ABSTRACT

Industrial complexes rely on measurements of flow rates, qualities, and concentrations for monitoring and optimizing their operation. Corporations use the data from the various sensors and measurements to make business decisions, which affect the profitability of the operation. However, gross errors, due to a variety of reasons like faulty sensors, bad instrument calibration, or incorrect process models may corrupt the actionable information supplied to operations, quality managers, and maintenance personnel. The solution is to use the sophisticated new tools to model the process, sift through the available data to locate the gross errors, and use statistical data reconciliation to validate the sensors and instruments. In this way the data are unified to give the most accurate plant information for use by the monitoring and decision making processes.

Most mining and metallurgical plants use predictive maintenance policies based on statistical analysis and special techniques, like vibration analysis, and oil and lube analysis for critical equipment. Process control strategies are installed in several metallurgical sites. All of these depend on reliable and accurate data. The data unification methods validate the individual measurements by using the concept of balances and statistical techniques where each instrument is no longer independent of the other measurements in the facility. This paper refers to the data unification and analysis methods required for profitable plant operations. Continuous improvement and monitoring of the measurement system at the plant and analysis of the reconciled data provide the best information for the decision-making process. On-line gross error detection and elimination methods are required to ensure efficient evaluation of process performance and process optimization. An open discussion of the new methods for gross error detection and data unification will be presented.

Keywords: plant information, data cleansing, data unification, data reconciliation, gross error estimation, Kalman filtering.

INTRODUCTION

One of the biggest challenges to process plant management is the accumulation of accurate information on process operations. These data are necessary for any analysis and decision-making within the plant and enterprise. Therefore, there is a requirement for meaningful, accurate and consistent data.

Material balances calculated from data measured at various locations around process units, tanks inventories, stockpiles, silos, bins, and assays are useful for many purposes, such as yield accounting, on-line control, and process optimization (catalyst selections, reagent schemes, liner replacements, water management, utilities management). To achieve these actions, gross errors or anomalies in the production data must first classified, detected, and the source of the data examined.

Often, it is possible to calculate material balances by several independent procedures when excess measurement information, i.e., redundant data, is available. Clearly, if the data were collected without measurement errors (a theoretical condition never found in practice) all material balances calculated from redundant data would be in agreement. The real situation is that error exists in practical measurements, so that the results of material balances determined from available optional procedures differ. Consequently, best-fit computational procedures to adjust the material balances by taking measurement errors into account have been formulated.

In 1972, Nielson and Diaz described a method to adjust data for metallurgical balances. Lagrangian multipliers were introduced to locate the extremes of a differentiable objective function with the number of multipliers equal to the number of constraints equations. Several extensions of this method have been made since 1970. Reid, et.al, 1982 presents a comparison of several metallurgical mass balance techniques. Hodouin, et.all, 1993, 1997 and 2000 have presented additional research in the field.
In 1988, Bascur presented a data hierarchy where process data are validated, classified, modeled and used to provide proper data to higher-level applications to optimize the whole process complex. For each level in this data hierarchy different methods can be used to detect instrument malfunctions depending on the severity; however, it only when all data are integrated that a good assessment of the data quality can be achieved.

Both steady state and dynamic applications can be implemented to obtain the optimal state estimation of the measured and unmeasured variables. The requirements for improved data in grinding/flotation integrated circuits are described in Bascur, 1991.

The raw material is changing every hour as it is processed in a plant. It is important to track the input characteristics and resources to calculate final yield. As such, we need the topology of the plant to identify the connectivity of all measurements and process units, inventories and transactions.

One of the most important aspects are to be able to evaluate plant performance with different raw materials subject to the current process conditions and strategies. The answer must integrate the supply chain variables from concentrators, smelters, refineries, power plants, and tailing ponds. As we add value to the minerals and metals we need to access the current state of the production effectiveness. As such, more robust and user-friendly tools are required for practical use of the available technology.

The mathematical algorithms for optimal state estimation are available but the environment on how to apply the technology has to be included in the design of an overall strategy.

One of the key new developments is the availability of real-time information systems, which are capable of tracking the data structures as the plant evolves in time. The main problem is that once a model is developed it is often difficult to maintain. The user should be able to maintain and adapt the structure of the calculations performed each day.

This paper will highlight some practical issues in implementing the data hierarchy strategy to transform data into actionable information. Standardization is also the only way companies can get an accurate view of the value added to a raw material by tracking their variable costs.

Know your data. Identify what data is used for and determine what level of quality is required. The level of precision needed varies with how data is used.

Make it a continuous process. Achieving data quality is not just about breaking out data scrubbing tools once and having a clean house. The key is institution of a methodology and best practices for entering, classifying and checking information, to which all employees adhere.

Measure results. Once the data quality program has been in place long enough to achieve basic benchmarks, institute regular audits and other measurement devices to ensure standards are being enforced and to determine any cost savings.

**Data Unification, Reconciliation and Gross Error Detection Technology**

The unification can be described as defining the process unit interconnectivity between receipts, inventories, process flows and analyzers by a plant block diagram or a process flow diagram depending on the problem being addressed. One of the most important aspects in the development of process connectivity data it enables integration of dissimilar data with the business perspective of a plant. As such, all related flows to a SAG Mill could be captured (feed, water addition, lime addition, flotation reagents, power addition, etc.) Not all information is used for the mass and composition mass balance but is available for transformation in accounting or performance monitoring exception reports.

Sigmafine is a tool used to model the process flowsheet describing the connectivity of the units and instruments. The final result is an operational information management system that integrates and unifies data to enable to track yields, inventories and variable costs. Once the topology of the plant is defined, all measurements are checked and verified for consistency. This defines the network to be reconciled. In addition, a solvability analysis determines the redundancy level of the instruments and evaluates the ability for estimating unmeasured streams, accurate location of instruments and the quality requirements in the measurements for improved overall data unification.

The statistical characteristics of the various instruments and services being measured are entered into the model, together with the live data from the facility. A rigorous statistical reconciliation is performed to evaluate the instrument performance for the given time period. Sigmafine formulates the reconciliation process as a constrained weighted least-squares optimization. Sigmafine uses an extended Kalman filter to obtain the best states (measured and unmeasured) variables. This method ensures the minimum of total adjustments of the instrument measurements and gives the best estimate of the true values for both the measured and the unmeasured streams. The reconciliation results highlight...
The instruments that deviate by more than their tolerance indicating a possible instrument fault such as a bias. Sigmafine also highlights balance errors with an unexpectedly high imbalance indicating a potential loss or severe instrument problem.

The output reports can be designed and customized to the particular requirements of the process plant using conventional database access.

Reconciled value reports highlight those value estimates that have deviated from raw measurement by more than expected, indicating a possible instrumentation fault. Balance error reports highlight the units with unexpected high "imbalance" indicating potential loss. Since Sigmafine operates with a totally interactive environment, user interfaces are friendly and flexible. PI ProcessBook can show the results in the context of the raw and cleaned data. The results can also be viewed using Web Browsers using PI ActiveView Technology or using ODBC data access.

These simple steps define the process for building a plant mass balance.

1. Define the equipment components (stock piles, reactors, separators, mixers, tanks, nodes, etc.).
2. Define the streams (feeds, intermediates, products, tails, reagents, utilities, water, etc.).
3. Configure the process flow diagram from a business perspective.
4. Define connectivity to access the data, and
5. Define the exception reports and performance calculations.

Figure 1 shows a simple flotation plant will several flotation banks, mixing nodes, tanks and all the flow and analyzer measurements by stream. The results are written to a database for presentation to plant personnel. Several types of reports can be configured.

**Figure 1. Presentation of Process Data Unification, Gross Error Detection and Solvability Analysis.**

**Outlier Elimination**

The analysis of the instrument bias and precision should be performed using the history of reconciled results for that instrument in the same process. It is recommended that at least 30 reconciled results be used. Before analyzing the instrument reconciliation it is important to eliminate any outliers in the instrument correction so that the estimates of the bias and precision are not skewed by these values.

One method of outlier elimination that has achieved a wide acceptance is Chauvenet’s Criterion, which defines an acceptable scatter around the mean value of a given sample of N readings from the same parent population. Chauvenet’s Criterion is a statistically objective method for rejecting data points that can improve the accuracy of estimates made from experimental data. If the statistical method is unbiased, the mean of these estimates will approach closer to the ‘true’ value. The method of using Chauvenet’s criteria is as follows. Compute the mean and standard deviation of the data set. Assume that the errors are normally distributed, which is a reasonable assumption for looking at the meter corrections. Then all the data points

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to be retained must fall within the probability band around the mean of 1 - 1/(2N). Data points falling outside of this range are "rejected". If the sample contains 90 data points, a data point will be rejected if it is outside of 1 - 1/180 = 0.9944.

Chauvenet's criteria for removing or 'rejecting' data points that appear to be 'erroneous' is applied to the data sample to see how this changes the average value and the standard deviation. After 'rejecting' data points the new estimate for the sample mean and standard deviation is calculated. The elimination of possible outlier data points will generally give a better estimate of the mean correction error for the meter and a tighter tolerance estimate for the meter.

**Composition Tracking**

Ore being mined from different parts of the mine will have variable clay and rock contents. As such, it is important to be able to track the composition of the ore as it travels from trucks to stockpiles, bins, conveyors, etc. As such, a good estimate of the material composition is available for proper addition of reagent and process optimization.

**DATA UNIFICATION APPLICATIONS**

The use of the data unification technology provides quality data and diagnostics for:

- Prioritization of instrument maintenance requirement
- Economic justification of optimal location of instruments
- Identification of source and magnitude of losses
- Use as a preprocessor to analysis, data mining, mathematical modeling and planning tools
- Rapid identification of faulty instruments.

During implementation, business practices for sampling data, calibration of instruments, procedures, are reviewed and automated. As such, best practices for transforming data into unified set of performance indicators are enabled.

The instrument sensitivity information, diagnostic data and reconciled values generated by the tool define a number of roles for use of unified data in process plant management.

- Valued Material Loss Accounting
- Yield and Mass Accounting
- Unit Optimization
- Instrument Management
- Instrument and Measurement Sampling and Location Strategy (solvability analysis).

**Metal Loss Monitoring**

Loss is a direct reduction in profitability for all mineral and metal processing companies. It arises due to poor measurement of sales and purchases and from losses to the environment. Both have financial implications, but losses to the environment also represent a safety concern and health risk and lead to pollution. Before losses can be controlled the sources must be identified. Sigmafine identifies losses at units and vessels and allows accurate prioritization of lost prevention maintenance. Calculation of loss can become meaningful if the errors are found to be larger than the loss itself. Sigmafine allows losses to be calculated with much improved tolerances leading to more effective loss control.

- Tails in mineral processing
- Slags in smelting, iron and steel making
- Dusts in gas handling equipment
- Muds in many hydrometallurgical operations
- Emissions in all pyrometallurgical operations
- Water treatment in all type of operations
- Solution handling systems

**Yield and Mass Accounting**

Poor import / export measurements and losses to the environment are the main sources of loss within a plant. The financial implication of a 0.5% loss for a 100,000 BPD refinery may be in excess of 2.75 million US dollars per annum, dependent on whether tax is paid on loss and whether loss is valued as finished product. Introduction of loss control methodologies allows this loss to be identified and controlled. Although monitoring operational performance is heavily dependent on laboratory analysis, yield accounting provides an essential part of the monitoring procedure.

Uncertainty of yield data leads to imprecise operational decisions; therefore it is important that mass flows are both consistent and available within maximum possible accuracy. Sigmafine forms an essential part of these procedures by highlighting inconsistencies between custody transfer measurements and onsite metering, identifying potential losses and providing realistic accuracies for metering.
Potential applications are currently being implemented in mine/conminution circuits, mineral concentrators, extractive metallurgy, smelters and cement plants.

Figure 2 shows a mineral processing concentrator process flow diagram with all the units, receipts, metering, nodes, and stockpiles objects required to integrate the information required for data unification.

Plant Area Optimization

Optimization of process units either by use of simulation models or by other methods such as LP's, is one of the keystones to successful and economic plant operation. In order to get the most out of optimization, process engineers and planners need accurate data on flows, yields and inventory changes. Realistic plant data must be available to optimize a plant. Sigmafine calculates the optimal state variables for the plant based on raw observations, their statistical analysis and process topology required to satisfy a material mass balance.
Figure 4 shows an integrated grinding flotation circuit where data cleaning is required for calculation of recovery/grades for model predictions. The data cleaning is a requirement to eliminate the fog in the process data for concentrator grade recovery optimization.

**GRADE RECOVERY MAP**

<table>
<thead>
<tr>
<th>GRADE</th>
<th>RECOVERY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimize Grade</td>
<td>Optimize Efficiency</td>
</tr>
<tr>
<td>Ore Type 1</td>
<td>Ore Type 1</td>
</tr>
<tr>
<td>Optimize Recovery and Grade</td>
<td>Optimize Recovery</td>
</tr>
</tbody>
</table>

Figure 5: Elimination of data fog for determining grade

Figure 5 shows the grade recovery curves for each ore type. This is only possible after proper cleaning of the metallurgical data and by collecting the mine, mill data accurately. A composition tracking subsystem and process and equipment event tracking are required to obtain the subset of data for unification and reconciliation.

**Plant Process Simulation and Planning**

Planners and Process Engineers use sophisticated modeling systems and planning tools to provide not only unit-by-unit optimization of metallurgical plants but also global plant optimization. This includes sophisticated constraint capabilities, time period analysis and inventories. Accurate simulation is of vital importance to the effective economic operation of a plant. Accurate performance figures for inter-unit optimization are necessary to plan mine/mill production or smelter production or mine/leach/SXEW production.

**Data Quality**

![Diagram](image)

Figure 6: Adding structure and performing many mass balances to unify the data.

Sigmafine's data reconciliation capabilities will provide realistic figures for recovery, flows and inventory that will ensure that these sophisticated optimization models are tuned using accurate and realistic data.

**Instrument Management**

The solvability analysis capabilities of Sigmafine allow the program to analyze the process flowsheet and check each stream for its ability to "solve" the measurement. The solvability or nonsolvability of each stream identifies the need of additional instrumentation. The reconciliation results include sensitivities indicating the most influential instruments. These data help the instrument engineers identify the most effective locations to put new instruments and which instruments are most important to the process operation. Traditionally, if two instruments are faulty, the instrument with the highest flow is given maintenance priority. Instrument sensitivity information indicates that this should not always be the case. Using the diagnostic capabilities it is possible to ensure accurate priorities. Sigmafine provides data for monitoring of instrument performance encourages familiarity with the total instrumentation system and promotes a greater awareness of instrument accuracy.
CONCLUSIONS

There is a critical need to transform process data into actionable information. A methodology based on adding the process structure (plant topology) and knowledge of the measurements systems and its strategic locations will minimize the global error based on satisfying the material balance constraints. Process topology is key to defining the operational management database for implementation of variable costs management, yield accounting and dynamic performance monitoring.

These technologies are available today to rethink plant operations and to increase the performance of current production systems. Data unification simplifies the integration of information from the process, laboratory, receipts and manual data entry. It generates high quality performance information from process data. The synergy of combining process data with transactional data provides a deeper understanding of the data for continuous improvement and innovation. It simplifies and speeds up the accounting process and detection of gross errors. It simplifies the identification of process, equipment, quality problems and opportunities. These data can be used for plant optimization, environmental reporting, costing, gross error detection, accounting, instrument management and assessment of the global measurement strategy.

The unified information can be exposed into web centric environments. The Web is quickly becoming a key driver of data cleanliness (or dirtiness) as it gains ground as a way for knowledge personnel, managers, research groups, services providers and customers to input and access business information.

The key to re-engineering is linking people, business processes, strategies and the best enabling technologies. It is important to recognize that the cleaning data is a process. As such, several groups (instrumentation, maintenance, process engineering, accounting and managers) collaborate in the data unification process. This team effort should be rewarded.

The major ingredients for a successful implementation are:

- A solid real time information management infrastructure that provides historical data base access and historical database structure access.
- Implementing total quality management guidelines and people empowerment for continuous improvement and innovation.
- A desktop environment to unify the access of enterprise information.

Benefits can be obtained using current process control, instrumentation and information systems investments. Thus, the returns are very attractive.

It is critical to invest in a real time information management infrastructure to collect, validate, classify, aggregate, and clean the data for better decision-making.

The successful application should be judged on how it provides added value to the overall information system, such as new ways of storing data and events, classifying, aggregating, combining and visualizing existing data and information.

REFERENCES


