Detection of Leakage Using Data Reconciliation

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1. Introduction

Recently, we have begun to develop the algorithm of data reconciliation (DR) using physical models. At the same time, we are looking for a good example to demonstrate the concept and the benefit of the DR. We have studied the advanced algorithms for the detection of the RCS unidentified leakage [1]. The conventional algorithm to resolve this problem is based on the mass balance using filtered signals. Discussing the applicability for the detection of tank leakages, we found the DR may be a good solution in considering the instrument channel uncertainties involved in the parameters. In this paper, we will discuss the basic principles of the DR and will present an algorithm to resolve the leakage detection problems.

2. Methods and Results

2.1 Basic Principles

The data validation that means improving data quality can be attained in particular by elimination of the gross or systematic errors as well as minimization of the influence of random errors. The random errors are an unavoidable part of any measurement; they are characterized by standard deviation. The gross or systematic errors are remarkably greater than random errors and if the whole measurement has not to be disvalued, they must be eliminated from the measured data set. If we have several sets of data (time series) and the error is deterministically repeated in time, we call it as the gross error. The most obvious approach may be to adjust the data such that they obey the valid first principles exactly. The typical representatives are the balance models for mass and energy (the conservation laws) that hold true under very general conditions. The basic idea of the DR is, therefore, the adjustment of the measured values in the manner that the reconciled values are as close as possible to the true (unknown) ones on the basic of mass and energy balance. The governing equation of the DR is shown in Equation (1) [2].

$$\boldsymbol{F(x,y,c)} = \mathbf{0}, \tag{1}$$

where is $\boldsymbol{F}$ is the vector of model equations, $\boldsymbol{x}$ is the vector of directly measured variables, $\boldsymbol{y}$ is the vector of directly unmeasured variables, $\boldsymbol{c}$ is the vector of precisely known. The reconciled value, x_i' results from the $x_i' = x_i^+ + v_i$ where x^+ is the measured value added by adjustments, v_i. The adjustments must satisfy two fundamental conditions:

1) The reconciled values obey $\boldsymbol{F(x,y,c)} = \mathbf{0}$, we say that they are consistent with the model $\boldsymbol{F(x',y',c)} = \mathbf{0}$.
2) The adjustments are minimal. Most frequently, one minimizes the weighted sum of squares of the adjustments using the well-known least squares method in Equation (2).

$$\sum (v_i / \sigma_i)^2 = \sum \left(\left(x_i - x_i^+ \right) / \sigma_i \right)^2 \tag{2}$$

The inverse values of the dispersions (squared standard deviations), referred weights, guarantee that more statistically precise values are less corrected than the less precise ones. Equation (2) is used in the case of uncorrelated errors, which means statistically independent. In the case of correlated errors a more general criterion is minimized: minimize $\boldsymbol{v}^T \boldsymbol{F}^{-1} \boldsymbol{v}$ where $\boldsymbol{v}$ is vector of adjustments and $\boldsymbol{F}$ is covariance matrix.

If there are no errors, then no adjustments will be necessary. Therefore, $Q_{\min} = \Sigma (v_i / \sigma_i)^2$ is equal to zero. If only random errors with Gauss distribution are present, one can show that $Q_{\min}$ is the random variable of χ^2 distribution, and there must hold with probability $(1-\alpha)$: $Q_{\min} < Q_{crit} = \chi^2_{(1-\alpha)}(n)$ with n degrees of freedom. If the inequality is not satisfied, the possible presence of a gross error is considered.

It is universally accepted that any measurement is charged with some error. The measurement error is defined by Equation (3).

$$x^+ = x + e, \tag{3}$$

where x is the true (unknown) value and e is the measurement error. Information about possible errors in measurement, sometimes referred as uncertainty or maximum error, is indispensable. The uncertainty has the character of a maximum error assumed at the measurement or guaranteed by the manufactures. The uncertainty expressed with the instrument's range is called the class of accuracy.

$$x \in < x^+ - e_{\max} ; x^+ + e_{\max} > \tag{4}$$

where $e_{\max}$ is the maximum error. In practical DR, we take half the maximum error as a standard deviation.

2.2 Uncertainty and Channel Allowance

The maximum error can be taken from the uncertainly analysis of the instrument channel. Channel Statistical

Allowance (CSA) is the term given to all kinds of quantifiable uncertainties which occur in an instrument channel as shown in Equation (5)

$$CSA = \sqrt{PMA^2 + PEA^2 + (SCA + SD)^2 + SPE^2 + STE^2 + (RCA + RD)^2 + RTE^2} \quad (5)$$

where PMS (process measurement accuracy) is the inherent noise in the process, PEA (primary element accuracy) represents the error due to the use of a metering device, SCA (sensor calibration accuracy) is the inherent accuracy of the sensor at the reference conditions, SD (sensor drift) is the observed change in sensor accuracy as a function of time, SPE (sensor pressure effects) and STE (sensor temperature effects) are sensors' denature under difference pressure or temperature, RCA (rack calibration accuracy), RD (rack drift), and RTE (rack temperature effects) are the uncertainties coming from the racks [3]. The CSA corresponds to e_{max} which should be strictly applied to the DR models.

2.3 Leakage Model and Detection Algorithm

In this section, we described the leakage detection model using the principles of the DR. We first simplified the leakage process using a single tank with a single input and a single output and its equivalent model for applying the DR.

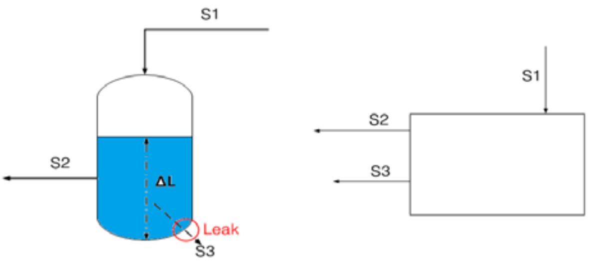

Figure 1. Tank leakage model and its equivalent DR model

In the tank leakage model, S1 is entering flowrate, S2 is going out flowrate, and S3 is water level of tank. The mass flows at S1, S2, and S3 are calculated by Equation (6)-(8)

$$S1 = \rho_1(P_1, T_1) \times \dot{v} \times \Delta t \quad , \qquad (6)$$
$$S2 = \rho_2(P_2, T_2) \times \dot{v} \times \Delta t \ , \qquad (7)$$
$$S3 = \rho_3(P_3, T_3) \times \Delta L \times A, \qquad (8)$$

where ρ is water density, P is pressure, T is temperature, $\dot{v}$ is volume flowrate, and ΔL is the water level of tank, A is the area of tank. The equation, S1 = S2 + S3 must be applied as the constraint to ensure mass balance. Figure 2 depicts the flowchart of the leakage detection algorithm. If gross errors are not found, the tank does not leak. If there is leak at the tank, a gross error should be identified at S3. In particular, the leakage occurring at the tank can be found by the gross error resulting from the unexpected variation of the water level in the tank. In this case, we have to consider both sensor problems and leakage. Sensor problems should be managed using different methods. Excluding the sensor problems, the only possibility of this gross error is tank leakage. In order to get the leak rate, we have to reconcile the value of S3 while S3 is checked as an 'unmeasured' variable. Finally, we are able to get the amount of leakage which is the difference between the measured S3 with initial data and the reconciled.

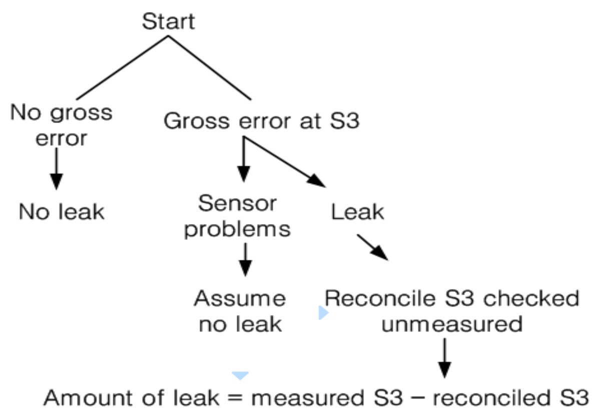

Figure 2. Leakage detection algorithm

3. Conclusions

This study suggested the fundamental concept to detect the leakage of tanks using the DR based on physical models. Even though we proposed the detection algorithm for a single tank in this paper, it was demonstrated that the method would be extended to develop the full-scope algorithm for the RCS unidentified leakage problem. We are planning to implement an advanced system for detecting the RCS unidentified leakage or other leak problems using the DR in future.

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