical test value. If at least one entry of E_N is out of the confidence interval then, there is a "bad" measurement. The defective measurement can always be shown to correspond to the greatest standardised adjustment residual (Fayolle, 1987).

For the linear case, instead of (26), Tamhane (1985) has shown that for a non diagonal covariance matrix V , a vector of test statistics with the maximal power for detecting a single fault is obtained by premultiplying E by V^{-1} . Then, the transformed residual, $e = V^{-1}E$, is normally distributed with zero mean and a variance matrix $V_e = V^{-1}V_EV^{-1}$. The power of the test (the probability of correctly detecting and identifying gross errors when they are present in the process data) has been established and discussed by Iordache (1985) under different conditions (various networks, errors location, variance values ...) using the Monte Carlo simulation.

6. Sequential technique for gross error detection

The use of residual criterion analysis coupled with a sequential procedure of measurement elimination allows one to locate the faulty measurements. For the set of all process measurements one first calculates the residual criterion ϕ_R ; if an error is indicated by the global test, all measurements are considered as suspect candidates. Then, the measurements are "deleted" sequentially from the process (in groups of size 1, 2, ...). After each deletion the global test is again applied. In this approach we wish to assess the effect of deleting a particular set of measurement on the objective function and on the estimations. This scheme, firstly proposed Rippis (1962), was also used by Nogita (1972) under a slightly modified form. Moreover, it is possible to have the same approach as the one developed in the case of multiple-observer for state reconstruction (Frank, 1989) by comparing together the different estimations obtained after each deletion. It is also possible to consider suspect measurements

by assigning them an infinite variance. The corresponding variation of the criterion f is then used to detect the possible gross errors.

Let us consider the following example :

$$\begin{cases} x_1 + x_2 - x_3 = 0 & \text{(equation 1)} \\ x_3 + x_4 - x_5 = 0 & \text{(equation 2)} \\ x_5 + x_6 - x_2 - x_7 = 0 & \text{(equation 3)} \\ x_7 - x_8 - x_9 = 0 & \text{(equation 4)} \end{cases}$$

The following table gives the values of measurements and their respective standard deviations.

Table 1. Measurements and their accuracies

Variable	1	2	3	4	5	6	7	8	9
Measurement	111.3	18.2	191.4	23.8	148.7	13.6	181.2	106.4	39.7
Standard deviation	2.8	0.5	3.2	0.6	3.7	0.3	3.5	2.7	1

All the variables are assumed to be measured. Practically, if it is not the case, the redundant part of the system must be extracted.

The table 2 shows the considered equations, the corresponding residual values, the normalised residuals (residuals divided by their standard deviations), the nature of the residual (normal or abnormal), the threshold being fixed to 2 and the variables involved in the calculus of the residual.

The last eight rows of the table correspond to residuals which are issued from the aggregation (sum) of some primary equations. The analysis of this table is based on the following remark. If the residual of an equation is not abnormal, the measurements used in the calculus of this residual are not contaminated by gross errors. This assertion lies on the hypothesis of simultaneous occurrence of only one gross error (elsewhere some compensation may occur).

So, for the considered example, the measurements which intervene in the calculus of equations 1+2, 3+4, 1+2+3+4 are fault free. Then, it is easy to conclude that the remaining measurements x_3 et x_7 are probably faulty.

Table 2. Analysis of residuals

Equation	Residual	Normalised residual	Abnormal residual	Variables
1	-61.9	-14.5	yes	1,2,3
2	66.5	13.4	yes	3,4,5
3	-37.1	-7.2	yes	2,5,6,7

Equation	Residual	Normalised residual	Abnormal residual	Variables
4	35.1	7.8	yes	7,8,9
1+2	4.6	0.9	no	1,2,4,5
1+3	-99.0	-14.9	yes	1,3,5,6,7
2+3	29.4	6.1	yes	2,3,4,6,7
3+4	-2.0	-0.4	no	2,5,6,8,9
1+2+3	-32.5	-7.2	yes	1,4,6,7
1+3+4	-63.9	-10.1	yes	1,3,5,6,8,9
2+3+4	64.5	14.8	yes	2,3,4,6,8,9
1+2+3+4	2.6	0.6	no	1,2,6,8,9

This error detection-isolation procedure may be implemented as follows. The boolean value "true" coded by the value "1" is affected to the variables which intervene in an abnormal residual and the boolean value "false" (0) is affected to the variables which intervene in a normal residual. When the variable do not intervene in the considered equation, the symbol "." is used. The last row of the table 3 is the logical product of the boolean values in a column (in this calculus, the symbol "." is not taken into account). The elements equal to "1" in this last row indicate the suspect measurements. Notice that the aggregation of equations may be achieved sequentially as well as the logical product, so the isolation may be obtained before doing all the possible combinations.

This technique may be extended to dynamical equations or non-linear equations. However, elimination of variables (aggregation of equations) in the non-linear case may be more difficult and may required the usage of specific techniques.

Table 3. Logic analysis

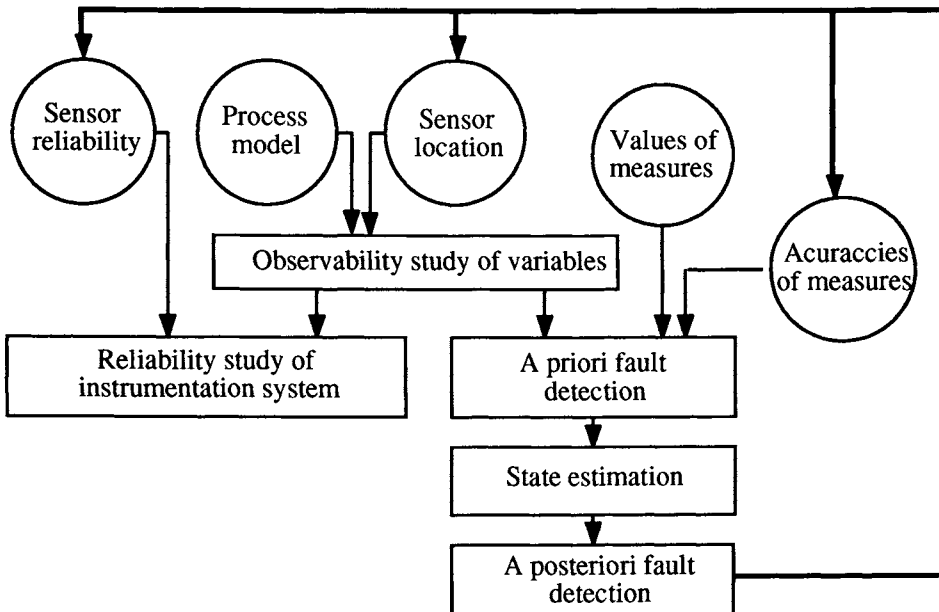
Equation	Abnormal residual	1	2	3	4	5	6	7	8	9
1	yes	1	1	1
2	yes	.	.	1	1	1
3	yes	.	1	.	.	1	1	1	.	.
4	yes	1	1	1
1+2	no	0	0	.	0	0
1+3	yes	1	.	1	.	1	1	1	.	.
2+3	yes	.	1	1	1	.	1	1	.	.
3+4	no	.	0	.	.	0	0	.	0	0
1+2+3	yes	1	.	.	1	.	1	1	.	.
1+3+4	yes	1	.	1	.	1	1	.	1	1
2+3+4	yes	.	1	1	1	.	1	.	1	1
1+2+3+4	no	0	0	.	.	.	0	.	0	0
Product		0	0	1	0	0	0	1	0	0

7. Architecture of a measurement validation system

The different stages of the measurement validation of a process are depicted in figure 1. The different sources of information allowing the analysis are shown : the process model, the location of sensors, the values and the accuracies of measurements and the reliabilities of sensors. These information may be used in different levels : structural data (process model and location of sensors) are used in observability and redundancy analysis of the variables. The reliabilities of sensors may be useful for introducing failure rate of sensors and analysing the whole reliability of the instrumentation scheme. The values and the precisions of the measurements are used by state estimation and residual generation. The analysis of measurements for fault detection and gross error localisation may be done a priori (analysis of the residuals generated from the process model) and/or a posteriori (analysis of the residuals generated by comparison of the measurements and their estimations).

The bold lines indicate an eventual modification stage of the measurement validation system. Indeed, when the fault detection-isolation is not possible, the number, the location, the accuracies or the reliabilities of sensors must be modified. This problem may be expressed as a constrained optimisation problem ; the constraints taking into account the redundancy of variables and the fault detectability and isolability (Maquin, 1995, 1997).

Figure 1. Architecture of a measurement validation system



8. Conclusion

One of the main difficulties in decision making using plant data is that true values for stream flow are not known. Because of perturbations in environmental conditions and malfunctions in equipment and instrumentation, it becomes necessary to adjust or rectify the process data. Analytic redundancy among process variables have been used to filter out measurement noise in data reconciliation. Throughout this communication, the authors have presented a short overview of the important problem of data validation in the linear case. We have shown that redundancy can filter not only the measurement noise but also gross errors due to sensor malfunctioning. However, we have to point out, that the implementation of such techniques need the knowledge of the process model. It is obvious, that the robustness of the data reconciliation techniques have to be improved in regard of uncertainties of the model. Probably, techniques taking into account parameters uncertainties, such as fuzzy modelization or interval arithmetic, may be used to reduced the effects of a bad modelization.

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