

APPLICATION OF DATA RECONCILIATION TO AN ATMOSPHERIC CRUDE UNIT TO CALIBRATE INSTRUMENTS

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Traditionally, data reconciliation has been used to obtain more accurate estimates of plant measurements. The accuracy is assumed to be improved by taking more information into account, ie additional measurements and knowledge of the process. Mass balance reconciliation has been used to get a consistent set of mass flow rates. Plant-wide material balance in oil refineries are providing an accurate representation of the interconnectivity of the entire plant complex and resolving and reconciling data discrepancies associated with plant operating data sources. The process of reconciliation is often an inexact and arduous task. Meters measure within tolerances, measure volume not mass, and often do not measure all the material movement in the plant. The task of reconciliation, then, becomes one of surmising the missing flows and determining where the errors are in the measurement system. Process data are generally corrupted by gross measurement errors. Using data reconciliation of process data we can use the operational performance of field instrumentation and plot calibration curves and the problematic instruments can be determined. Plotting reconciliation vs measured data we can produce a reliable mass balance for the distillation crude unit.

1 INTRODUCTION

Data reconciliation is an online method used to resolve inconsistencies between plant data measurements and produces a single, reliable and consistent measurement for plant optimization. It uses raw process measurements, statistical techniques, material & energy balances and instrument calibration tolerances to produce reconciled flows, gross errors, and a list of instruments to be calibrated.

Measured process data are usually contaminated by random and gross errors due to sensor noise, disturbances, instrument degradation, and human errors. Since the performance of process operation tasks depends on the quality of information extracted from the measured data, the collected data need to be cleaned or "rectified" for efficient process operation.

Data rectification is an ill-posed problem since given just the measured data, they can not be rectified without additional information. Depending on the type of additional information used, techniques for data rectification may be categorized as: rectification with fundamental process models, rectification with empirical process models, and rectification without process models. Rectification with fundamental process models minimizes the error between the measured and the rectified signals while requiring the rectified variables to satisfy a linear or nonlinear, steady state or dynamic model.

2 DATA RECONCILIATION METHODS

Methods in this category have received significant attention in academic research and often consist of the separate tasks of gross error detection and data reconciliation. Data reconciliation refers to the model-based removal of random errors, whereas data rectification is a more general term which includes the reduction of random as well as gross errors with or without process models.

For data from steady state processes, data reconciliation may be performed as a weighted least squares estimation where the sum of square errors normalized by the error covariance is minimized [1]. Crowe [2,3] used a transformation called matrix projection in multivariate rectification problems with linear constraints, which exploits the redundancy among dependent process variables to eliminate Gaussian errors from data under steady state conditions. Veverka [4] extended the same approach to problems with non-linear constraints.

For dynamic process data, a wide range of approaches have been employed for data reconciliation. Kalman Filters are popular for the reconciliation of linear dynamic processes. When fundamental process models are used for data rectification, the quality of the rectified data depends on the accuracy of the process models. Rectification with empirical process models overcomes the need for accurate fundamental process models by extracting the relationship between the variables by an

empirical modeling method such as principal component analysis or recurrent neural networks [5]. Data containing non-Gaussian or gross errors may be rectified by applying various statistical outlier detection techniques such as hypothesis testing and generalized likelihood ratio approach. These tests may be applied to autocorrelated measurements by prewhitening the measurements using time-series modeling. Gross errors in multivariate data may also be detected by PCA [6]. For data from dynamic processes, robust reconciliation methods have been developed by Albuquerque and Biegler [7] and Kim et. al., [8].

3 WHERE DATA RECONCILIATION IS NECESSARY ?

For proper optimization we can use data reconciliation in:

- Where accurate yields and inventory are necessary for planning & scheduling
- Identification of plant losses
- Reconciliation of feed and product transfers for accounting purposes
- Where important flows are difficult to measure accurately
- To streamline on line maintenance of instruments

4 STEADY-STATE MASS BALANCE

Typical sources of such redundant information are material and energy balances for an entire process or a particular process unit; known reaction paths and performances; known performances of other types of equipment, such as distillation columns, heat exchangers or pumps and compressors; or even typical operational paths during equipment startup, shutdown, and feed or product changes. In fact, every plant is a well of redundant data waiting to be tapped.

In order to detect any instrument mal function in the crude distillation unit a data mass balance with data reconciliation application was developed. The DCS provides continuous measurements of process variables like flow rates, tank level, temperatures and pressure, controllers set point as well as process characteristics.

The relational data base system collects and process all the data from the DCS, compress and archive the data. This is a client-server system. The relational data base supports data retrieval operations over a specific operating period. The system simultaneously execute statistical functions. All the process results, include laboratory data, are made available as object to spreadsheet and database application. Customized applications using these objects perform specific tasks, such as process performance analysis, process monitoring and troubleshooting.

In the Excel worksheet the data retrieval is automated by functions residing on the worksheet. Graphical representation of process data is achieved via custom made process flowsheets. The client is able to monitor the values of all process variables corresponding to specific measuring instruments on a monitor.

With this capability, we model the process with an overall mass balance for each stream node of the flowsheet. The objective function of the data reconciliation problem is formed by the sum of squares of weighed deviations between the measured and reconciled data. We use the Excel Solver algorithm to carried out the optimization. We can use the MATLAB 5.0 from The MathWorks, as well. In this case, the Excel worksheet will provide the data file to the program.

The REGAP's atmospheric and vacuum crude distillation units scheme is presented in Fig.1.

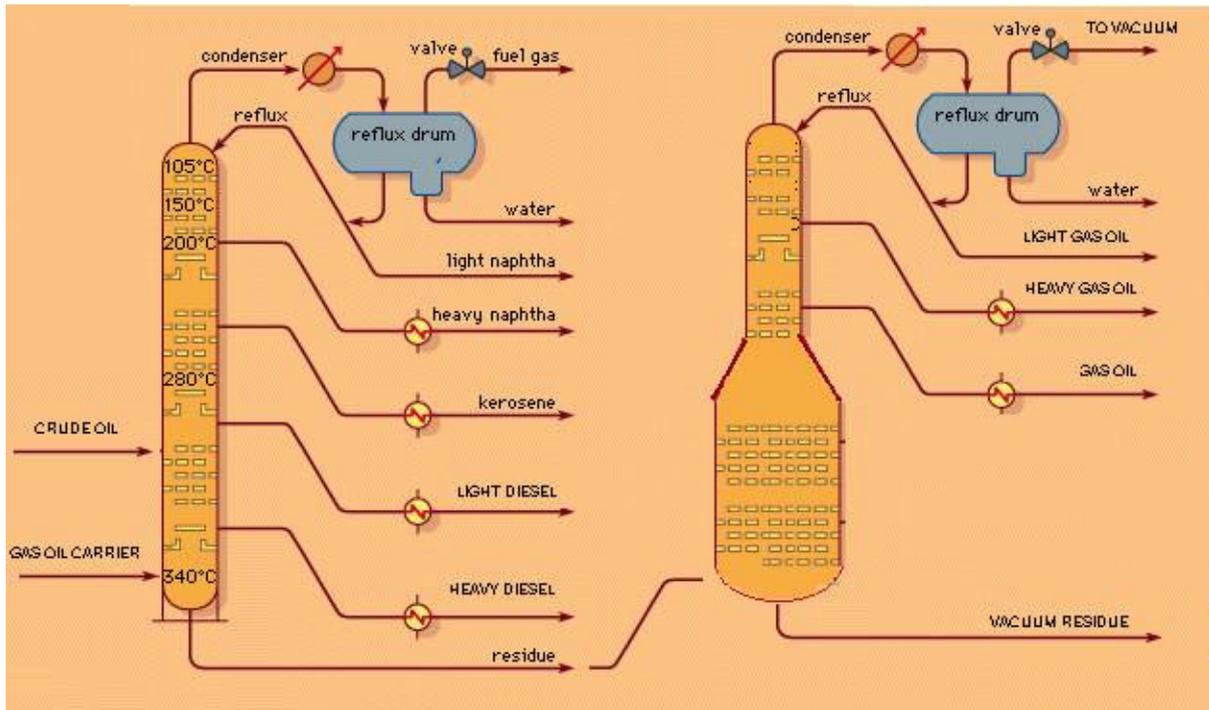


Fig. 1 - Crude unit distillation scheme

As we can see, there are two main mass balance that we can use. One considering just the atmospheric unit and another considering all the distillation unit, vacuum unit included.

In the data reconciliation problem we use the weighted least square error minimization method. Our objective is to minimize the function:

$$\sum_i \left(\frac{x_i - x^+}{s_i} \right)^2 \Rightarrow \min$$

with the constrain $f(x,y,c) = 0$ (1)

where x is a vector of reconciled data and x^+ is a vector of measurements, y represent the unmeasured variable and c is a constant, intact by reconciliation. Assuming that the error covariance matrix has zero nondiagonal elements, that is, one particular instrument of flow rate is not affected by the other instrument, then the standard deviation is proposed for each variable. The standard deviation is always

evaluated from historical data. After reconciliation we get that reconciled values are more precise than directly measurement:

The benefits of an advanced application using the DCS system, such as those for multivariable control and plantwide optimization, depend on accurate mass and energy data from instruments in the process plant. However, instruments errors, present in all plant data, frequently reduce the benefits of such applications and can even cause applications like advanced control loops to be permanently off-line.

To solve the problem, many facilities are turning to software-based systems that check and sometimes correct plant instrument readings. The software systems do this by comparing the data from plant sensors with the predicted results of sensor models. Using such data reconciliation and validation, engineers can more accurately control processes, improving the efficiency, safety and profitability of the higher level applications.

5 HOW IT WORKS

In most manufacturing plants key process instruments are already validated by taking second measurements with an independent instrument, so-called custody transfer measurements. For example, a vortex flowmeter used to measure the amount of product sold or traded between plants is frequently validated using a second measurement from an orifice-plate meter. If the two measurements differ by a more than specified amount (e.g., 1%), both meters are recalibrated. However, it is too expensive and often impractical to install secondary measurement devices throughout a process plant. Instead, engineers have turned to software tools for data validation.

These tools compare measurements from plant instrumentation with the output of a model that is primed with redundant information from within the plant's data gathering system. The data reconciliation systems can provide reliable data for the data measurements. Software-based data validation automates these tasks.

The raw values from plant instruments are taken from the process computer systems associated with a process unit and fed into a sensor model. The model includes known process measurement relationships, which are generally of the form $y = f(x)$. These equation sets are then solved using conventional equation-based techniques. The most appropriate technique varies from application to application, but any deterministic process can be modeled within the acceptable measurement accuracy and noise limitations.

Some processing of the data -- to automatically eliminate known bad measurements and to provide any required filtering -- usually occurs. Using the input data, the data reconciliation model generates a calculated value for each measurement in the problem. If the difference between the calculated value and the measured value is less than a specified tolerance, the actual measurement is validated and passed on for use in further calculations. If the difference exceeds the specified tolerance a calibration in the instrument is necessary.

For optimal accuracy, data collection and any required processing for filtering or time dependencies should be as automated as possible. Any manual data entry increases the costs, introduces the possibility of errors and increases the probability that the system will be used less frequently, and its benefits diminished.

6 INSTRUMENTS ERRORS

Although regular maintenance improves performance, instruments errors are part of every process instrument system and have to be consider when preparing mass and energy balances. In determining accuracies and weight-factors, the more important and direct measurements -- in this case flows -- are the most complicated.

A general rule of thumb is that 2.5% of range for orifice-plate meters is usually accurate enough. This is, however, a minimum. Meters that measure a recycle flow or a product or feed at a plant boundary are calibrated more frequently and are usually more accurate.

Other measured process variables, such as a column reflux, are important primarily as a relative indicator of plant operation from one situation to the next. These relative indicators are calibrated much less frequently and tend to have larger errors. The best strategy in monitoring instrumentation accuracy is to review the typical changes in a measurement during its routine calibration with respect to the minimum accuracy as described above.

Since information about the calibration history of individual instruments is normally not directly available, it is advisable to double or triple the above minimum for less-frequently calibrated instruments. Also, the 2.5% of range should not be confused with 2.5% of the actual measurement. For square root flow measurements, values in the lower ranges are more inaccurate than values at the ideal 70% of range.

A good way to calculate the weight-factors for the objective function in the data reconciliation, is to take the reciprocal of the above described instrumentation errors squared. If a well-calibrated flow measurement has a range of 1,000 m³/d its weight factor could be $((1/(0.025*1,000))^2) = 0.0016$.

The same errors could be used to determine when a measurement is faulty. If the reconciled dependent or independent model value is further from the measured value than its expected error, it could be indicated by an alarm and replaced by a reconciled value.

For the original problem of validating and improving the plant material balance, such a labor-intensive model development and maintenance effort could only be justified if the same model is used for additional purposes, such as plant optimization, or optimizing control.

Table 1 – Instruments Specifications. Before and After Reconciliation

Instrument TAG	Units	Description	Instrument		Std. Dev.
			before	after	
001FIC001	m3/d	HEAVY DIESEL	522,23	518,53	71,06
001FIC002	m3/d	LIGHT DIESEL	2.593,00	2.575,74	422,94
001FIC003	m3/d	KEROSENE	1.582,00	1.459,93	81,91
001FIC004	m3/d	HEAVY NAFTA	1.407,00	1.402,50	81,11
001FIC006	m3/d	CRUDE OIL	14.788,00	15.031,10	875,42
001FI024	Nm3/h	FUEL GAS TO FCC (01-V-02)	1.224,00	2.375,30	47,33
001FIC025	m3/d	LIGHT NAFTA	1.960,00		69,37

001FIC026	m3/d	LPG	145,82		18,02
001FI213	Nm3/h	FUEL GAS TO FCC (01-V-01)	2.200,38	2.857,70	58,04
002FIC001	m3/d	FURNACE PASS 3	2.040,00	2.592,20	103,03
002FIC002	m3/d	FURNACE PASS 2	2.040,00	2.592,20	142,25
002FIC005	m3/d	LIGHT GAS OIL	1.036,00	1.057,10	618,72
002FIC009	m3/d	HEAVY GAS OIL	3.421,00	3.408,60	
002FIC010	m3/d	HEAVY GAS OIL TO FCC	2.163,00	2.184,10	131,91
002FIC012	m3/d	GAS OIL	137,70	246,73	396,06
002FIC019	m3/d	VACUUM RESIDUE	5.307,75	6.323,37	335,45
002FIC026	m3/d	FURNACE PASS 1	2.040,00	2.592,20	159,14
002FIC027	m3/d	FURNACE PASS 4	2.040,00	2.592,20	486,45
002FIC033	m3/d	QUENCH	1.774,81	1.937,00	47,99
002FIC040	m3/d	GAS OIL CARRIER	197,80	248,04	86,56

This underlines that the scope of a sensor validation application should be clearly defined and limited. As described, to set up such a system, a sensor model must be built, tolerances and relative weighting factors must be specified, and communication routines -- to permit access to the reviewed plant measurements and distribution of required alarms and validated results -- would be the next step.

Ongoing maintenance of such a system should include a review of the identified faulty instruments, as well as a periodic review of the model's accuracy to insure that it reflects plant changes. These changes can include new equipment and lines, "revamps", changing equipment performances (e.g., from fouling and regeneration), as well as any instrumentation changes.

For a smaller investment it is possible to achieve only targeted improvements to a material balance by using a smaller model. That is our case here. In our atmospheric unit, we eliminate energy and performance calculations for the compressors, distillation columns and heat exchangers of the separation section as well as simplifying the furnaces to eliminate the combustion and convection sections, in order to significantly decrease the size and complexity of the application. This reduces the process modeling effort, the size of the model, and the number of points used in the sensor validation problem.

The standard deviation and the factor of all instruments used in the steady-state mass balance are presented in Table 1.

Now that we have all the reconciled data we can evaluate the instruments. Each graph represents an individual meter. We plot the instrument value versus the reconciled value.

The graph on Fig.2 represents the crude oil to the atmospheric tower. As we can see, this instrument is providing very accurate data and a high degree of confidence can be placed on this meter for control applications.

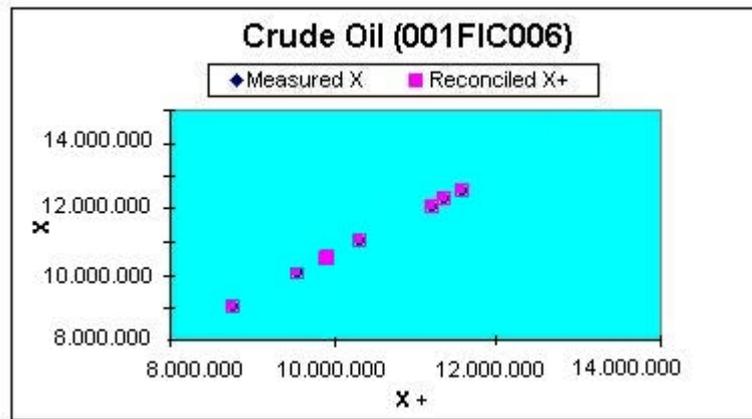


Fig. 2. Instrument with good measures.(ton/d)

The graph on Fig.3 represents the bottom of the vacuum tower. The discrepancies between reconciled measured data show us an instrument where there is a lot of inaccuracy. Its not a good think to use this instrument for unit control because it will have a major negative impact. This instrument need calibration.

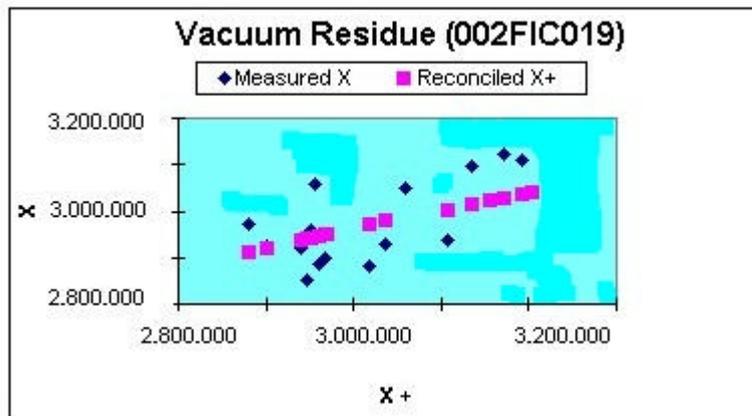


Fig. 3. Instrument that need calibration.(ton/d)

7 FUTURE WORKS

Using the data reconciliation technics we can investigate a lot of discrepancies in the plant data. The next step will be the identification of plant losses and leaks. We are planing an overall steady-state mass balance for the diesel production, as well.

8 KEEP IT SIMPLE

Reconciled data can be used to calibrate the problematic instruments to eliminate the bias. To succeed, identify your target. Data reconciliation can be used to increase the utility and achieve the theoretical benefits of the DCS systems and applications. It can verify and even correct input data used by plant optimization, advanced control and process performance calculations.

The keys to a successful implementation are to keep in mind the justification for the application and limit the effort to match the desired goals. Do not attempt to model the entire plant when the major benefits come from only one or two distillation columns.

The working principle here is: Keep it as simple as possible, but no simpler.

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