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Robust data reconciliation of combustion variables in multi-fuel fired industrial boilers

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ABSTRACT

This paper introduces an application of simultaneous nonlinear data reconciliation and gross error detection for power plants utilizing a complex but computationally light first principle combustion model. Element and energy balances and robust techniques introduce nonlinearity and the consequent optimization problem is solved using nonlinear optimization. Data reconciliation improves estimation of process variables and enables improved sensor quality control and identification of process anomalies. The approach was applied to an industrial 200 MW_{th} fluidized bed boiler combusting wood, peat, bark, and slurry. The results indicate that the approach is valid and is able to perform in various process conditions. As the combustion model is generic, the method is applicable in any boiler environment.

1. Introduction

Safe and sound operation of systems has a very important role in modern energy industry due to economic, environmental, and safety related aspects. The soundness of systems can be evaluated only if there is reliable information available about the state of the processes. This information is needed to enable optimum performance and to fulfill the requirements set by authorities. Development of process and operation strategies is based on information collected from running processes. Thus, correct decision making requires correct information, and actions based on false information can be expensive, and even dangerous. Furthermore, complying with permitted emissions levels and monitoring of cumulative carbon dioxide emissions must be based on reliable process information. Optimal operation of emission reduction systems such as filters, scrubbers, and converters should be based on reliable information about existing emission levels, and trading with carbon emission allowances is, as well, based on reliable definition of cumulative emissions. Today, a significant share of the electric energy market takes place in energy exchanges, where trading is based on the marginal costs of individual producers. The lowest bid gets the transaction. To be successful on these markets, the producers should have reliable information about the states and marginal production costs of their power generation systems. Thus, there is without a doubt a need for and value generated from on-time and reliable information from production systems.

Real industrial plant measurements are almost without exception corrupted by measurement noise and occasional gross errors. Malfunctions or incorrect calibration in sensor equipment may cause systematic errors or atypical statistical characteristics in the measured values and lead to suboptimal system operation, hazardous situations, and significant monetary losses. Sensor faults may be observable only intermittently or may require a plant wide analysis to uncover their sources which motivates the development of automatic monitoring systems. Power plants present a promising application area for automatic monitoring as they are large, consist of multiple interconnected subsystems, and economic volumes are high. Even a small improvement may have a great impact on the economic result. Unfortunately, the trivial solution to increase measurement reliability by adding extra measurements is often impossible due to economic reasons, so other solutions must be found. An alternative to hardware redundancy is analytical redundancy which utilizes existing process measurements, models, and data analysis to provide more insight into measurement reliability. The major drawbacks of this approach are model development and maintenance costs, which can to some extent be managed by employing generic combustion models. This approach is utilized in this article.

Model based Fault Detection and Identification (FDI) has been studied and developed actively since 1980s. The two main procedures for model based fault detection are dynamic observers and

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parameter estimation based methods often augmented with applications of artificial intelligence for fault identification. In observer based methods, estimated system state information is compared with measured information and in fault detection with system parameter estimation incipient faults are detected by repetitive identification of system parameters. These methods are documented in several books, e.g. (Chen & Patton, 1999; Gertler, 1998; Korbicz, Koscielny, Kowalczuk & Cholewa, 2004; Patton, Frank & Clark, 1989, 2000).

Power generation plants have been a common target for process diagnostics. This is motivated by the high reliability requirements set for energy production systems and remarkable monetary flows related to efficient operation. Early detection of incipient faults can prevent unexpected shutdowns and will help power system operators maintain the balance in the power system. Non-optimal operation of a power plant due to false information from unreliable or faulty measurements or defective process components will easily lead to hundreds of thousands of euros in extra annual operation costs. Examples of diagnosis applications in different kinds of power generation systems, such as steam boilers, thermal gasifiers, nuclear power plants, and wind turbines are reported in Majanne (2008), Majanne, Lautala and Lappalainen (1995), Majanne, Ruokonen, Kurki and Ala-Siuru (1992), Odgaard, Lin and Jorgensen (2008), Odgaard and Mataji (2008), Ruan and Fantoni (2002).

The origin of measurement errors can be determined by examining the statistical properties of received data and analyzing corrections made by data reconciliation procedures. Data reconciliation corrects process data using optimization methods to satisfy process constraints. The process model is defined in the form of equality and/or inequality constraints derived from conservation laws, equilibrium constraints, and physical process constraints. In other words, the process model defines the mass and energy balance of the system and takes into account the physical limitations of the sensors. The objective function weights corrections of the measured values by their reliability calculated from the measurement variance of normal operation.

The first steady-state data reconciliation method was proposed by Kuehn and Davidson (1961). The initial data reconciliation solutions relied on simple mass balances where the problem may be solved using linear programming. The iterative successive linearization method was first used to solve nonlinear reconciliation problems in Knepper and Gorman (1980), MacDonald and Howat (1988). Matrix projection, proposed in Crowe, Campos and Hrymak (1983), Crowe (1986), enabled the solution of further linear and nonlinear problems. These and other reconciliation methods have typically relied on the least squares objective function that has a prerequisite that gross errors must be detected and filtered out of measured data before the data reconciliation. A general review of data reconciliation and gross error detection methods may be found in Narasimhan and Jordache (1999).

The robust statistics methods of Huber (1981) have been applied to data reconciliation to overcome the need for iterative procedures which first remove gross errors and then perform the reconciliation. Simultaneous data reconciliation and gross error detection was first used in Tjoa and Biegler (1991) where the objective function was based on a contaminated Normal distribution and the ensuing problem solved using nonlinear programming. Different robust estimators and their feasibility have been examined in Albuquerque and Biegler (1996), Arora and Biegler (2001), Johnston and Kramer (1995). A comparative review of different estimators was presented in Özyurt and Pike (2004). Successful application of the robust estimators has been reported in Prata, Schwaab, Lima and Pinto (2010) using data from an industrial polypropylene reactor.

In power plant environments, data reconciliation has been applied in several cases. For example, Fellner, Cencic & Rechberger (2007) used data reconciliation to determine the fractions of biogenic and fossil matter in a waste to energy plant. Gulen and Smith (2009) derived a generic form for data reconciliation when mass, energy and/or momentum balances are available and demonstrated the method with simulated data from a single shaft combined cycle system. Heyen, Vrielynck and Kalitventzef (1998) used data reconciliation to improve data reliability for parameter identification in a power generation setting. Szega (2011) used a data reconciliation method to improve the reliability of measurement data in calculation of parameters characterizing the thermal process in a waste-heat boiler. Touš, Frýba and Pavlas (2013) utilized nonlinear optimization and data reconciliation to improve the evaluation of lower heating value of waste and efficiency evaluation. Huovinen, Laukkanen and Korpela (2012) present an on-line data reconciliation application used to estimate the reliability of measurements in the water-steam cycle of power plants. Jiang, Liu and Li (2014a), (2014b) demonstrated data reconciliation and gross error detection in integrated sensor and equipment performance monitoring with simulated data from the feed water heating system of a coal-fired power plant. Karlsson, Dahlquist and Dotzauer (2004) used data reconciliation and gross error detection with simulated data to correct the mass flow measurements from a bio-fuel fired heat and power plant. Martini, Sorce, Traverso and Massardo (2013) presented the application of data reconciliation and gross error detection to a microturbine-based test rig. Syed, Dooley, Carl Knopf, Erbes and Madron (2013) demonstrated the efficacy of data reconciliation and gross error detection in examples from gas turbine cogeneration systems. Valdetaro and Schirru (2011) used a robust data reconciliation method to select models, detect outliers and improve measurement data in a simplified thermal reactor using particle swarms. As a conclusion, most of these papers focus on limited sub-processes and mainly on the water-steam cycle of power plants.

In this paper, simultaneous nonlinear data reconciliation and gross error detection is applied to monitoring of combustion variables in a complex multi-fuel fired industrial fluidized bed boiler. Utilization of the method requires a mathematical model, which in this case is a first principle combustion model. The model is founded on element balance equations that are formed from the main chemical reactions taking place in combustion environments. Element balances have been utilized previously in some applications, especially in waste incineration applications, to estimate some interesting characteristics. Element balances have been utilized e.g. in estimation of fuel heating value by Fellner, Cencic and Rechberger (2007), Hsi and Kuo (2008), Van Kessel, Arendsen and Brem (2004), fuel burning rate (Hsi & Kuo, 2008), in separation of defined fractions of fossil organic and biogenic waste components (Fellner, Cencic & Rechberger, 2007), and in calculation of flue gas specific heat and specific exergy value (Coskun, Oktay & Ilten, 2009). For monitoring purposes it has been applied by Korpela, Björkqvist, Majanne and Lautala (2014) where element balance calculus was utilized for indirect online monitoring of flue gas CO_2, H_2O, and SO_2 concentrations in addition to flue gas and combustion air flows. In the model, the analytical solution of element balances enables computationally light numerical calculus, which is a prerequisite for computationally intensive nonlinear optimization required in simultaneous nonlinear data reconciliation and gross error detection. This paper extends the approach presented in Korpela, Björkqvist, Majanne and Lautala (2014) with an extended model and especially with adaptive features.

This work addresses the enhancement of an existing reconciliation system to simultaneous data reconciliation and gross error detection in combustion environment. The structure of the article is as follows. Section 2 presents the nonlinear optimization