



QUANTIFICATION OF THE DATA IMPROVEMENT PRODUCED BY OPTIMISED METALLURGICAL PLANT MASS BALANCES

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ABSTRACT

The data improvement, as achieved by optimising a mass balance of inconsistent experimental data, was quantified statistically using a Monte Carlo technique. It was found that an increase in the number of levels in the mass balance problem produced further increases in the data improvement. However, the improvement was lost when, for example, the solids split value was numerically in the vicinity of the flow split value. Furthermore, accuracy in the data at one level of the mass balance was found to be transferred to only one adjacent level of the mass balance. For example, accurate assay data produced improvement in the solids and assay split values, but not in the flow split values. Similarly, accurate pulp density data produced improvement in the flow and solids split values, but not in the assay split values. And, accurate flow data produced no significant improvement in the solids split or assay split values. In general, the transfer of improvement only occurred in the direction of lower level data (eg., from the assay to the solids level, or from the solids to the flow level).

Keywords

Optimisation; mass balance; simplex; sampling; process plant

INTRODUCTION

Unit operations in metallurgical plant are increasingly assessed using mass balance audits. Samples of the input and output streams of the section of the plant concerned are obtained in order to determine, for example, the flow rates, solids content, and assay species content. Invariably the information fails to satisfy basic material balance criteria, sometimes to the extent that the results cannot be interpreted. With the availability of high speed computers, it has become common practice to utilise sophisticated mass balancing packages. The software produces a mass balance, with the error dispersed as broadly as possible amongst all of the data.

There is an expectation that the balanced data set is a better representation of the conditions in the plant, than is the experimental data set. However, to date the assessment of a particular mass balancing method has often been limited to merely a comparison of alternative function minimization techniques [1] and mass balancing philosophies [2], or to a subjective assessment based on whether the balanced data appears to be sensible. An element of blind faith is required, even by experienced tacticians.

The purpose of this paper is to present a Monte Carlo technique, first used by Galvin and Firth [3], to statistically quantify the level of data improvement produced by optimising the mass balance. In order to

measure the degree of improvement, it is necessary to know the correct values of the data in the problem, referred to in the paper as "the true data set". In the context of an operating metallurgical plant, of course, such values are impossible to obtain. Consequently, for the purpose of quantifying improvement, it was appropriate to firstly obtain a balanced data set, by whatever means, and declare it as the true data set. Each data value in the set was then disturbed using a random number, thereby producing a simulated, unbalanced, experimental data set. The mass balance software was then used to balance the simulated experimental data, and the true data set was used to calculate the deviations and hence assess the degree of data improvement. The technique was repeated 5000 times in order to obtain a statistical measure of improvement.

Many unit operations in metallurgical plant are separators, consisting of an input feed stream, and two output streams. A material balance around a separator is effectively calculated at a series of levels, each corresponding to a different material group. At the 0th level is the mass flow of all material (solids and water), at the 1st level is the mass flow of solids only, and at the 2nd level is the mass flow of each particular component of the solid. In this study only one assay was considered at the 2nd level, referred to as the assay fraction.

The separation, occurring at a given level, is usually described in terms of the mass proportion of the material group reporting to a specific output stream, relative to that entering the separator. Such quantities are referred to in the paper as the flow split, the solids split, and the assay split, for the 0th, 1st, and 2nd mass balance levels respectively. The 2nd mass balance level, incidentally, may consist of several assays and, or, size fractions. A 3rd mass balance level may then consist of an assay conducted on a particular size fraction.

While many plants consist of unit operations involving more than three flow streams, or of complex networks of unit operations, the study was limited to an examination of the mass balance around a single separator involving just one input and two output streams. By using the simplest possible mass balance problem, it was possible to focus on the issue of data improvement, especially the improvement in the values of the various mass splits, rather than just the improvement achieved for individual data values.

There are a number of reasons for using the above approach. Firstly, when the performance of a unit operation is to be assessed, it is often the accuracy of a mass split which is important, rather than the accuracy of a particular data value. For example, the efficiency of a classifier, such as a sieve bend, is usually assessed by determining the partition curve, and noting the value of the cut point and the steepness of the S shaped curve. Each data point of the curve is in fact the mass split of the solids in a given particle size range.

Indeed, Kapur *et al.*, [4] recognised the fundamental importance of the mass splits, referred to as performance indices, in developing their mass balancing procedure. Their approach was based on the philosophy that only the data of flow streams either entering or leaving a given separator should be allowed to influence the final mass split values of that separator. Thus Kapur *et al.*, in the first instance, determine the mass splits for each unit operation, at each level. The mass split values are then used as a rigid framework for producing the global balance around the overall plant. The individual data values are permitted to vary, but with minimum perturbation of the mass split values.

Secondly, for a given separator the inclusion of additional mass balance levels, or additional sub-groups within a level, leads to a greater over specification of the mass balance problem, and hence the prospect of achieving greater data improvement. However, the numerical values of the various mass splits also effects the level of improvement [5]. For example, if the assay split is numerically identical to the solids split, then the assay species material simply flows through the separator with the solids, and thus there is no real assay species separation with respect to the solids. Hence, there is effectively a loss of one level of data in the mass balance, and a loss of potential improvement. It is desirable, therefore, to examine the dependence of the mass split improvements on various combinations of assay and solids split values.

True Data Set Mass Balance

A schematic representation of a separator is shown in Figure 1, along with a true data set. The feed slurry enters the system at a mass rate, F_1 , of 100.0, with a pulp density fraction, P_1 , of 0.20, and an assay fraction, A_1 , of 0.25. The slurry leaving the system via stream 2 has a mass rate, F_2 , of 30.0, a pulp density fraction, P_2 , of 0.50, and an assay fraction, A_2 , of 0.0333. The remainder, which reports to stream 3, consists of a mass flow rate, F_3 , of 70.0, a pulp density fraction, P_3 , of 0.0714, and an assay fraction, A_3 , of 0.90. The mass balances at the three levels are given below:

$$\begin{aligned} \text{0th level (total mass flow):} \quad F_1 &= F_2 + F_3 \\ 100 &= 30 + 70 \end{aligned} \quad (1)$$

$$\begin{aligned} \text{1st level (solids flow):} \quad F_1 P_1 &= F_2 P_2 + F_3 P_3 \\ 20 &= 15 + 5 \end{aligned} \quad (2)$$

$$\begin{aligned} \text{2nd level (assay material flow):} \quad F_1 P_1 A_1 &= F_2 P_2 A_2 + F_3 P_3 A_3 \\ 5.0 &= 0.5 + 4.5 \end{aligned} \quad (3)$$

The mass splits, defined as the proportion of the feed mass reporting to stream 2, are given below for the three levels:

$$\begin{aligned} \text{0th level (flow split):} \quad \alpha_F &= F_2 / F_1 \\ &= 0.30 \end{aligned} \quad (4)$$

$$\begin{aligned} \text{1st level (solids split):} \quad \alpha_S &= F_2 P_2 / (F_1 P_1) \\ &= 0.75 \end{aligned} \quad (5)$$

$$\begin{aligned} \text{2nd level (assay material split):} \quad \alpha_A &= F_2 P_2 A_2 / (F_1 P_1 A_1) \\ &= 0.10 \end{aligned} \quad (6)$$

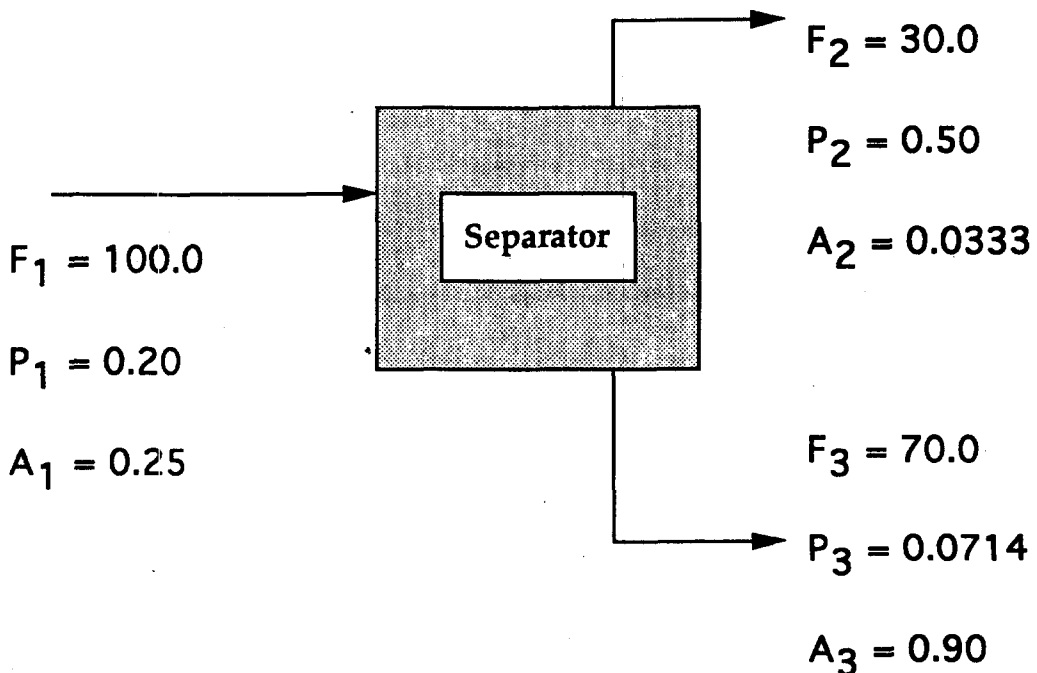


Fig.1 An example of a true data set for a separator with one feed and two output streams. The data consists of flow, pulp density, and assay values, and satisfy material balance criteria.

Simulation of an Experimental Data Set

A Monte Carlo technique was used to simulate the experimental data sets. A simulated experimental data set is shown in Figure 2, produced using the true data set in Figure 1, and random numbers based on a relative standard deviation of 0.1 for each entry. In practice, of course, some data is known with greater confidence than other data, and hence appropriate relative standard deviations should be used where required.

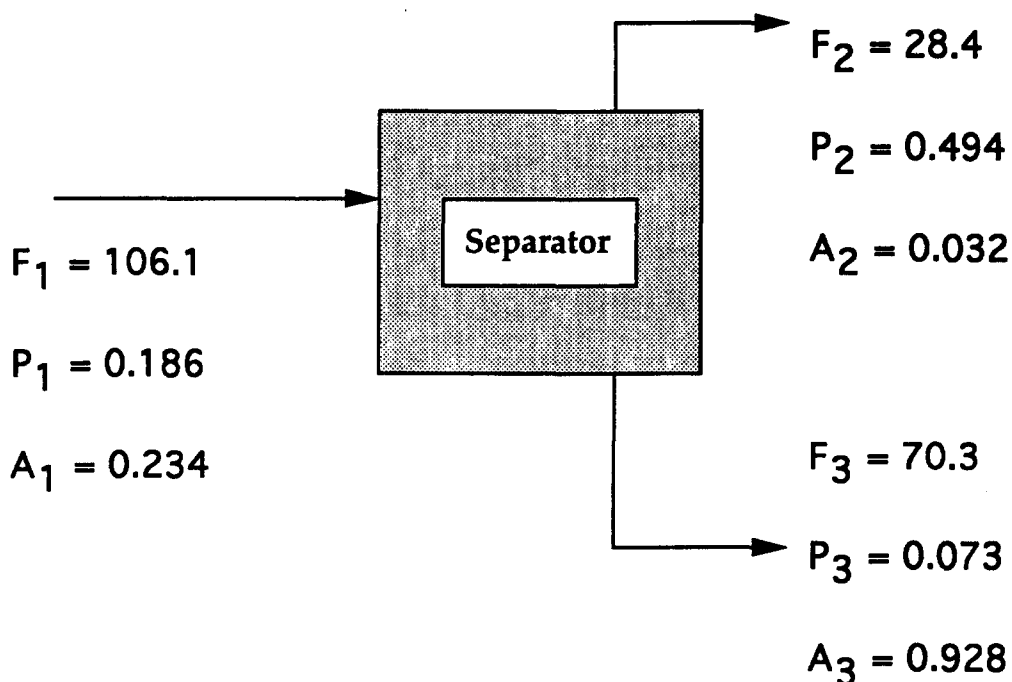


Fig.2 An example of a simulated experimental data set, produced by disturbing the values in Figure 1 using random numbers.

Random numbers from a rectangular distribution ranging from 0 to 1 were used to produce random numbers from a normal distribution. A sequence of six random numbers from the rectangular distribution was averaged in order to produce a normalised random variable. The normalised random variable was then standardised to a mean of 0 and a standard deviation of 1 by, subtracting 0.5, and multiplying the result by $\sqrt{12}$. The normalised random variable was then designated as $N(0,1)$.

The disturbance applied to a true value to produce a simulated value was calculated by multiplying the random value from the $N(0,1)$ distribution by the standard deviation. In the case of the F_1 value, the standard deviation was 0.1×100 . Consider a sequence of six random numbers from a rectangular distribution, 0.411, 0.866, 0.705, 0.381, 0.904, 0.788, having an average value of 0.676. The simulated experimental F_1 value was,

$$F_1 = (0.676 - 0.5)\sqrt{12}(0.1 \times 100) + 100$$

$$= 106.1$$

The other simulated values shown in Figure 2 were obtained in the same way. These data were then balanced using the mass balance software, described later, producing the balanced data set shown in Figure 3.

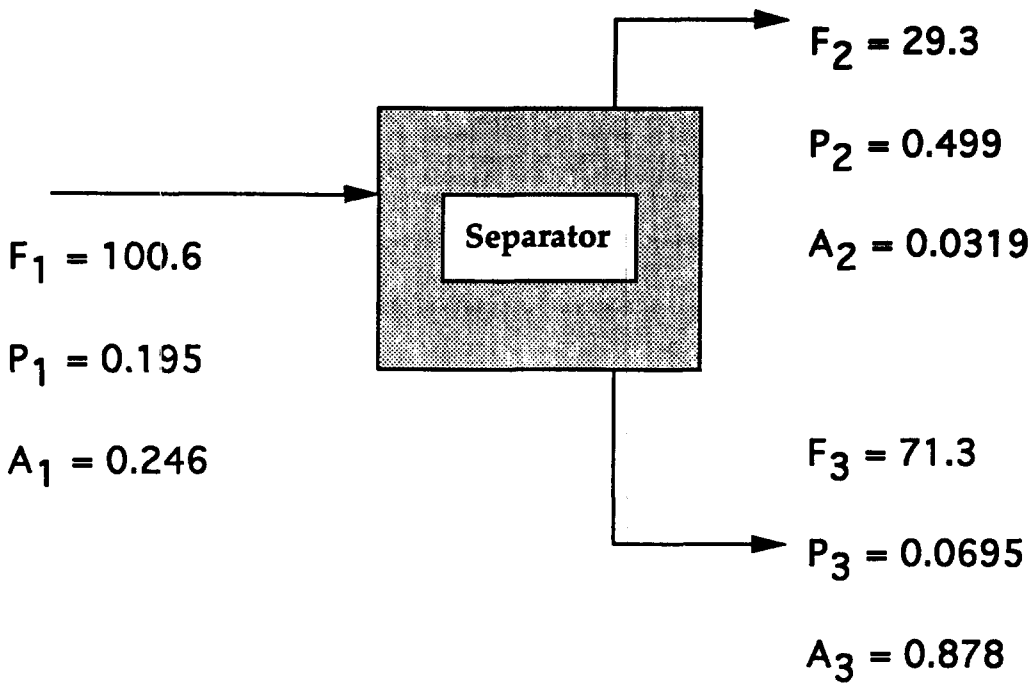


Fig.3 A balanced data set, obtained by optimising the mass balance of the data in Figure 2.

Definition of Improvement

The focus of the study was on the improvement in the values of the mass splits. The improvement index, I , for a given split was defined as the standard deviation of the experimental split values divided by the standard deviation of the balanced split values. That is,

$$I = \sigma_{(\text{experimental mass split})} / \sigma_{(\text{balanced mass split})} \quad (7)$$

In essence, the improvement index quantifies the factor by which the uncertainty of a given mass split is reduced.

A total of 5000 simulated experimental data sets, similar to that shown in Figure 2, were generated in order to examine a given problem, and determine the index, I , for a particular mass split. The experimental mass split was calculated for each data set, thereby producing a population of 5000 split values, and hence a standard deviation. Each experimental data set was fed into the mass balance program to produce an optimised mass balance, and a corresponding balanced mass split value. The standard deviation of the 5000 balanced mass split values was then determined. Then, finally, the improvement index was calculated using equation 7.

The main difficulty in using equation 7 is in selecting a suitable basis for calculating the values of the experimental mass split values, and hence the standard deviation of the distribution of values, given that the experimental data does not satisfy a mass balance. For example, the flow split value for the simulated experimental data in Figure 2 is either,

$$\alpha_F = F_2 / F_1 = 28.4 / 106.1 = 0.268 \quad (8)$$

or

$$\alpha_F = F_2 / (F_2 + F_3) = 28.4 / (28.4 + 70.3) = 0.288 \quad (9)$$

Although equation 9 often provides, by far, the better estimate, there are circumstances where it is also unsatisfactory. Therefore, an exact analytical solution to the problem, which actually produces the optimum mass split value, α , for a system with input M_1 and outputs, M_2 and M_3 , was derived (see Appendix A). The only assumption was that the data of the three flow streams had identical relative standard deviations. The result is,

$$\alpha = (M_2^2 (M_1 - M_3) + M_2 (M_1^2 + M_3^2)) / (M_1(M_2^2 + M_3^2) + M_1^2 (M_2 + M_3)) \quad (10)$$

The calculated value of α_F , for the data in Figure 2, is 0.287. Experimental flow splits were obtained by substituting the F_i values for the M_i values. Similarly, experimental solids splits were obtained by substituting the FiP_i values for the M_i values, and experimental assay material splits were obtained by substituting the FiP_iA_i values for the M_i values.

Equation 10 produces optimum mass splits based on the data at one level of the mass balance only. The mass balance program, however, produces optimum mass splits based on all levels of the mass balance problem. Information at one level flows across to another, and visa versa, producing a better overall result, and hence data improvement. Clearly, the use of equation 10 to obtain the experimental mass splits leads to a conservative measure of the data improvement. Indeed, it is the improvement that results from information flow across the various levels of the mass balance that is quantified by the improvement index.

Mass Balance Optimisation Procedure

There are several methods available for optimising material balances [2,4,6-7]. In this study a series of dependent variables were selected for the purpose of calculating the mass balance.

An objective function, based on the errors in the mass balance, was minimised through the use of the Simplex search technique [8] of Nelder and Mead [9], resulting in a dispersion of the mass balance error amongst all of the data values. The objective function, G , used in this study, was defined as,

$$G = \sum_i w_i (E_i - B_i)^2 \quad (11)$$

where E_i is the i th experimental value, B_i is the i th balanced value, and w_i is the i th weighting factor. Here, the weighting factor was equal to the inverse of the variance of the i th value. That is,

$$w_i = \sigma_i^{-2} \quad (12)$$

In effect, the objective function was equal to the sum of the squares of the number of standard deviations of adjustment [10]. Therefore, data with a relatively low standard deviation will produce a relatively high contribution to the total error for a given adjustment. Consequently, such data are likely to undergo less adjustment.

The Simplex technique is just one of a number of optimisation techniques. White *et al.* [1] has compared the Fletcher-Powell, Powell direct, Rosenbrock and the Simplex methods. Although not as efficient as Powell's method, the Simplex method is easy to incorporate into a mass balance program, and is reasonably fast.

Each row of the Simplex contains a set of N independent parameter values, sufficient to define a single mass balance. There are $N+1$ such rows. Initially, the first row consists of the raw experimental data, and the following N are formed by adjusting, in turn, one of the N values using a step size equal to 25% of the experimental value. A three flow stream problem at the 0th level only consists of $N=2$ degrees of freedom. In two dimensions the Simplex is a triangle, while in three dimensions it forms a tetrahedral geometry. In the Simplex method, the objective function is evaluated at each vertex. It is then reflected from the vertex of greatest error, through the centroid, and towards regions of lower error, and eventually towards the solution.

RESULTS AND DISCUSSION

The mass balance experiments fall into two parts. In Part 1 the objective was to examine the effect of each level of the mass balance, and the numerical effects of the various mass split values on improvement. In Part 2 the objective was to assess the effect of the accuracy of data at a given mass balance level on the improvement in the mass split values at other levels.

Part 1

In Part 1 a relative standard deviation of 0.1 was used for all the data. The true data sets used in most of the experiments are listed in Appendix B.

Figure 4 shows the flow split improvement index, I_F , as a function of the flow split, α_F . It is evident that when the mass balance problem only involves flow data the level of improvement is exactly 1.0 because the experimental flow splits, obtained using equation 10, are already optimum values. The inclusion of 1st level pulp density data into the problem causes an increase in the flow split improvements, an effect also repeated when 2nd level assay data is included. The pulp density data was based on the condition of a constant solids split of 0.75. Thus, the pulp density parameter produced very little increase in the flow split improvement when the flow split value was also equal to 0.75. Indeed, for reasons yet determined, there was no improvement produced beyond the flow split value of 0.75. The improvement resulting from the inclusion of the assay data, however, was significant at all flow split values because of the numerical difference between the solids split value of 0.75 and assay material split value of 0.10.

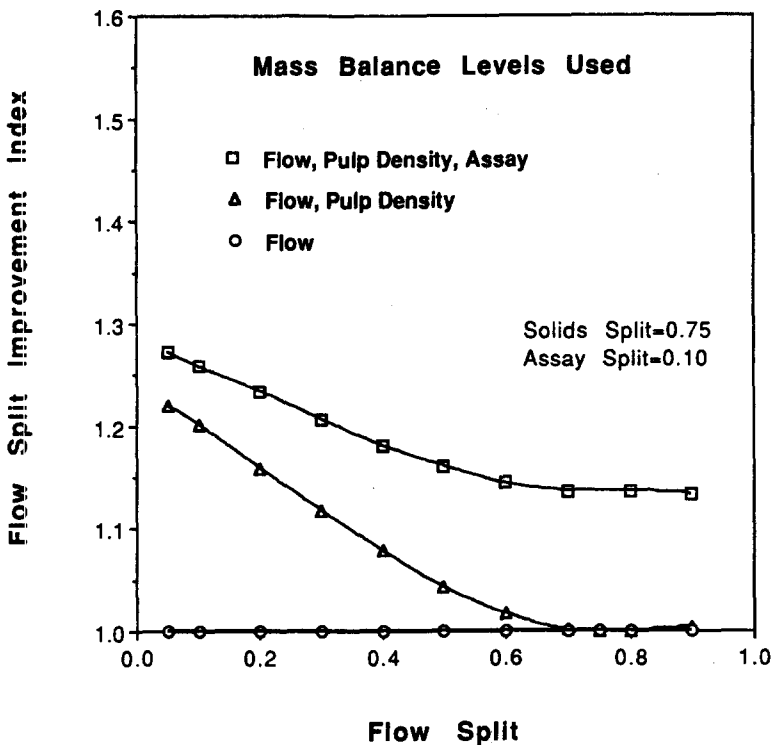


Fig.4 The improvement in the flow split is shown as a function of the flow split value. The improvement increased as the number of levels used in the mass balance increased. There was less improvement when the solids split value was equal to the flow split value.

Figures 5 and 6 show the data improvement achieved at all levels of the mass balance problem. The results obtained when only flow and pulp density data are used are shown in Figure 5. The flow split and the solids split improvements are similar, with the worst case occurring when the two split values are identical.

However, as shown in Figure 6, the inclusion of the assay data into the mass balance problem brought significant levels of data improvement at all levels.

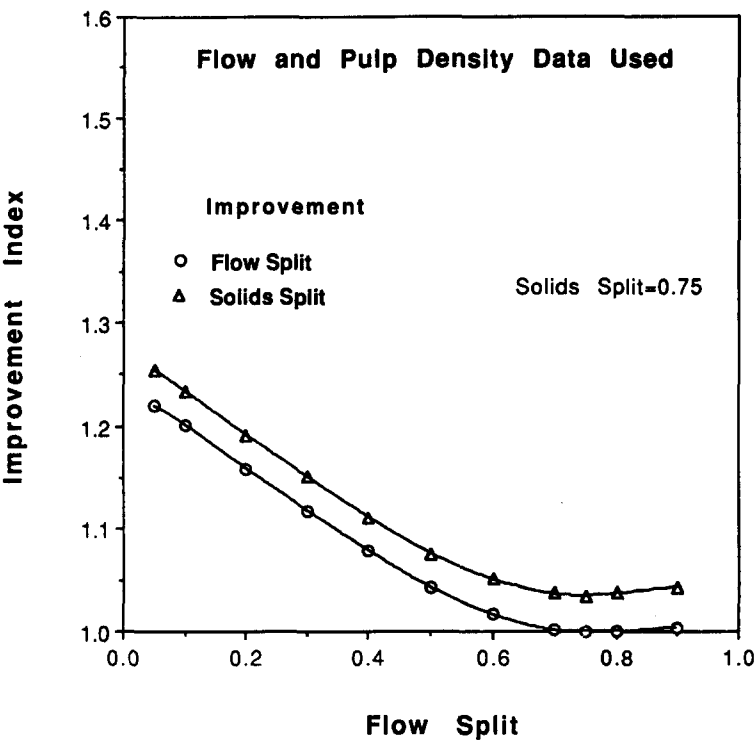


Fig.5 The improvement in both the solids and flow split values as a function of the flow split value. In this case, only the flow and pulp density mass balance levels were used.

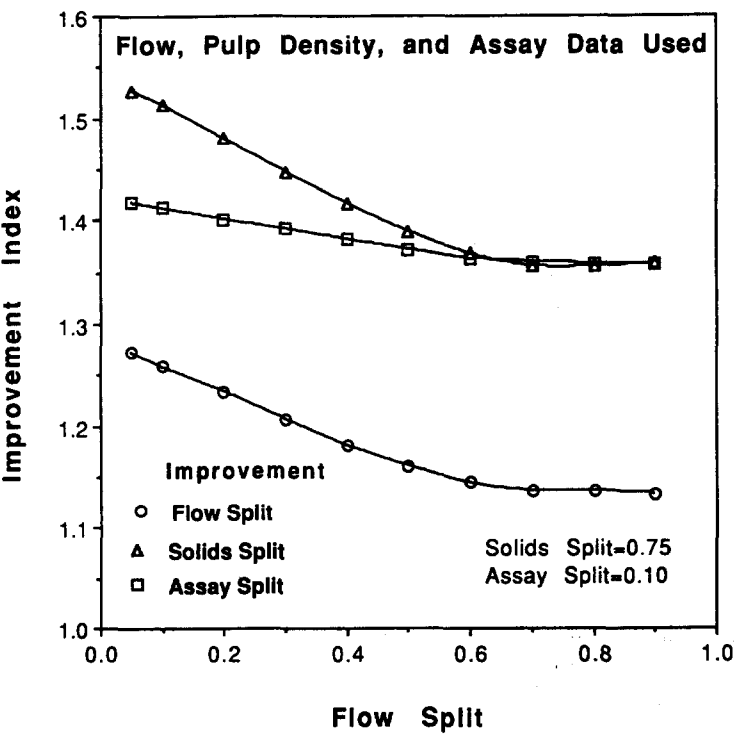


Fig.6 The improvement in all three mass split values, as a function of the flow split value. In these experiments all three mass balance levels were used. It is evident that the inclusion of the assay data produced additional improvement at all levels of the mass balance.

The distributions of the experimental and balanced solids split values are shown in Figures 7A and 7B respectively for the specific case of $\alpha_F=0.30$, $\alpha_S=0.75$, and $\alpha_A=0.10$. The results, based on 5000 experimental data sets, show that the mass balance program produces a narrower distribution of solids split values, and hence a solids split improvement index, in this case, of $(0.0147/0.0102)=1.44$.

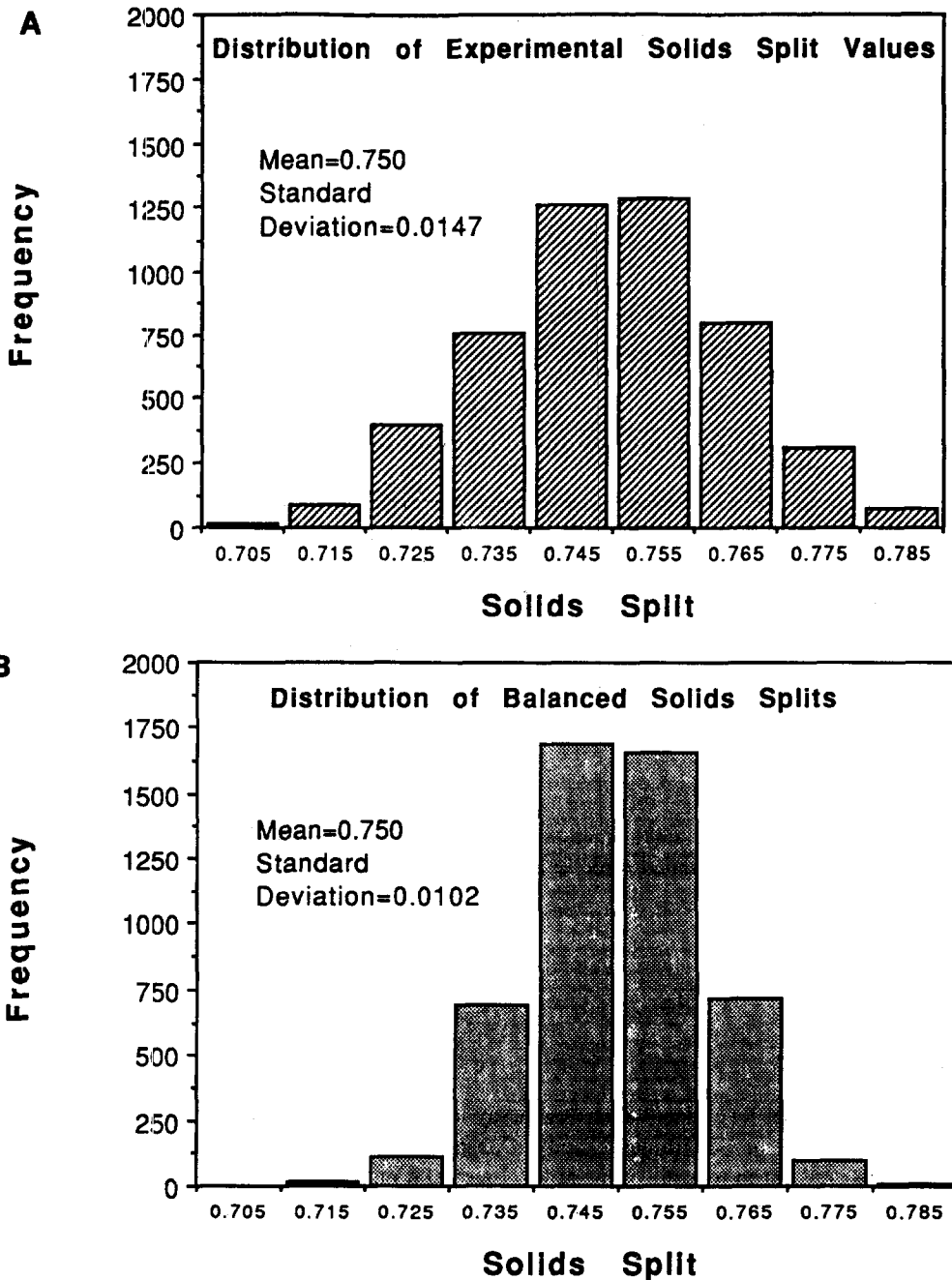


Fig.7 The distribution of the (A) experimental solids split values, and the (B) balanced solids split values, as obtained for 5000 simulated experimental data sets. It is evident from the reduced spread of the solids split values, that improvement in the solids split values was obtained. In this experiment the flow split was 0.30, the solids split was 0.75, and the assay split was 0.10.

The effect of changing the assay material split value from 0.10 to 0.75 resulted in a significant reduction in the flow split improvement, as shown in Figure 8. Indeed, the net effect was a loss of the 2nd level of the mass balance. The curve shown in Figure 8, for $\alpha_S=0.75$, is identical to the curve shown in Figure 5 for flow and pulp density data only.

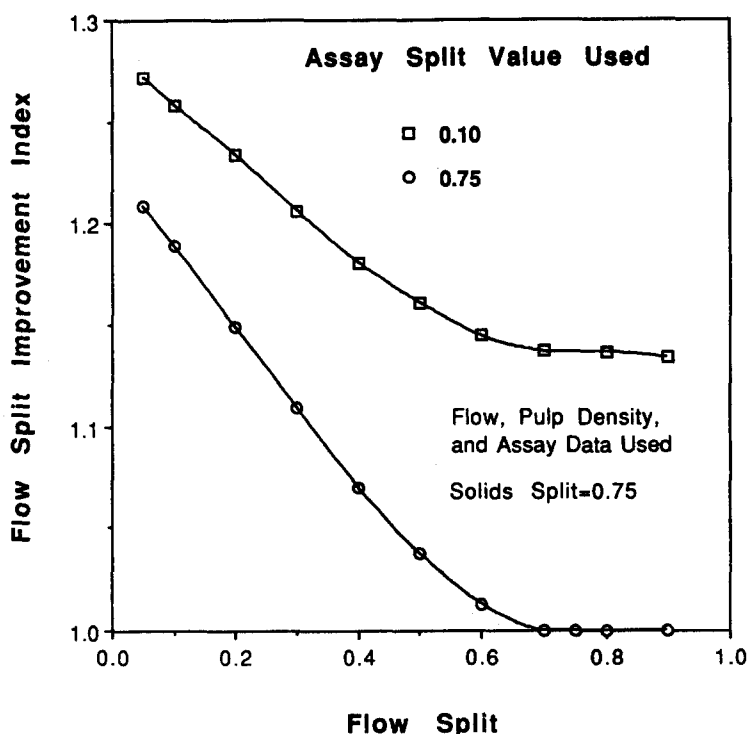


Fig.8 The effect of changing the assay split value from 0.10 to 0.75. The flow split improvements decreased to the levels obtained in Figure 5 where only flow and pulp density data were considered.

Part 2

It is theoretically possible to calculate the split value at level n based on the data at level $n+1$. For example, the solids split value can be calculated directly using the assay fraction data only. That is,

$$\alpha_S = (A_1 - A_3)/(A_2 - A_3) \quad (13)$$

and the flow split value is given by,

$$\alpha_F = (P_1 - P_3)/(P_2 - P_3) \quad (14)$$

Consequently, if the higher level data values (eg. assay level) are known exactly, then the lower level split value (eg. solid split) can be determined exactly. Consequently, as the accuracy of the data at level $n+1$ increases, the improvement in the split value at level n should increase. In other words, information should flow from a high level to an adjacent lower level. The purpose of this part of the paper is to determine the limitations of the information flow.

In this section, data at the three mass balance levels were used (see Appendix B) and, unless stated otherwise, the relative standard deviations of the data remained at 0.1. In Figure 9, the effect of using a relative standard deviation of 0.01 for the flow data is shown. Interestingly, there was no improvement achieved in the flow split values. The flow data, and flow split values were certainly relatively accurate. However, because the other data in the problem were relatively inaccurate, no further improvement was

possible. Some improvement in the solids and assay material split values was achieved, probably as a result of information flow from level 2 to level 1, and then back to level 2.

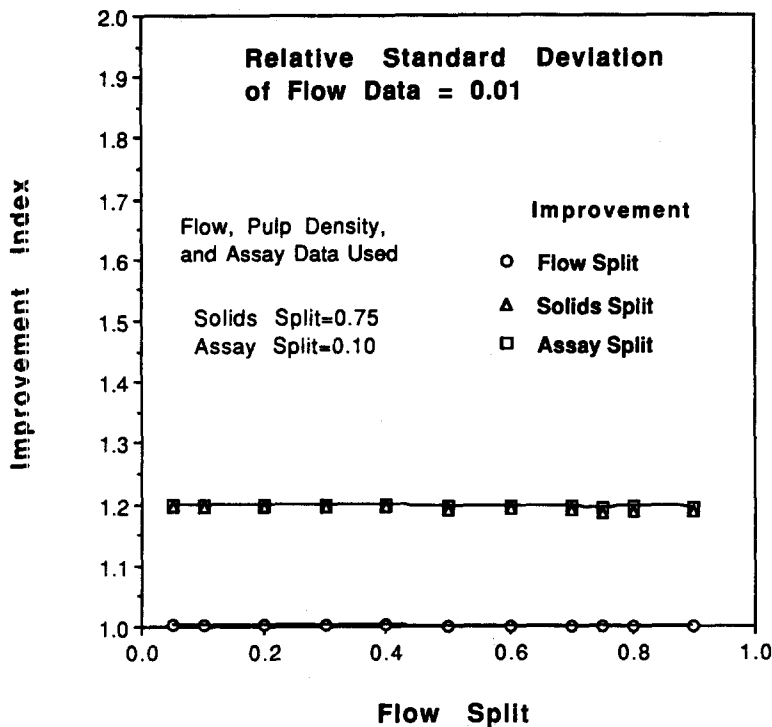


Fig.9 The effect of increasing the accuracy of the flow data using a relative standard deviation of 0.01. The improvement of the three mass split values remained relatively low.

One of the most interesting results from the study is shown in Figure 10. Here, the relative standard deviation of the pulp density data was set at 0.01. The accurate pulp density data resulted in very significant improvement in the flow split values, an effect easily explained through equation 14. It is also interesting that there was very significant improvement in the solids split values. The experimental solids split values, which depend on the FiP_i values, would have been inaccurate because of the inaccurate flow data. Hence, there existed potential for data improvement. The subsequent improvement was produced by a reversal in the information flow, from the accurate flow split values to the solids split values, during mass balancing. However, the flow of information did not continue to the next level of the mass balance, as evidenced by the relatively low improvements in the assay split.

The improvement index for the flow and solids splits was a minimum when the solids split and flow split values were equal at 0.75. Here, the accurate pulp density data produced no additional improvement in the flow split value. In turn, there was no return of improvement to the solids split value.

In the final series of experiments, as shown in Figure 11, the relative standard deviations of the assay data were set at 0.01. The accurate assay data led to very significant improvement in the solids split values, in accordance with equation 13, which in turn led to significant improvement in the assay split values. However, the improvement in the flow split values was relatively poor. Accurate solids split values, which depend on accurate FiP_i values, may consist of inaccurate Fi and P_i values. Hence, the benefits of the accurate assay data was not transferred to an improvement in the flow split values. It is also interesting to note that when the flow and solids split values were equal to 0.75, the improvement in the solids split value remained high, a consequence of the accurate assay data.

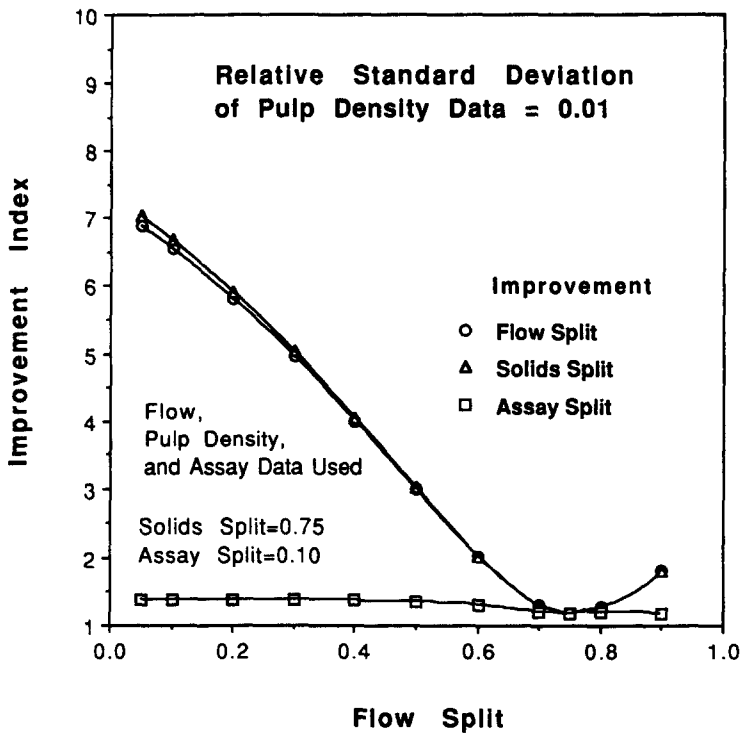


Fig.10 The effect of increasing the accuracy of the pulp density data using a relative standard deviation of 0.01. There was a very significant increase in the improvement in the flow and solids split values, and little additional improvement in the assay split values.

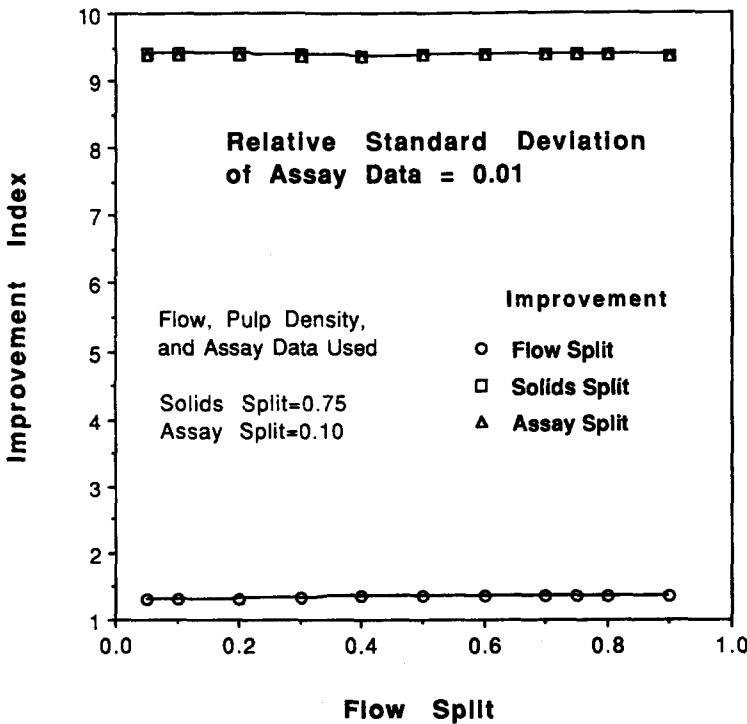


Fig.11 The effect of increasing the accuracy of the assay data using a relative standard deviation of 0.01. In this case there was a very significant increase in the improvement in the solids and assay split values, and little additional improvement in the flow split values.

CONCLUDING REMARKS

There are a number of implicit assumptions made in using the technique described in this paper. Firstly, the standard deviations of the simulated experimental data are known exactly, whereas in practice such data can only be estimated on the basis of trials and, or, experience. Secondly, the errors, associated with a parameter value, are random and normally distributed. However, in practice bias and systematic errors are introduced at all stages, from sampling to final analysis [11]. Thirdly, for every simulated experimental data set, there exists a true data set that satisfies material balance criteria. However, in an operating plant there exists short and long term variability, and there is no guarantee that the plant is operating close to steady state. Hence, the notion that a true, and balanced data set exists, may be ill-founded.

Although the quantification of the improvement is based on a set of ideal circumstances, the technique can still be applied to real situations. Every mass balance problem involves a unique framework of inconsistent non-linear equations. A standard mass balance of the raw experimental data can be used to arrive at a true data set, and relative standard deviations based upon past experience can be used in the simulation of experimental data. One can then assess the prospect of data improvement, and the relative reliability of the balanced splits determined for each unit operation in the plant. Furthermore, the circumstances that lead to more reliable balanced data can be determined, thereby assisting the planning of the sampling trial.

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APPENDIX A — DERIVATION OF EQUATION 10

Consider a separator for which an experimental data set of M_1 , M_2 , and M_3 has been obtained. The corresponding balanced data set is given by,

$$B_1 = B_2 + B_3 \quad (A1)$$

The objective function, for constant relative standard deviations of 1.0, is given by,

$$G = (1 - B_1/M_1)^2 + (1 - B_2/M_2)^2 + (1 - B_3/M_3)^2 \tag{A2}$$

Combining equations A1 and A2 gives,

$$G = (1 - (B_2 + B_3)/M_1)^2 + (1 - B_2/M_2)^2 + (1 - B_3/M_3)^2 \tag{A3}$$

Differentiating equation A3 with respect to B_2 and then B_3 , and setting the two equations equal to 0 produces two algebraic expressions involving the unknowns B_2 and B_3 . The expression for the mass split, as defined by equation 9, is then used to obtain equation 10.

APPENDIX B

Table B1 provides a list of most of the true data sets used in this study.

α_F	F_1	F_2	F_3	α_S	P_1	P_2	P_3	α_A	A_1	A_2	A_3
0.05	100	5	95	0.75	0.20	3.000	0.053	0.10	0.25	0.033	0.90
0.10	100	10	90	0.75	0.20	1.500	0.056	0.10	0.25	0.033	0.90
0.20	100	20	80	0.75	0.20	0.750	0.063	0.10	0.25	0.033	0.90
0.30	100	30	70	0.75	0.20	0.500	0.071	0.10	0.25	0.033	0.90
0.40	100	40	60	0.75	0.20	0.375	0.083	0.10	0.25	0.033	0.90
0.50	100	50	50	0.75	0.20	0.300	0.100	0.10	0.25	0.033	0.90
0.60	100	60	40	0.75	0.20	0.250	0.125	0.10	0.25	0.033	0.90
0.70	100	70	30	0.75	0.20	0.214	0.167	0.10	0.25	0.033	0.90
0.75	100	75	25	0.75	0.20	0.200	0.200	0.10	0.25	0.033	0.90
0.80	100	80	20	0.75	0.20	0.188	0.250	0.10	0.25	0.033	0.90
0.90	100	90	10	0.75	0.20	0.167	0.500	0.10	0.25	0.033	0.90