Improving the Quality of Iron Ore Shipments

James E. Everett, Department of Information Management and Marketing
The University of Western Australia, Nedlands, Western Australia 6009
e-mail: jeverett@ecel.uwa.edu.au

Abstract Customers for Western Australian iron ore are concerned that successive shipments are uniform in composition, with respect to several elements (particularly Iron, Phosphorus, Silicon, Aluminium and Calcium). Although mine production can be planned to average a target grade over several months, local variations in the ore body mean that individual train loads arriving at the shipping yard vary unacceptably in composition. Variations in composition can be smoothed at the shipping yard by appropriate stacking and restacking of the ore. Methods used can vary from simple random filtering through an array of holding stacks to implementing an intelligent policy of stacking and restacking incoming ore based upon its composition and the composition of the holding stacks to which it may be added. Composition variations are to some extent correlated, both between the various elements and across time. It is necessary to optimise with respect to a composite of the multiple composition criteria. The benefits of improved uniformity in composition must be traded against the costs of handling and of storage. Consequently, the problem is not soluble analytically. Simulation provides a useful way of exploring the implications of various possible ore handling policies, and can lead to improved quality performance. This paper describes the design and application of a simulation model that has been used for the planning of iron ore handling procedures. The simulation model, written in Extend™, has a dynamic graphical interface which has proved helpful both for debugging the model and for constructive interaction with managers and operating staff.

1. INTRODUCTION

Iron ore is a major export from Western Australia. From a number of mines inland, ore is railed to a seaport, where it is stock piled and then shipped out.

Customers require that the ore composition be of acceptable uniformity with respect to several minerals (notably iron, silica, alumina, calcium oxide and phosphorus). Although the mining production can be planned to average a desired composition over a lengthy period, mining operations result in shorter term fluctuations and variability in composition. To some extent these fluctuations in composition can be smoothed out by the way the ore is handled at the port, in being unloaded from rail wagons, stored in stock piles and loaded onto the ship.

Clearly, some smoothing in composition can be achieved just by loading the ore onto large stockpiles, and then recovering it from the completed stockpiles in such a way that it is thoroughly mixed.

If the ore composition was not serially correlated, the amount of smoothing obtained would depend only on the size of the stockpiles. However, because of the mining operations, the composition is serially correlated over hours or days. In this situation, more smoothing can be obtained by building several stockpiles in parallel. Feeding incoming ore to each of several stockpiles in automatic sequence provides some benefit, but it might be expected that more smoothing could be achieved by using the ore composition (or a forecast of the ore composition) to decide intelligently which of the current stockpiles should be used for the incoming ore.

This study describes a simulation model developed to investigate the assay variability achieved using automatic and intelligent sequencing methods for building shipping dumps.

2. SOURCE DATA

Typically the incoming ore is assayed at intervals at the port, for each of the minerals of interest. The assays take some hours to complete, so the handling of incoming ore has to be decided before its particular assays are available.

For each of the minerals, the target percentage is known as well as shipping limits outside which it is undesirable to wander. The assays can therefore be converted to measures of stress. For each mineral:

$$\text{Stress} = (\text{Assay} - \text{Target})/(\text{Upper Limit} - \text{Target}) \qquad (1)$$

For example, if the target percentage for iron is 56%, with shipping limits of 55.4% to 56.6%, then an iron assay of 55.1% corresponds to a stress of -1.5 for this mineral.

The data used for this model comprise about 2,000 records, hypothetical production for about a year, assayed at four-hourly intervals on four minerals, iron, silica, alumina and calcium oxide. The four-hour production tonnage (or "rake") varied, but averaged about 12,500 tonnes. Converting the assays to stress values, each had zero mean. The four standard deviations lay in the range 0.9 to 1.7.

As is the case in reality, the assays show strong correlations across time and between minerals. It is therefore possible to use earlier assays to forecast future assays. For the particular data set, the best exponential forecast is with an alpha value of about 0.7. For value V_t and forecast F_t at time interval (or rake number) "t":

$$F_t = 0.7V_t + 0.3F_{t-1} \qquad (2)$$

A data file was prepared of approximately two thousand records, representing four-hour production intervals or "rakes", each with nine fields, being the tonnage, four assays and four forecast assays. This file was used as input to the simulation model to be described in the following sections of this report.

3. PERFORMANCE CRITERION

We have seen how each data record includes the stress and forecast stress for each of the four chemical constituents that are being monitored.

Stress is defined as the number of outer shipping limits an assay is away from its target value. A set of assays will include four stresses S_i , with i = 1, 2, 3, 4 corresponding to iron, silica, alumina and calcium oxide. The set of stresses S_i can be referred to as the vector $\underline{S}$. For a set of assays, it is convenient to define the aggregate stress "A" as:

$$A^2 = \Sigma_i S_i^2 \qquad (3)$$

For a shipping dump containing ore of weight W, we can define the "pain" P to be minimised as:

$$P = W A^2 = W \Sigma_i S_i^2 = \Sigma_i W S_i^2 \qquad (4)$$

For a rake of weight w and stress s, we want to choose which dump (j = 1, 2, 3) to add it to. A sensible criterion is to choose the dump for which the rate of increase in "pain" per tonne added is minimised. Let dump j currently contain weight W_j , with stress $\underline{S}_j$.

Rate of change of pain for dump j

$$= \text{Lt } [\partial \Sigma_i (W_j S_{ij} + w s_i)^2 / \partial w] \text{ , as } w \to 0 \qquad (5)$$

$$\Rightarrow 2\Sigma_i W_j S_{ij} s_i \qquad (6)$$

So an appropriate criterion in choosing a destination dump j is to select the one for which the criterion $[\Sigma_i W_j S_{ij} s_i]$ is minimum.

4. THE SIMULATION MODEL

A simulation model was designed to investigate the effects of building shipping dumps using a range of automatic and intelligent stacking procedures. The simulation model was built using the computer package Extend™, which is available for both Macintosh and Windows computer environments. The model is graphical and animated, and built of inter-related blocks.

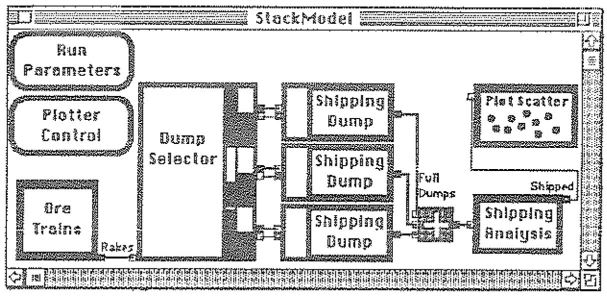

Figure 1: The Simulation Model

Each block contains programming code (in a dialect of the language "C") controlling its operation and its inputs and outputs. The thick lines joining blocks represent material flow, while the thin lines represent information flow. Each flow begins at a black connector, and flows to a white connector on the connected block.

The blocks include coloured animations (not visible in Figure 1) which change as the simulation progresses. At each step of the simulation, the "Ore Trains" block reads data for the next rake, as one record from the input data file containing tonnages, stresses and forecast stresses. This rake is passed on to the "Dump Selector" block, which decides which "Shipping Dump" block is to receive the rake. A green animation (to the right of the Dump Selector block) indicates which shipping dump has been selected, and an ochre animation in each Shipping Dump block shows proportionately how full each dump is currently.

To avoid switching between dumps too often, the dump selection can be changed only when the currently selected dump passes a level "m/n" full, where "n" is a chosen integer specified in the Run Parameters block, and "m" is any integer from one to n.

For automatic sequencing, the dump selector sends rakes to each dump in turn, changing to the next destination dump in sequence when the currently selected dump passes a level "m/n" full. For intelligent sequencing, whenever the currently selected dump passes a level "m/n" full, the dump selector calculates the rate of increase in the "pain" function that would be occasioned by sending the rake to each of the shipping dumps, and selects the dump that would incur the least increase in pain, using the criterion of equation (6). With intelligent sequencing, it is of course possible that the destination dump selected is the current one, so at that review the destination remains unchanged. Red animations in the Dump Selector block show the rate of increase in pain for each potential destination.

When a shipping dump block is filled, it is immediately emptied into the "Shipping Analysis" block. The details of the shipped block are displayed in the "Plot Scatter" block, and also fed to an output text file, recording details of completed dumps. At the end of each simulation, when all rakes have passed through the system, summary statistics for the run are fed into another text file, recording details of completed simulations. The "Plot Scatter" block can be used to display statistics dump by dump, or summary statistics for each completed simulation, as the computer run progresses.

4.1 Run Parameters

Double clicking on the "Run Parameter" block opens it up to allow parameters to be set for a simulation run. The open block dialogue is shown below. The parameters within each box can be set as chosen for each simulation run.

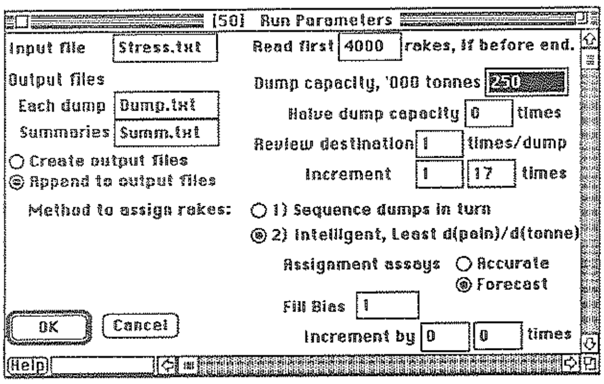

Figure 2: The "Run Parameters" Block Dialogue

In this example, the input file containing the rake tonnages and assays is a text file called "Stress.txt". If it is desired to use only the first part of a data file, then a nominated number of rakes can be read in. If this nominated number exceeds the data file, then the whole file is used.

The completed shipping dump tonnages and assays are output to a text file which in this example is named "Dump.txt". Summary statistics are output at the end of each simulation to another text file, in this example called "Summ.txt". The output files can be either created at the beginning of the run or, as here, the output can be appended to existing files.

The size of the shipping dumps, in thousands of tonnes, is input. Shipping dumps are built to include the rake that just takes them past this tonnage. Any one computer run can be set to report repeated simulations with successively changed parameters. For example, if the dump capacity were set to halve twice, then the simulation would be repeated with shipping dumps of 250,000; 125,000; and 62,500 tonnes.

The model allows rakes to be sent to any of three shipping dumps being built at any one time. Changing the destination shipping dump is costly, so the destination is reviewed only at preset intervals, corresponding to a set fraction of a dump capacity. Repeated simulations in one computer run can use progressively changing review intervals. In the example, the first simulation reviews once per shipping dump, so that only one shipping dump destination is used in the simulation model (although of course with different physical locations). For the second simulation, the dump destination is reviewed every time a dump is half filled, then every time a dump is one-third or two-thirds full, and so on. Seventeen increments are shown for this example, so the last simulation will review each destination dump eighteen times. If a dump takes approximately three days to fill, this corresponds to a four hourly review interval.

The rakes can be assigned to dumps by automatic sequencing, so that each time the destination dump is reviewed rakes begin to go to the next dump in sequence. Alternatively, intelligent assignment can be used, with the destination dump being the one that gives the smallest rate of increase in "pain", according to equation (6) above.

Intelligent assignment requires rake assays be used for equation (6). In practice, the decision will have to use forecast assays, based upon previous assays, since the accurate assays will not be known in time. For the simulation, the rake assignment can be chosen to be based upon either the accurate or forecast rake assays. A dump's assays are calculated based upon the accurate assays of the rakes it has already received.

From equation (6), the criterion was to choose the destination dump minimising $[\Sigma_i W_j S_{ij} s_i]$. This criterion can be modified to $[\Sigma_i W_j^b S_{ij} s_i]$, where the fill bias "b" controls the relative influence of a fuller compared to an emptier shipping dump. If $b > 1$, then more influence is given to a fuller dump. If $b < 1$, more influence is given to a less full dump. This fill bias can be set, and successive simulations can increment its value by a chosen amount, a chosen number of times. This report does not consider varying b from unity, but experimentation suggests that the results are not appreciably sensitive to the value of b.

4.2 Plotter Control

Double clicking on the "Plotter Control" block opens it up to allow the parameters to be set to control the display in the "Plot Scatter" block. The block when opened is as shown in Figure 3. The parameters within each box can be set as chosen for each simulation run, to control the selection and display of the statistics to be plotted.

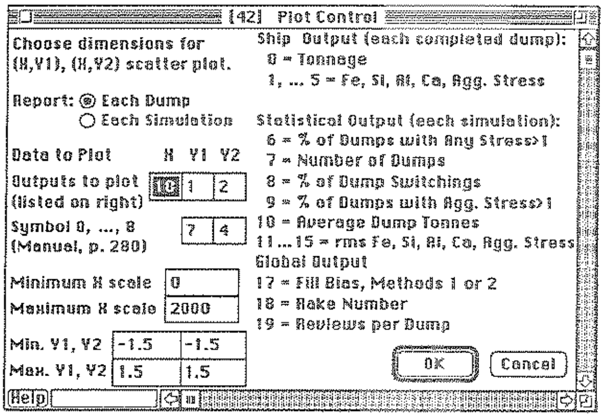

Figure 3: The "Plotter Control" Block Dialogue

Output can be plotted for each dump, so that a new plot starts for each simulation. Alternatively, for computer runs of multiple simulations, where a run parameter is successively changed, summary statistics can be plotted to show the effect of changing the parameter.

Two "Y" coordinates can be nominated for two variables to be plotted, each against the same "X" coordinate. In the example shown, the Iron and Silica Stresses (Y1 and Y2) are to be plotted for each dump, with chosen symbols, against the Rake Number (X).

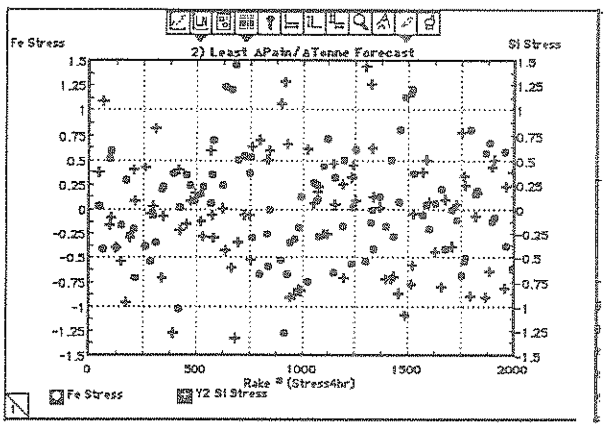

Figure 4: The "Plot Scatter" Block Display

The scale ranges for the Y and X coordinates can also be set. In this cases, the stresses are plotted in the range -1.5 to +1.5, and the rake number is plotted from zero to 2,000. The resulting plot can be viewed by double clicking on the "Plot Scatter" block, either during or after the computer run. The finished plot (for three reviews per shipping dump) is shown in Figure 4.

The "Plot Scatter" block also displays a spreadsheet of the plotted output, but the output is more fully reported in the output text files.

4.3 Input Text File

The input text file contains one record (or line) of information for each rake or assay time interval. Each record comprises nine fields, separated by tabs.

The first field shows the rake tonnage, the next four fields are the accurate iron, silica, alumina and calcium oxide assays, and the final four fields are the forecast values for these assays (based upon the exponentially smoothed previous assays, with an alpha of 0.7 and an initial value of zero).

Each record in the input data file "Stress.txt" used for these studies represented one "rake" or four hours of production, with stress values computed as described in the Data Preparation section.

At the beginning of each simulation within a computer run, the input file is rewound so that the same input data can be processed again, with revised parameters.

4.4 Output Text Files

One output text file ("Dump.txt" in this example) stores one record (or line) of information for each completed shipping dump. Successive simulations within the same run are listed to the file. For each computer run, the output either goes to a new text file or is appended to an existing file, as specified in the Run Parameters block dialogue of Figure 2.

The other output text file ("Summ.txt" in this example) records one record of summary statistics for each completed simulation. Again, for each computer run, the output either goes to a new text file or is appended to an existing file, as specified in the Run Parameters block dialogue of Figure 2.

For each output file, the fields are separated by tabs. The text files can be opened using a spreadsheet, enabling any desired plots to be constructed or subsequent calculations to be carried out.

5. SIMULATION RESULTS

The simulation model was run for three sets of simulations, each exploring the improvement in quality obtainable with 250,000 tonne stacking dumps, for the destination dump being reviewed once, twice, three times per dump, and so on up to 18 times per dump.

The first set of simulations used automatic sequencing, with the destination dump being changed in turn at each review interval.

The second set of simulations used intelligent sequencing, with the forecast assays being used to decide which destination dump to choose, on the "least rate of increase of pain" criterion of equation (6).

The third set of simulations was as for the second, except that now the accurate assays were used to determine the destination dumps. This use of the accurate assays would of course not be possible in practice, but the simulation provides an indication of how much power is lost in having to use the forecast assays instead of the accurate assays, on the "least rate of increase of pain" criterion.

The graphs in Figures 5 and 6, on the next page, show the effect of the various procedures on the quality performance achieved. The objective function used in deriving equation (6) was to minimise the aggregate stress in the completed shipping dumps. Figure 5 shows the root mean square aggregate stress of the completed shipping dumps, built according to each of the sets of criteria.

It is undesirable that shipping dumps be outside the shipping limits in any of the four constituent minerals being considered. Figure 6 shows the proportion of completed shipping dumps which end up violating any of the shipping limits.

Similar effects are seen for each set of statistics, and can be summarised as follows:

- Using the forecast assay values to determine the dump sequencing gives just about as good a result as would the accurate assay values.
- Using intelligent sequencing based on forecast assay values, most of the achievable benefit is attained by reviewing the destination three times per shipping dump. That is to say, the shipping dump destination should be reviewed each time a shipping dump is one-third full, two-thirds full or completed.
- Intelligent sequencing gives appreciably higher shipping dump quality, with less frequent review, than does sequencing automatically to the shipping dumps in turn.

It is clear from the graphs in Figures 5 and 6 that little further benefit would be gained by reviewing more often than three times per shipping dump. Most of the variation between solutions of higher review frequency is apparently random.

6. DISCUSSION AND CONCLUSION

This study has illustrated the design and application of a dynamic and graphical simulation model to compare the assay variability achieved using automatic and intelligent sequencing methods for building shipping dumps of 250,000 tonnes.

The model has been used to show that appreciable improvement can be achieved by intelligent sequencing based on forecast assays instead of automatically sequencing the ore to the dumps in turn. Using intelligent sequencing based on forecast assays is found to be just about as good as would be achieved using accurate assays, were they available. This is fortunate, since in practice the accurate assays are not available until after the stacking decision has had to be made.

Most of the sequencing benefit can be achieved by reviewing the destination dump three times per dump, that is, whenever a shipping dump becomes one-third, two-thirds or totally full. Since a 250,000 tonne dump takes a little over three days to fill, this corresponds to a review interval of slightly longer than a day.

The criterion for intelligent sequencing is quite simple to apply. It requires that the destination dump be chosen which has the lowest pain gradient, as developed in equation (6).

This study considers only the configuration of three shipping dump sites, being built to a 250,000 capacity. However the simulation model supplied can be used for any size of shipping dump, and for any data file of assay stresses. If a different number of shipping dump sites is to be investigated, then the simulation model can be modified accordingly.

The simulation package "Extend" used for this study is now available on Windows as well as Macintosh platforms. A compiled version of the simulation model can also be run on the Runtime version of Extend making the code inaccessible to the user.

7. REFERENCE

Diamond, P. and Hoffman, P., *Extend™ Performance Modeling for Decision Support*, Imagine That, 510 pp., San Jose CA, 1995.

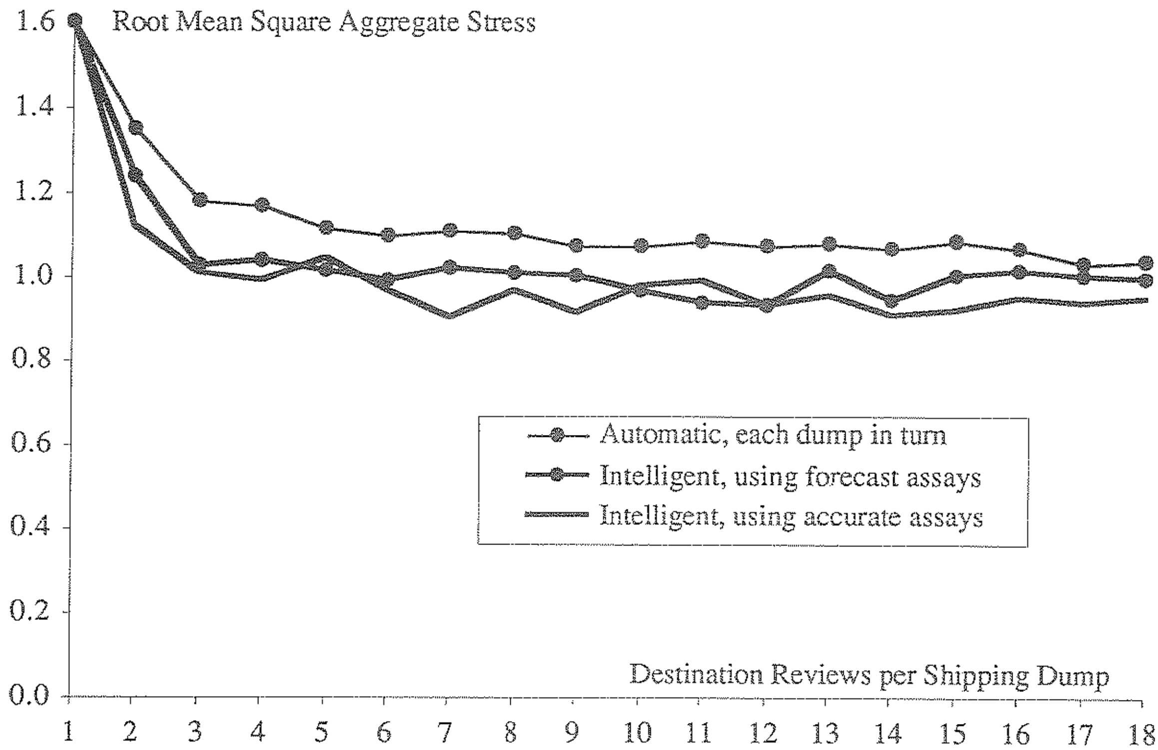

Figure 5: Root Mean Aggregate Stress Achieved

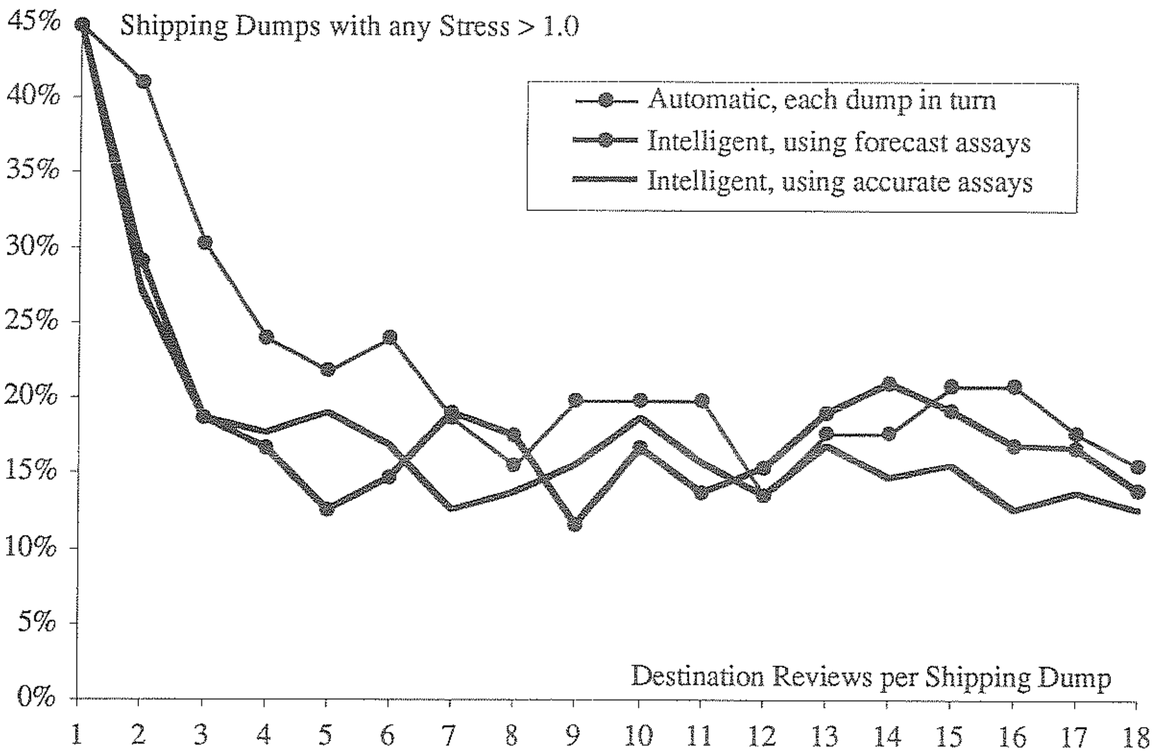

Figure 6: Proportion of Shipping Dumps Outside Shipping Limits