A Review on Data Reconciliation and Gross Error Detection for Process Plant Energy Management

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Abstract. Process plant is essential for energy management, especially for analysis that requires steady state data, such as Pinch Analysis. The data from the distributed control system (DCS) often recorded with fluctuations. Data processing is needed to obtain representable data for energy management related analysis. Data error occurs in several forms such as gross error, random error, bias error, and systemic error. This error affects the reliability of energy management studies. Data reconciliation (DR) and gross error detection (GED) come in place for the data processing required before the energy management analysis could be done. GED detects measurement variable error which works with DR technique for a new estimate or reconciled value will be gather and use for further data analysis. DR and GED are commonly used in mathematical programming optimization, such as model predictive control (MPC), which has proved its effectiveness in providing good data for further analysis. This means that DR and GED affect energy data manipulation and studies. In this paper, DR and GED on energy data for plant energy enhancement are reviewed. The specific method for DR and GED are classified and discussed in this paper.

1. Introduction
Parameters and data measurements in the chemical process industry are important items as these are measured, collected, and recorded through sensors and measuring instruments for process plant. These data are displayed in a distributed control system (DCS), and will be observed and manipulated by boardman to ensure the data such as flow, temperature, level, and pressure of the process data are in the required range for optimal production. However, the data collected might not be accurate because there are potentials presence of biases and errors which come from the malfunction of measuring instrument or disturbances of surrounding conditions such as weather in a real process which later will affect the production and energy management of the plant.

The data are also essential for energy optimization and management of projects; in which companies are looking into energy saving opportunities from time to time for sustaining the profitability margin. However, the methodologies used by these studies are dealing with single data for each parameter, which becomes difficult for the consultant to handle a large number of data available for a single measurement point from the history database. Its common that consultants are simulating the process to obtain a
reliable single data, which requires a deep understanding of the processes for performing such simulation. Therefore, data reconciliation and gross error detection are essential for this kind of study. This study reviews the state-of-the-art methodologies for data reconciliation and gross error detection for energy-related process plant data.

2. Industrial Energy System Optimisation
The industrial energy system involves heat transfer in equipment. For example, heat exchangers transfer thermal energy between utility stream (e.g. steam, hot oil, cooling water) and chemical material, as well as transfer between chemical materials for energy recovery. There is other auxiliary equipment for supporting the industrial energy system, which includes a boiler with combustion energy transfers to boiling feed water for steam production, as well as heat release or absorbs in reactors for maintaining the chemical reaction temperature. Steam turbine is also an example of equipment that uses heat energy and is converted to electrical energy via kinetic energy by a shaft. In real plant cases, there will be a waste of energy either caused by instrument error or surrounding conditions such as weather. They apply energy optimization to reduce the waste and maximize the energy transfer and usage in the site.

In the methodology of steam energy optimization, Klemes et al. [1] have introduced site-wide optimization which is the study of steam energy transfer from high-pressure steam (HP), medium pressure steam (MP) and low-pressure steam (LP) where, when there is an excess of steam in each level, the steam will be let down to a level below and total excess steam will be known and the steam generated can be further adjusted until the optimized amount of steam achieved. This technique is also called as Total Site Heat Integration (TSHI). The important parameters for this optimization are pressure difference, temperature, steam flow and energy balance. This type of graphical and numerical energy optimization through Pinch Analysis requires a single data set for each parameter related to mass and energy balance.

Process plant also capable to operate autonomously by keep changing parameter such as feed, temperature, chemical component or any other parameter which appear in DCS by applying MPC, where the sample was taken by plant step test and form a model, and in real-time optimization, MPC will predict a value for the targeting parameter to achieve optimal production and minimize energy wastage [2]. There are other tools which have been implemented to achieve energy optimization such as the application of machine learning tools [3], robust optimization framework through mixed integer nonlinear programing (MINLP) [4], multi-objective energy optimization through E-constraint and fuzzy satisfying approach [5] and real-time optimization with adaptive optimization convergence [6].

The similarity from all the energy optimization systems mentioned are they using data collected from the process plant either online or offline and might not be accurate. This lack of data accuracy might cause by errors in measurement which is the effect of sensor or instrument malfunction, which is also known as gross error or biases [7]. Tamhane et al. [8] mentioned leaks and the presence of depositions in process units also causes the error in the parameter. Systemic biases are the constant error value given by measurement devices and random errors which are caused by the irreproducibility of the measurement devices [9]. The measurement error will greatly affect the accuracy of data processing. For example, if these data containing the errors were used as inputs in energy optimization or other tools, the result will deviate and be less accurate from the actual situation and might cause false data will be the input for DCS. Therefore, a methodology called gross error detection (GED) and data reconciliation (DR) is introduced to identify and eliminate gross error and estimate value which is more accurate compared with using raw data. This will improve plant performance and energy systems.

The impacts of implementation of GED and DR estimation through online data modification have significantly improved plant performance and optimization. Abu-el-Zeet et al. [10] have researched combining dynamic data reconciliation with MPC where the data were reconciled before being transmitted to the controller and simulation of two coupled chemical reactors by using this technique have improved the reactor performance. A combination of the nodal test and simultaneous estimation of gross errors has been proved to improve the computation performance in the steam metering system [11]. In a nuclear reactor, a case on in-core neutron detectors performance had been investigated by
Yellapu et al. [12] where DR integrated with fault detection and isolation gave a satisfactory result which minimizes the random error effect and the data free from faulty. All these examples show the importance of DR and GED as a tool to rectify data prior become a parameter for plant optimization.

3. Review on Data Reconciliation and Gross Error Detection for Energy System

Tjoa and Biegler [13] define DR as data adjusting and rectifying to satisfy the process constraints and estimate the unmeasured data while reducing the error. The data collected from process plant often contain errors which might be due to calibration error or failure of the instrument which also called as a gross error where the data violate (break) the bound, it does not follow the data distribution from a set of data [14][15][16]. Therefore, GED is the term used to detect and eliminate the gross errors which will help in improving data accuracy [8]. Congli and Guohai [16] stated that GED usually takes place before reconciling data.

The DR and GED have been widely applied and integrated into a process plant to improve plant performance and optimization. In the energy system, the possibility to conduct DR and GED is high because the data are accessible and wide variety of them such as material flow rates, steam flow rates, temperature exchange, pressure drop and level indicator. All the mention parameter is the first layer of calculation of DR and GED which the estimates or reconcile value will be used in energy equations, for example, energy balance, power generation, and heat transfer equation to determine the energy value.

Methods existed to perform GED and DR are nodal test by Mah et al. [17], Mah and Tamhane [18] introduced measurement test (MT), matrix projection by [19], modified iterative measurement test (MIMT) by Serth and Heenan [20], generalized likelihood ratio (GLR) Narasimhan and Mah [21], Broyden’s method approached by Pai and Fisher [22], successive quadratic programming (SQP) by Tjoa and Biegler [13], non-linear dynamic data reconciliation (NDDR) by Leibman et al. [23], maximum power test Crowe [24], principal component analysis (PCA) by Tong and Crowe [25], Q-R factorization by Swartz [26], mixed integer linear programming (MILP) by Soderstrom et al. [27], robust approach of generalized T distribution by Joe et al. [28], Dubois et al. [29] implement fuzzy constraint, correntropy non-linear data reconciliation by Zhang and Chen [30] and maximum a posteriori by Alighardashi et al. [31]. Some method was extended to adapt GED and DR, for example, Taylor and Laylabadi [32] extend NDDR to novel adaptive NDDR.

Gross error detection (GED) and data reconciliation (DR) has been studied to overcome the inaccuracy of data. The data collected from a certain flow, concentration and temperature parameter will be reconciled and some of the unmeasured data will be estimated by using reconciled data which will result in the minimum weighted sum of the square of adjusted parameter and obey the conservation law [19]. To improve accuracy. Sun et al. [33] combined a few methods of MT-NT-MILP, which have proven to solve GED and DR tasks for large scale simulation-based problem. A lot of research has been done on DR and GED methodology to tackle data reconciliation in which the data appear in the form of linear steady state, linear non-steady state, nonlinear steady state, or nonlinear non-steady state.

3.1. Static Data Reconciliation

Static DR cases mean the data which have been reconciled are static data where the data are at a steady state or not changing with moving time. Almasy [34] stated that static DR cases are the cases where the data do not correlate with time or any other process behavior. In this subsection, we will review the research paper of DR and GED which is implemented to optimize the energy system. Stanley and Mah [35] did a study on the quasi steady state model and implementation of the Kalman filter which has successfully reduced 70% of error such as noise measurement. The estimation process will take place by first estimating a new value for flow and temperature parameters, then by using the new value, enthalpy and energy flow will be calculated from the crude oil distillation unit.

Implementing DR through QR factorization in creating a new heat exchanger network (HEN) model through two sets of linear equations which are mass balances and energy balances where it is linear in temperature [36]. First, computing mass balance, followed by calculating heat transfer coefficient, defining heat exchanger performance and the last step is to determine the energy balance equation which
is linear in temperature measurement where these steps are also known as Goyal’s reformulation [36]. Because of the reconciled data result in good convergence, Ijaz et al. [36] stated the technique was suitable to be performed for large scale site-wide energy models. Kongchuay and Siemanond [37] simulated the performance of the usage of DR and GED technique by using data measurement from hot-oil heat exchanger where the simulation will be compared the standard deviation of 3 conditions of data reconciliation; first, reconcile data containing the random errors only, second, reconciled data containing random and gross error and third, data containing the gross and random error will going through DR and GED processes. In this paper, the conventional GED method (global test and measurement test) was also simulated and compared with the modified MT test using non-linear programming (NLP) and the later shows the promising result with the constraints involved were mass balance, energy balance, overall heat transfer coefficient equation and heat duty equation [37].

Yong et al. [38] simulated data reconciliation for Heat Integration Analysis (HIA) which was conducted by an iterative method using NLP and simultaneous method applying global NLP, where iterative method means the reconciliation of temperature data measurement. which is conducted first and then flow rates data are reconciled, the latter method reconciles both parameters simultaneously where the result obtained from the simultaneous method gives higher accuracy compared iterative method however the iterative method much simpler than the simultaneous method where the simultaneous method might cause computational complexity issue. Yong et al. [39], simulated HEN data reconciliation of T (temperature) model and CP (heat capacity) model with 3 strategies of the iterative method where T model will keep the temperature constant in constraints to obtain CP value and the CP model is vice versa of T model while 3 strategies mentioned are first merging consecutive heat exchangers, second, assuming these heat exchangers in heat loop with different CPs and third, introducing a relaxation constant in every heat exchangers which the result from this investigation was iterative method are suitable to solve DR for HEN and less computational load compared to the simultaneous technique from previous the paper by Yong et al. [38].

Weighted least square for DR and global test GED were used to study the imbalance between raw feed and output mass flow of natural gas processing plant. The results from the studies were no gross error detection from the global test conducted and reconciled data were satisfactory [40]. Rafiee and Behrouzshad [40] also mentioned a case, which consists of total mass flow measurement only, can be classified as a linear constraint. They showed that, if chemical species are multiplied by the mass flow rate, the case becomes bilinear constraints and if the case further involves chemical reactions, it is categorized under nonlinear cases.

Guo et al. [41], had done a data reconciliation study on the real-life 1000 MW coal-fired power plant which involved constraints from mass balance, energy balance, pressure drop, Ellipse law and isentropic efficiency equations where this case was divided into 2 cases, which were Case A, where the data were manipulated by changing the loss and Case B was carried out by using 551 groups of steady sets measurement values to get the estimates of exhaust steam enthalpy and steam wetness fraction after measurement parameters were reconciled. The techniques used for DR and GED were weighted least-squares (for non-linear such as Lagrange multipliers or successive linearization) and global test where the result from this case was claimed had reduced the data uncertainty. Guo et al. [42], using data collected from the real-life 1000 MW ultra-supercritical coal-fired steam turbine to create a new framework for inequality constrained non-linear data reconciliation which consists of constraints, make up from mass balance, energy balance, pressure balance, characteristics equation and power generation equation where the method used in the case were SQP and global test as a solution for DR and GED. Li et al. [43] investigated a 200 MW fluidized bed boiler of combusting wood, peat, bark, and sludge where they implement nonlinear data reconciliation and GED which improved the sensor quality and anomalies detection where mass and energy balance used as constraints. The technique to solve nonlinear data reconciliation for this case was using Welsh robust estimator which gives better performance compared to the traditional weighted least square (WLS) technique and the effect of the gross error on the Welsh estimator was less than WLS which needs gross error identification and elimination [43].
Xie et al. [44] investigated the robust DR methods, Fair, Cauchy and Welsch including weighted least square were being compared their performance with the data collected from Bayer alumina production in the evaporation process where the mother liquor is heated indirectly with steam to achieve the desired concentration. Mass balance and heat balance data were reconciled and achieve the result where the robust estimator with layered reconciliation give better accuracy, GED involves in this study was a measurement test. The reconciliation of data from HEN which function as a pre-treatment before entering the crude oil distillation unit was studied to enhance the monitoring system which will give impact the production cost, emissions and safety issue where they used mass flows, energy flows and energy transfer as a constraint for DR. Successive linearization for Q-R decomposition and global test to estimates unmeasured values and detect gross errors [45]. Vaccari et al. [46] used the SQP method for DR to estimates the amount of mercury and hydrogen sulfide and also estimate the energy consumption of geothermal power plant, where the heat from underground will vaporize water indirectly and become steam which will travel into the steam turbine and generator will generate the energy while the pressure drop of the steam causes them to become condensate because of the energy conversion. Szega [47] reconciled data from the heat exchanger in 370 MW steam generation unit, a method of data validation and reconciliation (DVR) where the basis is from the weighted least square technique and also include means statistical analysis for GED to remove the errors which the constraints for this case were mass balance and energy balance.

3.2. Dynamic Data Reconciliation

Dynamic DR cases will be known when the cases involve when the data is greatly dependent on the moving time window. “Dynamic data reconciliation and gross error detection approach usually resort to a state-space model evolving over time” [48]. In this section, cases which classified under dynamic data reconciliation will be reviewed. Guo et al. [49] apply DR on online monitoring of real-life 1000 MW ultra-supercritical coal-fired steam turbine power plant which the result in this investigation has reduced the uncertainty measurement up to 50% which the constraints equation involved in this study were pressure drops, mass and energy balance, enthalpy and other thermodynamic parameters also included to perform DR of energy calculations. DR technique which was used in this study was successive linear data reconciliation where this method will linearize nonlinear constraints so the reconciliation will be done in linear form while the GED used was the global test to check the gross errors in the data [49]. Guo et al. [50] investigate the performance of 1,000MW thermal power plant by enhancing the monitoring value which reconciled with dynamic data reconciliation in moving time window and being compared with steady state data reconciliation where DDR give better result compare to the later with constraints involved in this case were mass balance, energy balance and pressure balance. Integrated DR and GED with fouling model parameters to reconcile data on a pre-heat train of tube and shell type heat exchanger so that the measurement errors can minimize and fouling of multiple instruments can be detected. The technique used in this study was SQP for DR and global test for GED where the constraints involve solving this issue were mass balance and energy balance [51]. Fadda et al. [52] did a study involve the combination of DDR and parameters estimation which is EKF where the data estimation of heat transfer, mass balance and energy balance was taken from the pyrolysis reactor of olefin plant where heat is used to crack the heavy hydrocarbon from raw material. Korpela et al. [53] had done a robust data reconciliation for combustion processes of multi-fuel fired industrial boilers where steam produced which the result from this case make the plant can monitor the amount of chemical component including the emission by the combustion processes. In this investigation, the Welsch estimator was used and no gross error was assumed under the ideal condition for this case with constraints involve were energy balance, mass balance, chemical composition balance and power balance Korpela et al. [53].

3.3. Applications of Static and Dynamic Data Reconciliation

The applications of static data reconciliation mainly on model development or optimization study which it using the unchanged data from process plant, usually the data collected will be in batch so that the
study on the model or optimization will keep updated. For example, system which suitable to undergo static data reconciliation is TSHI analysis which used a batch of data to achieve steam optimization analysis via pinch analysis. While dynamic data reconciliation application much robust where it is processing real-time data where the data keep changing in vector time. Dynamic data reconciliation normally implements in the plant processing for real-time production optimization because the raw data will directly be processed and give instant feedback to DCS. For example, MPC uses dynamic data which can use dynamic data reconciliation to reduce errors and predict parameters which become the input for DCS to give response for automated production optimization.

4. Conclusion

DR and GED can be divided into two categories, which depend on the raw data properties that are dynamic and static. Static data are constant data which are not moving with the time window. The study of DR in this type of data usually being done to investigate the validity of the DR technique, to develop a base model for optimization and to determine the uncertainty of the reconcile data. Dynamic data is raw data collected or recorded with the dependence of time. When time keeps moving all the parameter keep either keep changing or constant which usually this case of data involve online measurement from real-life process plant. The investigation of DR categories under dynamic data reconciliation has a purpose to develop a model for real-time optimization and process raw data before being the input in DCS which a platform to operate process plant. DR and GED have the capability to enhance plant performance and optimization including energy systems. Energy optimization through Process Integration and Pinch Analysis should develop a DR and GED methodologies for its usage for getting the data in the required format. Meanwhile, energy management in chemical process plant through Process Integration using mathematical programming method has managed to demonstrate the successful implementation of DR and GED as part of the optimization algorithm.

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