CHAPTER I
INTRODUCTION

In a modern chemical plant, a large number of measurements are available as a result of digital data acquisition systems and reliable low-cost sensors. Such data are important for process monitoring, model identification, online optimization, and process control. However, process measurements are inevitably contaminated with errors during the measurement, processing and transmission of the measured signal. The total error in a measurement, which is the difference between the measured value and the true value of the variable, can be represented as the sum of the contributions from two types of errors: random errors and gross errors. Random errors are usually small in magnitude and always present in any measurement. These errors are acceptably assumed to follow normal Gaussian distribution. They can be caused by power supply fluctuation, noises, change in ambient conditions and so on. On the other hand, gross errors (or systematic errors) are caused by nonrandom events such as instrument malfunctioning, miscabliration, wear and corrosion of sensors. Process leaks, although irrelevant to accuracy of measurements, are also considered gross errors because they affect process constraints model utilized in data reconciliation technique. Gross errors have a certain magnitude and sign which may be unknown. They occur less frequently but their magnitudes are typically larger than those of random errors.

Errors in measured data undoubtedly lead to deterioration in plant performance. They degrade performance of process control and online optimization system and in some cases, can drive the process into an uneconomic or - even worse – an unsafe operating regime. It is therefore important to reduce, if not completely eliminate, the effect of both random and gross errors. Among several data processing techniques, data reconciliation coupled with gross error detection technique is the most important and effective one to achieve this goal.

Data reconciliation (DR) is a technique that has been developed to improve the accuracy of measurements by reducing the effect of random errors in the data. It makes use of process model constraints (mass and energy balance) and obtain estimates of process variables by adjusting process measurements so that the estimates satisfy the constraints. If gross errors exist, they should be detected, identified and eliminated by gross error detection (GED) technique before data reconciliation can be applied.

One of the major obstacles in industry for the justification of the purchase and installation of data reconciliation software is that the benefit (in economic terms) is unclear and cannot be assessed. Two significant problems arise associated to any plant that desires to install a data reconciliation package. The first is to determine if the cost and the effort involved in purchasing such software and install it smaller than the benefits obtained. The second is the realization that there is not enough analytical redundancy in the system and therefore more instrumentation is needed. To address these issues, Bagajewicz *et al.*, 2003 and Bagajewicz, 2004b have presented the theory of economic value of precision and economic value of accuracy. Besides, the concept of software accuracy has been introduced as a base for developing the theory of economic value of accuracy (Bagajewicz, 2004a). Specifically, these papers developed expressions to obtain the expected downside financial loss DEFL associated to the precision and accuracy of the measurements and also the associated probability P which is viewed as the confidence with which the financial loss DEFL is known. The economical benefit of using data reconciliation software or adding a new instrumentation is the associate differences of financial loss with or without data reconciliation software or the new instrumentation (Bagajewicz, 2004b). While Bagajewicz (2004b) was able to derive analytical expressions for the financial loss under the presence of one gross error, he did not develop analytical forms for the expressions in the presence of more than one gross error, which consist of integrals with discontinuous integrands that do not reduce to a closed form solution. In this work, we present two methods for calculating the expected financial loss and the associated probability when two or more gross errors are present in a system: approximation method and Monte Carlo method. The approximation method allows the approximate calculation of these integral expressions in the presence of more than one gross error. The Monte Carlo method calculates the integral expressions numerically. An example of financial loss calculation is provided.