An Update on Automatic Dig Limit Determination

Karl P. Norrena (knorrena@ualberta.ca), Chad Neufeld (neufeld@ualberta.ca), and
Clayton V. Deutsch (cdeutsch@ualberta.ca)
Department of Civil & Environmental Engineering, University of Alberta

Abstract

An algorithm for automatic determination of dig limits has been proposed, synthetic examples, and a comparison betweeen hand drawn dig limits and automatic dig limits has been shown. Two papers summarizing the research have been presented; at the SME meeting in Denver and the APCOM meeting in Pheonix. This update summarizes recent results. We propose an alternative approach for constructing an expected profit map, a new starting point for the automatic dig limits. A framework for dealing with multiple and nested dig limits is developed. The idea of a digability catalogue is presented for selecting a digability factor. Other outstanding issues such as multiple ore types and guidelines on the annealing schedule are also discussed.

Background

The automatic dig limit selection algorithm aims to select dig limits that are robust with respect to uncertainty and that simultaneously account for profitability and limitations of mining equipment. Automatic dig limits are not simple grade contours: grade contours do not account for uncertainty or the non-linearity of the grade to profit conversion. Automatic dig limits are not a modified version of a block-by-block classification scheme: "blockwise" classification schemes rely on perfect selection and mining equipment does not mine cubic selective mining units with perfect selection.

The automatic dig limit selection algorithm starts with a map of expected profit. Uncertainty in grade, the effect of mulitple minerals and contaminants, and the non-linear transform of grade to profit are accounted for in the expected profit map. Initial dig limits are determined from the expected profit map. The profit is discounted by the "digability" of the dig limit. Digability is a term used to indicate how easily a dig limit can be mined. High digability means that the dig limits can be easily mined. Digability is quantified by converting angle of operation into a penalty for each vertex on the dig limit polygon. The penalty must be calibrated to a mining scenario. Random perturbations are performed to the dig limits until they maximize profit. Perturbations that increase profit are always accepted, perturbations that decrease profit are accepted or rejected by simulated annealing. The optimal dig limits are approached iteratively.

The final dig limits account for digability: dig limits near blocks that have high profit potential are smoothed very little or include adjacent low grade material and dig limits near blocks having low potential profit may be partially excluded from the dig limits depending on digability or equipment constraints.

Implementation

Our proppposed algorithm should be applied on a region-by-region basis for ore or waste polygons. We do not suggest fully automatic determination of mulitple dig limits although we admit the

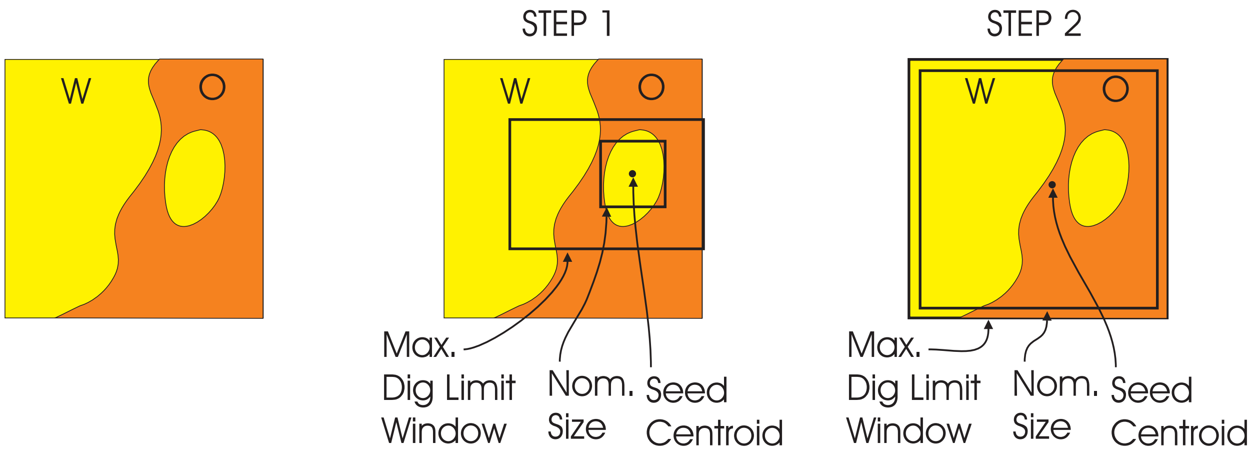

Figure 1: A decomposition approach is adopted for solving the problem of multiple dig limits. The ore/waste map shown on the left shows a waste pod in a larger ore body; the waste pod is to be mined seperately as waste. With the decomposition approach the dig limit is found for the waste pod first, as in the map labeled Step 1, then, as shown in the map labeled Step 2, the dig limit for the ore body is found.

usefullness of an automatic approach at the feasibility study stage for calculation of recoverable reserves.

The latest diglim program works for a single ore/waste polygon within a subarea of the model defined by minimum and maximum X and Y values. A central seed location must be specified with an option for either an ore or waste polygon. The initial dig limit and the optimal results will be within the subarea limits. Obtaining dig limits for nested ore/waste volumes requires a decomposition approach. An example of the decomposition approach is shown in Figure 1. The map on the left shows an ore/waste map with a waste pod nested inside of a larger ore body. The map in the middle shows the first step of the decomposition approach:

1. select the centriod of the waste pod for the seed location of the initial dig limits

2. select a nominal size for the initial dig limits. The nominal window should include as much of the nested pod as possible.

3. select a maximum dig limit window that represents the desired maximum extent that the dig limits may extend to. The dig limits are not perturbed beyond this window. The nominal initial dig limit window must not overlap the maximum dig limit window.

The map on the right shows the second step of the decompoosition approach. Step 2 is similar to the first step except that the waste pod is ignored. The final profit is the sum of the profits earned by the two dig limits - the algorithm maximizes the profit for the waste dig limits but they will be negative because the dig limits are waste dig limits. There are alternative approaches to the decomposition shown in Figure 1.

There are additional implementation considerations to be addressed in the future. A windows interface with the option for digitizing an input polygon would be useful. Directing the output to commercial mine planning software and AutoCAD-type drawing programs would also be useful. Our concern, however, is primarily with the algorithm and demonstrated optimallity of the results.

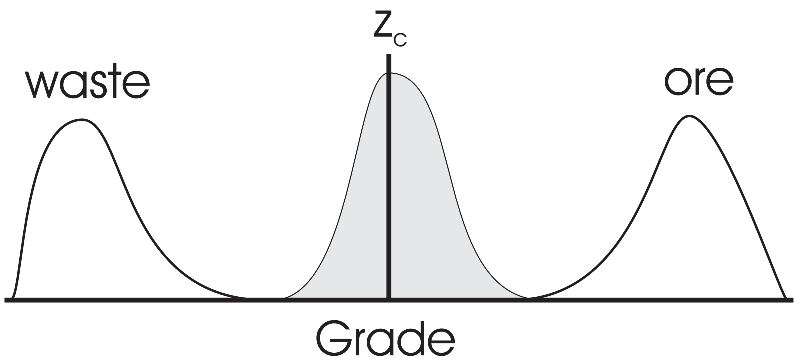

Figure 2: The distribution on the left is a distribution of material that is clearly waste. The distribution on the right is a distribution of material that is clearly ore. The distribution in the middle is a distribution of material that is not easily classified.

Grade to Profit Conversion

Using a cutoff grade for classification is common. The grade at unsampled locations is represented by a model of uncertainty because of data spacing and variability. Figure 2 shows distributions of uncertainty for three types of material. The material on the left is clearly waste, the distribution is centered about a grade that is much less than the cutoff grade. The material on the right is clearly ore because its distribution is centered about a grade that is much greater than the cutoff grade. The material in the middle is near the cutoff grade and is not easily classified; the true grade of the material has high probability for either classification.

Material should not be classified using "probability of ore" thresholds. Figure 2 shows two models of uncertainty. Both would have the same probability of being classified as ore. The model on the left has a higher lost opportunity cost because there is a higher probability of the material being high grade than in the distribution on the right. A lost opportunity cost is an expense equivalent to the profit that would have been made if the material had been sent to the mill. Even if the material is below the cutoff grade ore can be recovered and the proceeds used to offset the cost of treating the material. The expense is not accounted for in the economic workings of the mine, nevertheless it is expensive to waste ore.

Material should not be classified using expected grade. Expected grade does not account for the non-linear conversion of grade to profit. Consider an example scenario for a copper mine: a model of uncertainty consisting of 10 grade realizations for 1 ton of material, a cutoff grade = 0.8%, a selling price of $\$0.75/lb$ copper, and the hypothetical recovery curve shown in Figure 4. The grades, recoveries, and corresponding profits for each realization are tabulated in Table 1. The expected grade is less than the cutoff grade. Using an expected grade classification would indentify the block as waste. By definition the cutoff grade is the grade at which the mine makes no profit, therefore, material having an expected profit less than zero would be classified as waste. Due to the non-linearity of the recovery curve the expected profit in the example is not 0, the block is classified as ore. Counter examples could also be shown. The best decision depends on the full distribution of uncertainty and all econommic parameters.

Classification should account for the risk of misclassification. We propose a grade to profit

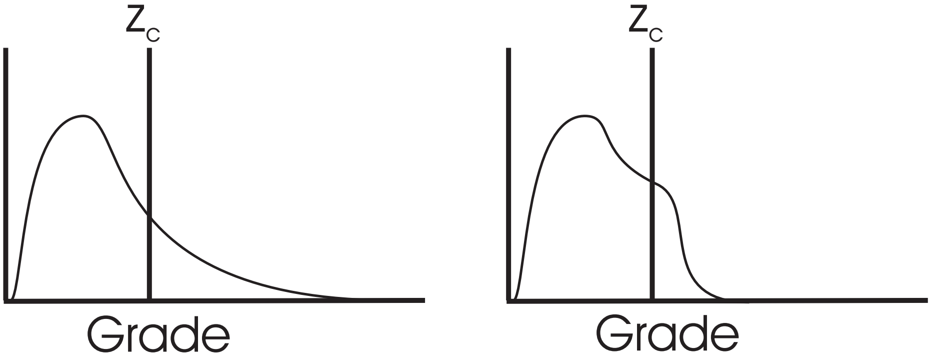

Figure 3: The two distributions have the same probability of being ore, but the distribution on the left has higher lost opportunity cost because it has higher probababability of being high grade.

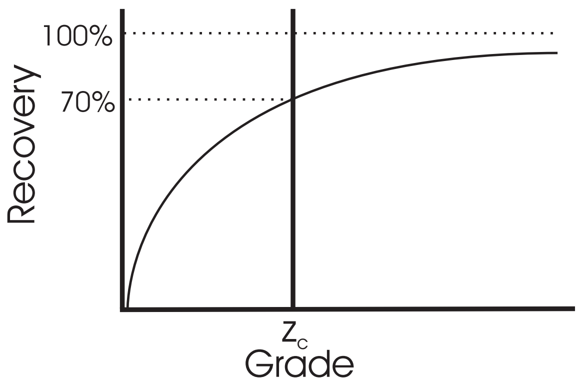

Figure 4: A hypothetical recovery curve. Note that the recovery changes with grade. The result is a non-linear transform from grade to profit.

Realization	Grade(%)	Recovery (%)	Profit
1	0.80	0.70	0.00
2	0.60	0.59	-306.65
3	0.71	0.66	-140.97
4	0.67	0.63	-202.24
5	1.30	0.93	973.50
6	0.59	0.59	-321.22
7	1.20	0.90	780.00
8	0.59	0.59	-321.22
9	0.60	0.59	-306.65
10	0.75	0.68	-78.78
Average	0.781		7.58

Table 1: Example results showing the non-linearity feature of converting ore to profit. The recovery for high grade material is higher than that of low grade material. Due to uncertainty and the non-linearity of the recovery curve some material may have an expected profit greater than 0 even though the expected profit is less than the cutoff grade, as shown here.

conversion that quantifies the risks associated with classifying material as ore or waste. This grade to profit conversion requires five essential parameters:

- **The grade information ($z^{(l)}(\mathbf{u}), l = 1, \ldots, L,\ \ \mathbf{u} \in A$):** The grades at unsampled locations are represented by an uncertainty model.
- **The cutoff grade (z_c):** The cutoff grade is often defined by management. In general the cutoff grade is interpreted as the grade at which the mine can operate and make no profit. Market conditions and the recovery process control the cutoff grade. Other considerations are the mining cost, administration cost, and contract obligations.
- **The recovery curve ($r(z)$):** In most mines the recovery factor varies with the grade. Often recovery increases with increasing grade.
- **The price per unit mineral ($price$):** The price per unit mineral consistent with units used for grade z.
- **The cost for processing waste (cpw):** The unit cost for processing material that have zero grade. In most cases the cost of waste is equivalent to the product of the cutoff grade, the recovery at the cutoff grade, and the price:

  $$cpw = z_c \cdot r(z_c) \cdot price$$

  In special cases the cost for processing waste can be different. There may be a greater cost of processing waste if the ore supply is abundant and milling cost is high. The cost may be less if ore supply is tight and processing cost is low, (e.g. heap leach operations). In these cases $cpw \neq z_c \cdot r(z_c) \cdot price$. We account for these special cases by scaling the profit when $grade < z_c$.

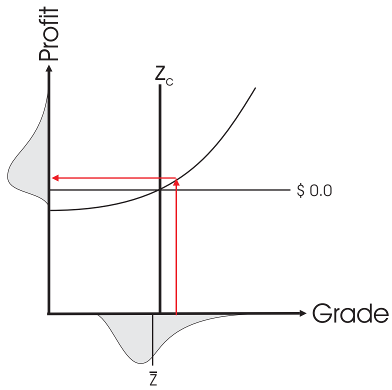

Figure 5: The grade to profit conversion takes place over the model of uncertainty for grade. The conversion is shown schematically. Alternatively, depending on the distribution of uncertainty and the recovery curve shape, material with expected grade above the cutoff may be classified as waste.

Profit for grade realization l, $l = 1, \ldots, L$ at location $\mathbf{u}$ is calculated as:

$$profit^l(\mathbf{u}) = \begin{cases} (z^l(\mathbf{u}) \cdot r(z^l(\mathbf{u})) - z_c \cdot r(z_c)) \cdot price, & if\ z^l(\mathbf{u}) > z_c \\ \frac{cpw}{z_c \cdot r(z_c)}(z^l(\mathbf{u}) \cdot r(z^l(\mathbf{u})) - z_c \cdot r(z_c)) \cdot price, & if\ z^l(\mathbf{u}) < z_c \end{cases}$$

The grade to profit conversion is shown in Figure 5. Grade is on the x axis and profit is on the y axis. The conversion function is represented by a curved line that falls on the intersection of the cutoff grade and zero profit. The non-linear curve represents the product of selling price and recovery which is a function of grade.

This profit calculation is shown in Figure 6. Three cases are shown where the profit is scaled to reflect different costs for waste: (1) $cpw < z_c \cdot r(z_c) \cdot price$, (2) $cpw = z_c \cdot r(z_c) \cdot price$, (3) $cpw > z_c \cdot r(z_c) \cdot price$. The ratio affects marginal blocks. If the ratio is less than 1 more marginal blocks are included in the dig limits. If ratio is greater than 1 fewer marginal blocks are included in the dig limits.

Expected profit for location $\mathbf{u}$ is calculated as:

$$\bar{p}(\mathbf{u}) = E\{profit(\mathbf{u})\} = \frac{1}{L}\sum_{l=1}^{L} profit^l(\mathbf{u})$$

Material is classified as ore if the expected profit is greater than 0 and waste otherwise. Four scenarios exist when comparing classification by expected grade and expected profit:

1. The block has an expected grade *greater* than the cutoff and an expected profit *greater* than 0, and is classified as ore.

2. The block has an expected grade *less* than the cutoff grade and an expected profit *less* than 0 and is classified as waste.

3. The block has an expected grade *less* than the cutoff and an expected profit *greater* than 0, and is classified as ore.

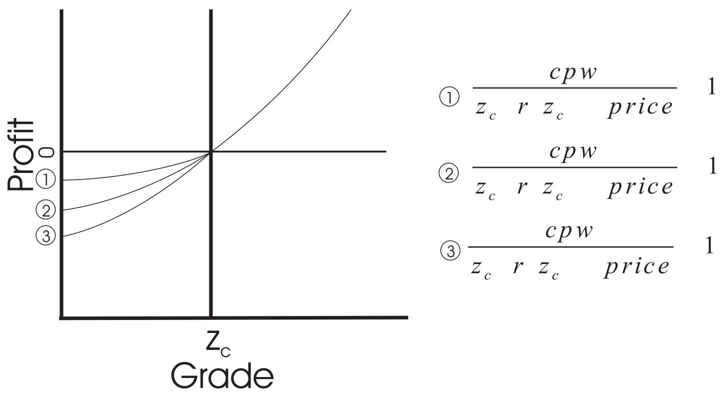

Figure 6: A hypothetical profit curve with three *cpw* scenarios: (1) the *cpw* ratio is less than 1, (2) the *cpw* ratio is equal to one, and (3) the *cpw* ratio is greater than 1. The first case implies that *cpw* is less than the cost of mining material at the cutoff grade. The third case implies that *cpw* is greater than the cost of mining material at the cutoff grade.

4. The block has an expected grade *greater* than the cutoff and an expected profit *less* than 0 and is classified as waste.

Scenario three occurs when the distribution of grades is positively skewed and/or the *cpw* is low. Scenario four occurs when the distribution of grades is negatively skewed and/or the *cpw* is high.

This technique accounts for the two aspects of accounting for lost opportunity cost: (1) uncertainty, and (2) classification. Transforming the distribution of uncertainty in grade to a distribution of uncertainty in profit accounts for the uncertainty aspect of accounting for lost opportunity cost. If the true grade were available lost opportunity cost would be straightforward to calculate, but only the distribution of uncertainty in grade is available. We evaluate profit over the entire distribution of uncertainty in grade and thus automatically account for lost opportunity cost in the construction of the distribution of uncertainty in profit. The second aspect is deferred to the automatic determination of dig limits algorithm. The idea behind accounting for lost opportunity cost is to classify the material such that the classification maximizes profit. This is the aim of the automatic dig limit algorithm, so the algorithm automatically accounts for the classification aspect of accounting for lost opportunity.

Selecting a Digability Factor

Digability is enforced by a penalty curve calibrated to the operating parameters of the mine. The penalty curve reflects equipment and operating conditions. A revised procedure is presented. The penalty curve is parameterized by a single number. This makes the process easier to apply. It turns out that flexibility is not lost by fixing the shape of the penalty curve. A digability factor is selected by reviewing a “catalogue” of dig limits that correspond to increasing digability values. An example catalogue is shown in Figure 7. The selected digability factor would be representative of the abilities of the mining equipment.

Figure 8 is schematic of the effect of different digability factors. Increasing digability factors “slide” the penalty curve to the right and increases the impact to profit. This permits single

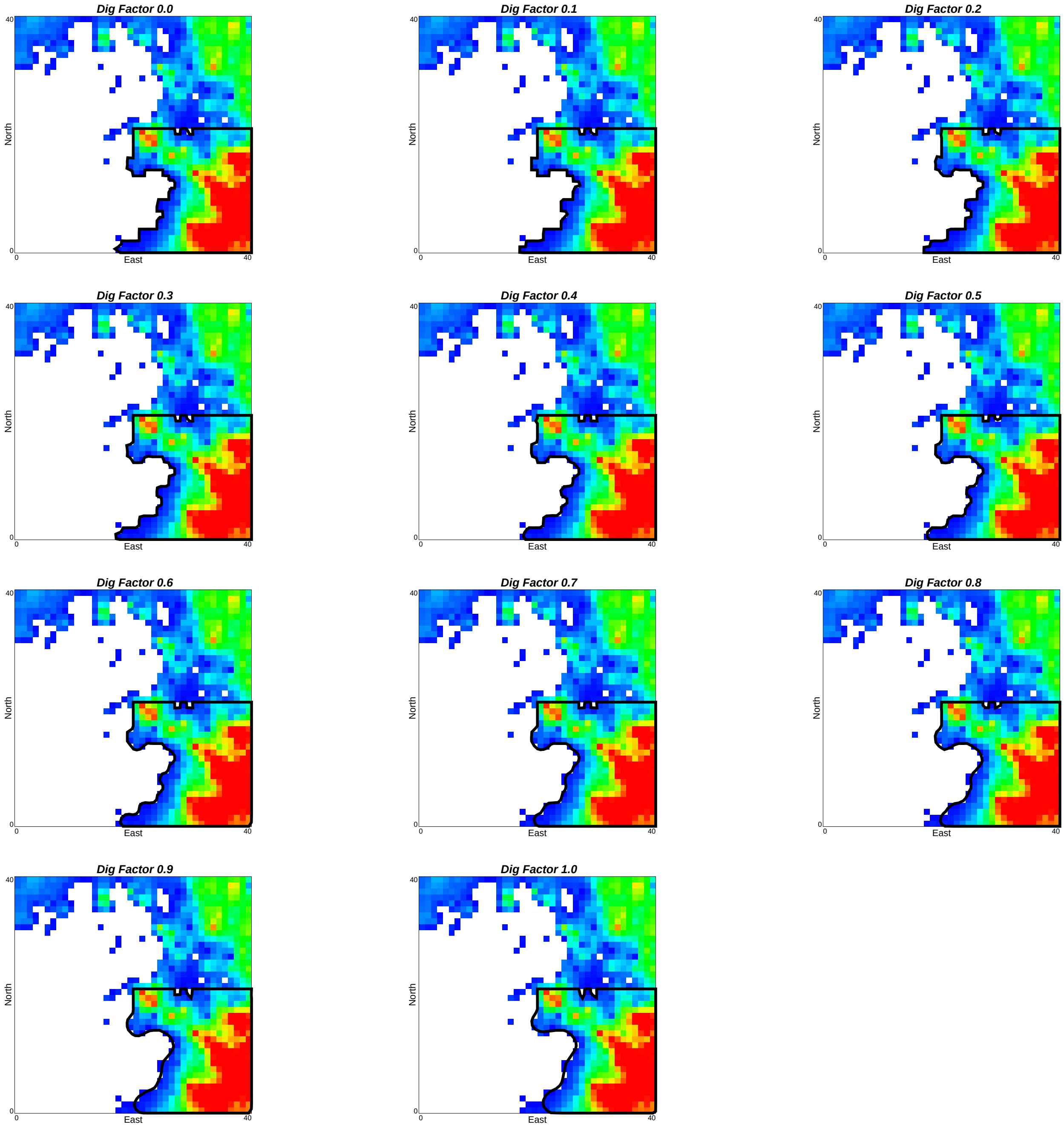

Figure 7: A digability catalogue. The maps show dig limits with increasing digability factor, starting from 0 and going to 1. The map on the top left has a minimum digability factor, and the bottom left has the maximum digability factor.

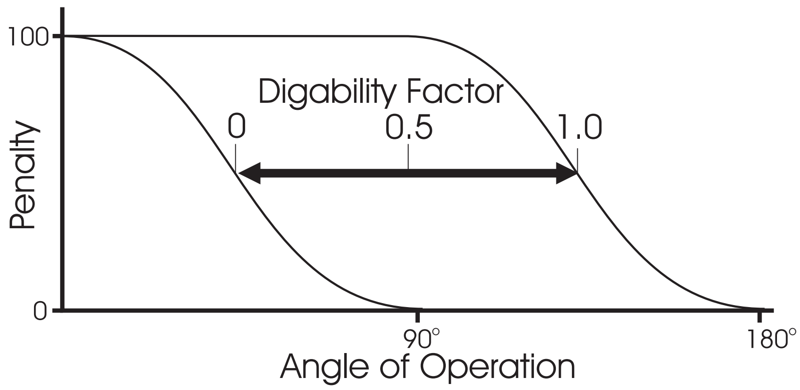

Figure 8: The digability factor "slides" the penalty curve. High digability factors impact the profit more than low values.

parameter accounting for mining equipment.

The Annealing Schedule

The simulated annealing schedule dictates how the perturbations are accepted or rejected. Recommended parameters are described below:

- **The initial temperature (t_0)**: The initial temperature specifies the initial decision criteria for accepting perturbations. Selecting a high t_0 allows almost all perturbations to be accepted. The consequence of selecting a high value for t_0 is greater CPU time is required for convergence. Selecting low values for t_0 will result in too few perturbations being accepted and the possibility that sub-optimal dig limits will be found. An initial temperature approximately equal to one-tenth the initial penalty is suggested.
- **The reduction factor (λ)**: The reduction factor is a multiplicative factor for reducing t_0. A λ between 0.75 and 0.5 is recommended.
- **Acceptance factor (k_A)**: After k_A perturbations have been accepted t_0 is multiplied by λ. A k_A of 5 times the initial number of dig limit polygon vertices is recommended.
- **Rejection factor (k)**: After k perturbations have been rejected t_0 is multiplied by λ. A k of 10 times the initial number of dig limit polygon vertices is recommended.
- **Maximum perturbations ($Maxp$)**: The maximum number of perturbations to ba carried out. Around 100,000 perturbations are suggested.

The suggested parameters are good starting points. Experience will play a significant role in fine tuning them. For example, if a large number perturbations are performed with no change in profit Maxp could be reduced.

Multiple Variables

In the presence of multiple variables the profit calculation is somewhat more complicated. There may be some minerals that contribute to profit and some contaminants that reduce profit. A procedure must be established to convert each realization of multiple grades to profit:

$$z_1^{(l)}(\underline{\mathbf{u}}), z_2^{(l)}(\underline{\mathbf{u}}), \ldots, z_K^{(l)}(\underline{\mathbf{u}}) \rightarrow profit^l(\underline{\mathbf{u}}) \qquad l = 1, \ldots, L$$

then

$$\overline{p}(\mathbf{u}) = \frac{1}{L} \sum_{l=1}^{L} profit^l(\mathbf{u})$$

The final mapped $\overline{p}$ values represent a summary of expected profit for each block for all variables of interest.

Guide to Geostatistical Grade Control and Dig Limit Determination

A Guidebook to Geostatistical Grade Control and Dig Limit Determination is currently under construction. The twofold focus of the guidebook is to (1) map the geostatistical modeling steps required to quantify the spatial distribution of grades from blasthole samples, and (2) transfer the predicted grades to economic parameters and determine optimal dig limits. The focus is not on geological mapping, sampling practices, the use of dedicated grade-control sampling, or the link to advanced positioning equipment and scheduling software.

The guide will take a pragmatic approach to the application of geostatistics for grade control. Each geostatistical study requires a certain degree of interpretation, customization, and iteration for a robust solution. The guide will represent a minimal guide to the complexity of geostatistical modeling. The reader is referred to the numerous papers and books available on the subject of geostatistics and geological modeling.

The guidebook will consist of six sections related to the steps required for geostatistical modeling and grade control for optimal dig limit determination:

- Introduction: This first section presents an overview of the manual and illustrates the practice of grade control with a preliminary example.
- Data Assembly: The second section discusses data handling, extraction of representative data, the use of rock type models, and grid specification.
- Geostatistical Modeling: The third section tackles the required geostatistical modeling for grade control.
- Economic Calculation: The fourth section covers cutoff grades and the calculation of expected profit.
- Dig Limit Determination: The fifth section describes the determination of dig limits that maximize profit.
- Case Studies: The sixth section presents a number of case studies and implementation details.

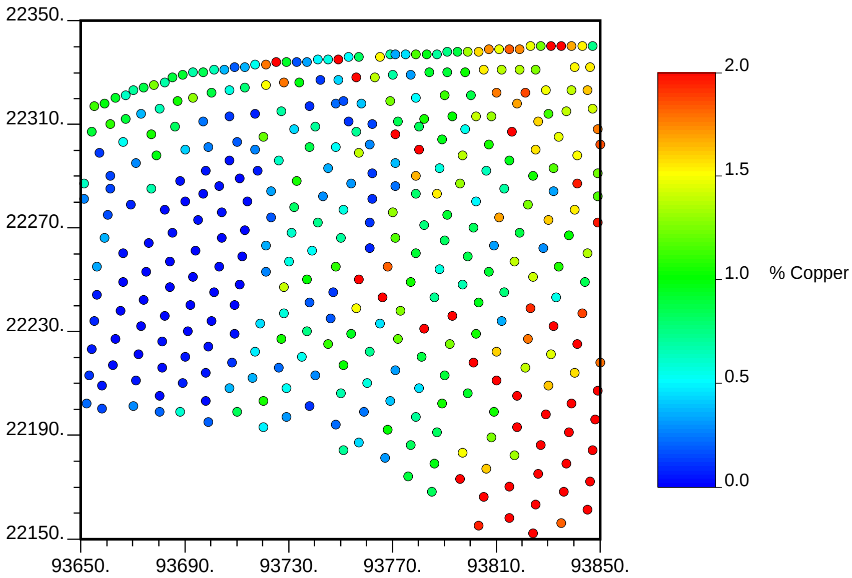

Figure 9: A location map of the blasthole samples. The drill hole spacing is about 10m.

The programs used in the guide will be documented in an Appendix and presented in the familiar GSLIB style. The guide is expected to be completed in early September, 2002.

Example

The following example is taken from the Guide to Geostatistical Grade Control and Dig Limit Determination. The data are percent copper assayed from blasthole data. Figure 9 shows the sample information in a color coded location map. The area is 200m x 200m. The histogram of grades is shown in Figure 10. The mean grade is 1.02%. A cutoff grade of 0.8% is selected. The normal scores variogram was calculated and Gaussian simulation performed using 2.5m x 2.5m blocks. The fine scale realizations are block averaged to 5.0m x 5.0m blocks on a 40x40 regular grid. One realization is shown in Figure 11. Expected profit, using a selling price of \$ 0.75 per lb of copper, was calculated over 100 realizations. The profit map is shown in Figure 12.

Figure 13 shows the fraction of blocks on the profit map that fall into each of the scenarios discussed in the Grade to Profit section. None of the blocks fall into scenario four.

One block from scenario 3 was selected for closer study (21,1). The coresponding grade to profit conversion, histogram of grades andprofit are shown in Figure 14. The expected grade is 0.7318% and the expected profit is \$83.81. Note that the blocks that would have been classified as waste by the cutoff grade only occur next to regions of waste in Figure 13. Using the cutoff grade for grade control would have incurred a higher lost opportunity cost than using expected profit.

The final step is to select a digability factor and "draw" dig limits on the expected profit map. Dig limits for two digability factors, 0.5 and 0.8, are shown in Figure 15.

Using a low digability factor results in dig limits that require greater selectivity of the mining equipment. Increasing the digability factor excludes more ore or includes more waste in the dig

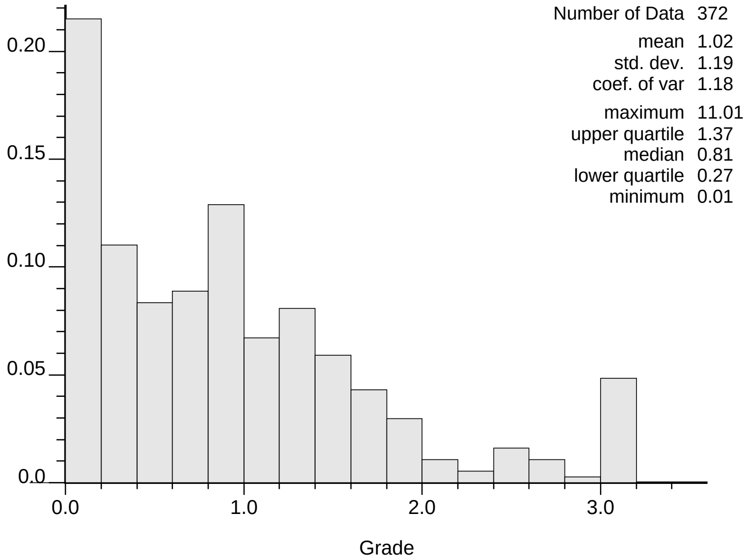

Figure 10: The distribution of copper grades for the blasthole samples. The mean is 1.02 and the cutoff grade is 0.8%

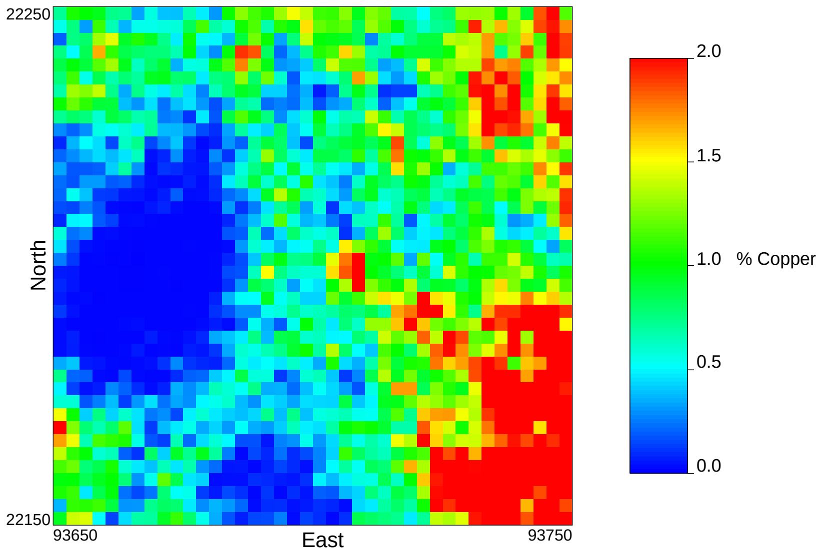

Figure 11: One realization of 100 in the model of uncertainty. The grades are percent copper.

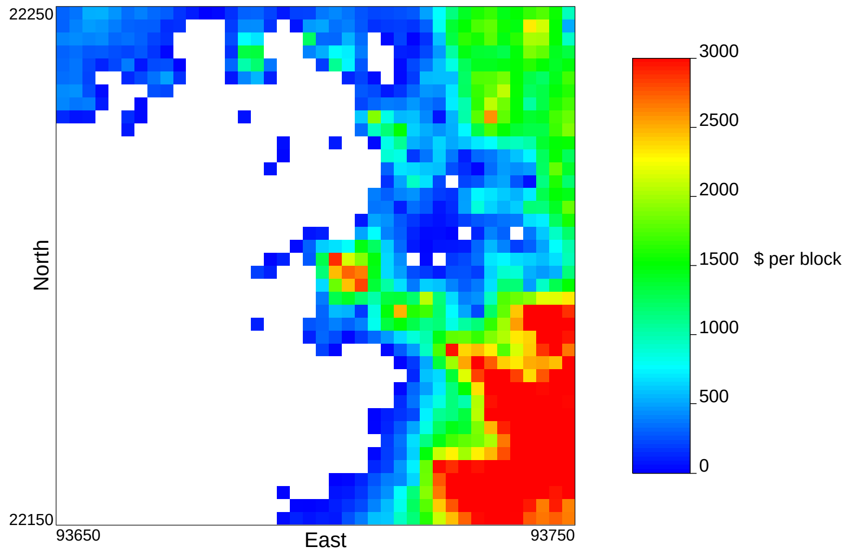

Figure 12: The example expected profit map. 100 realizations and a selling price of $\$0.75/lb$ were used. The cpw was not scaled.

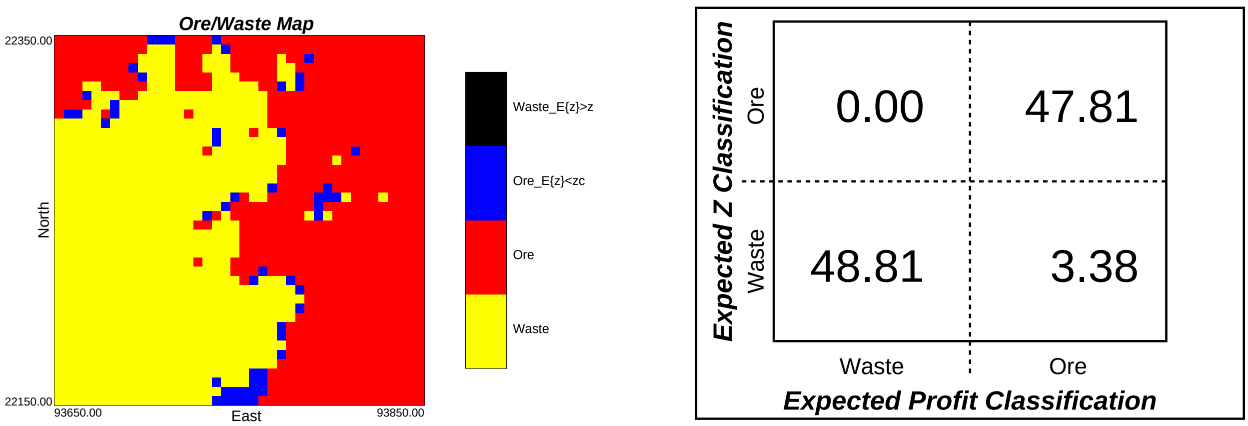

Figure 13: None of the blocks had an expected grade greater than the cutoff grade and an expected profit less than 0. Blocks with profit less than zero are classified as waste, all other blocks are ore. Some of the blocks have an expected grade less than the cutoff grade but are classified as ore because the expected profit is greater than 0. These blocks are shown in blue.

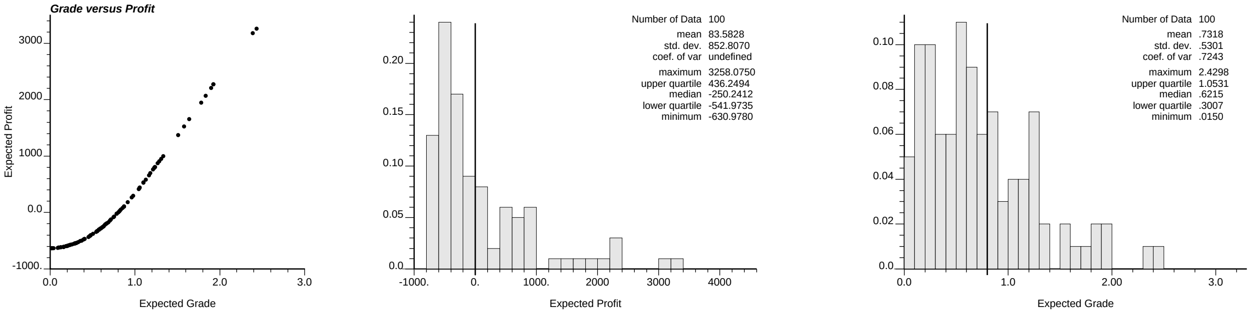

Figure 14: The image on the right shows grade to profit conversion for a single on the x axis and profit on the y axis. The points represent the grade to profit conversion for 100 realizations for a location where the expected grade is less than the cutoff grade. The expected profit is \$83.81. The histogram in the middle is the histogram of the 100 profit values. The histogram on the right is the histogram of 100 grades. The expected grade is 0.7318%.

limits. Manual dig limits attempt to trade ore or include waste to pay for digability but do so subjectively and inconsistently. The automatic dig limit selection algorithm does it systematically.

DIGLIM: Inputs, Outputs, Parameters

DIGLIM is the name of the program used to determine optimal dig limits. The program requires a 2-D map of expected profit and expected grade as a single file as input data. The outputs include:

- Dig Limit Output: The true x and y coordinates for each vertex in the dig limit polygon. These are in the Geo-EAS format and could be easily prepared for use in programs such as ACAD.
- Debugging File: This file includes the information reported to the screen while the program is running. The file is in Geo-EAS format. Plotting the objective function versus the number pertubations is usefull for evaluating convergence: there should be no change in the objective function near the end of the run. If the plot does not "flatten out" then more perturbations should be run. The tempertature should be zero for a large number of perturbations.
- Gridded Output: The gridded output give the fraction of the block included in the dig limits. Blocks that are not included in the maximum dig limit window are written as -1.0. Blocks falling within the maximum dig limit window range from 0 to 1 according to the fraction of the block within the dig limits.

An example paramter file is shown in Figure 16. The parameters required for the proram are listed below:

- **datafl:** file in simplified Geo-EAS format containing the expected profit and the expected grade.
- **icol and igcol:** column number for expected profit and expected grade.

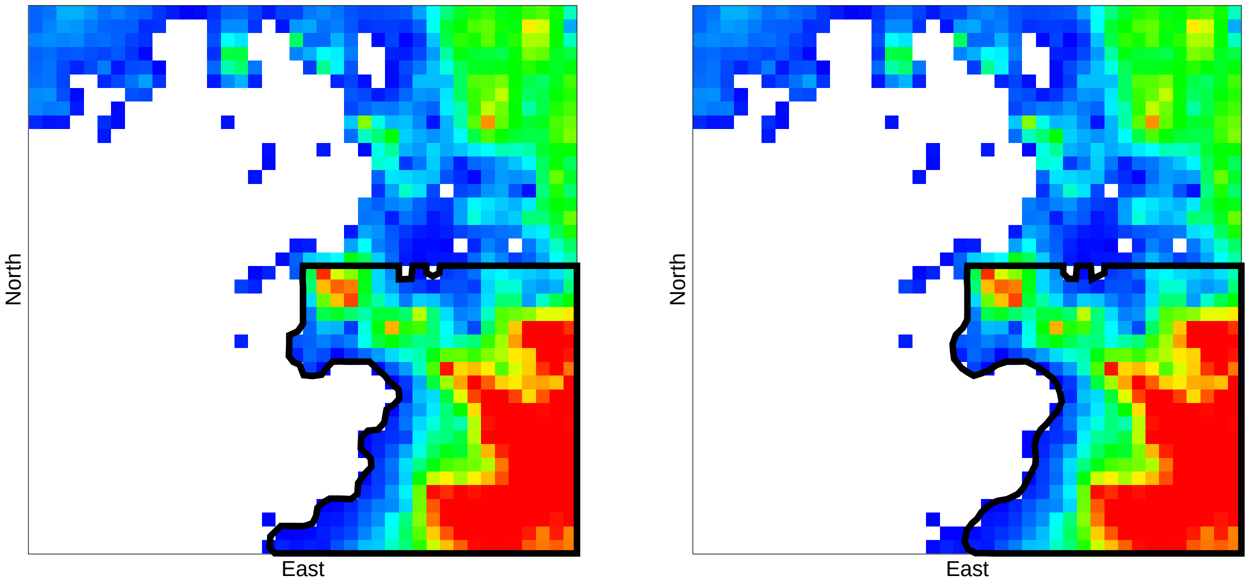

Figure 15: The map on the left shows dig limits using a low digability factor. The map on the right shows dig limits using a high digability factor.

- **outfl:** the x, y output dig limit polygon file in simplified Geo-EAS format.
- **dbgfl:** debugging file in simplified Geo-EAS format. The file includes the reporting information shown on the screen when the program is running.
- **porfl:** file with grid of block fractions within the dig limits in simplified Geo-EAS format. Blocks outside of the maximum dig limit window are written as -1.
- **nx, xmn, xsiz:** definition of the grid system (x axis).
- **ny, ymn, ysiz:** definition of the grid system (y axis).
- **xcent, ycent, psize:** center and size of the nominal seed dig limits.
- **wxmin, wxmax, wymin, wymax:** the dimension of the maximum dig limit window.
- **iorelim:** flag to identify as an ore or waste limit.
- **ixv(1):** random number generator seed (a large odd integer).
- **t0,redfac,kasas,ksas,num:** the annealing schedule: initial temperature, the reduction factor, the maximum number of perturbations at any one given temperature, and the target number of acceptable perturbations at a given temperature (maximum number of times that **ka** is reached).
- **maxpert, nrepo:** the maximum number of perturbations. After a fixed number of perturbations the number of perturbations, the profit, the penalty, the global objective scaled by the initial penalty, and the temperature is written to the debugging file and the screen.

```
                 Parameters for DIGLIM
                 *********************

START OF PARAMETERS:
eprofit.out                      \file with the data
2 1                              \   column for expected profit, grade
diglim.out                       \file for dig limit output
diglim.dbg                       \file for debugging output
grid.out                         \file for gridded output
40 93652.5 5.0                   \nx,xmn,xsiz
40 22152.5 5.0                   \ny,ymn,ysiz
93800 22200  40                  \dig limit: centroid, nom. size
93750  93850 22150 22250         \max window: xmin,xmax,ymin,ymax
1                                \dig limit: ore (1) or waste (0)
382769                           \random number seed
10.0  0.5  1000 300  100         \SA schedule: t0,redfac,ka,k,num
050000 100                       \   maximum perturbations, reporting
1.0   5.0                        \minimum and maximum interval length
1.0                              \maximum perturbation distance
0.70                             \weight for equipment
```

Figure 16: An example parameter file for the DIGLIM program.

- **dismin, dismax:** minimum distance and the maximum distance permitted between polygon vertices. If the minimum limit is exceeded one of the vertives is deleted. If the maximum is exceeded then a vertex is added equidistant between the violatin vertices.
- **dmax:** maximum perturbation distance. The selected distance is randomly chosen, but does not exceed the maximum perturbation distance. The distance is symetric.
- **dig:** digability factor. The digability factor as selected from the digability catalogue.

Summary

The primary aim of a mining operation is to excavate minerals of interest, process, and sell for a profit. We have shown one way to convert grade to profit. A profit based classification of material is not enough. The blockwise profit map needs to be further classified to account for the limitations of the mining equipment. Further processing of the profit map for classifying material as ore and waste must be done systematically accounting for the value of the block. We have devised an automatic dig limit selection algorithm that does this.

Further work may include a user friendly graphical interface for implementing dig limit selection. Demonstrated optimality, depart from the concept of a block model: mode the bench as a dense grid of points with increased density surrounding the dig limits, real-time classification of aterial on a truckload-by- truckload basis, incorporate direction of mining into dig limit determination (digging at an angle to the dig limits must incur additional penalty due to equipment induced dilution.

References

[1] C. V. Deutsch and E. Magri, and K. P. Norrena. Optimal grade control using geostatistics and economics: Methodology and Examples. *SME Transactions*, Vol 308, February 2000.

[2] I. M. Glacken. Change of support by direct conditional block simulation. In *Geostatistics Wollongong '96*, Kluwer Academic Publishers, v 1, September 1996.

[3] Norrena, K.P. and C.V. Deutsch, Optimal Determination of Dig Limits for Improved Grade Control, *30th International Symposium on Computer Applications in the Mineral Industries (APCOM)*, Phoenix, Arizona, February 25-27, 2002.

[4] Norrena, K. and C. V. Deutsch, Determination of Dig Limits Subject to Geostatistical, Economic, and Equipment Constraints, *SME Meeting*, Denver, Colorado, February 27-28, 2001.

[5] David, M., *Geostatistical Ore Reserve Estimation*, Amsterdam, Elsevier, (1977).

[6] Deutsch, C.V.: A Fortran 77 Subroutine for Determining the Fractional Area of Rectangular Grid Blocks within a Polygon, *Computers & Geosciences*, 16(3), (1990), pages 379-384.

[7] Srivastava, R.M., and Hartzell D.R., and Davis, B.M.: Enhanced Metal Recovery Through Improved Grade Control. In *23 Application of Computers and Operations Research in the Mineral Industry*, pages 243-249, Tuscon, AZ, April 1992. Society for Mining, Metalurgy, and Exploration, Inc