The use of neural network analysis of diagnostic leaching data in gold liberation modelling

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Synopsis

The interrelationship between mineral liberation and leaching behaviour of a gold ore is ill defined, mainly due to the complexity of both leaching and mineral liberation. This study presents a neural network approach to modelling the liberation of gold bearing ores. A complete mineralogical analysis of unmilled and milled ores, including gold deportment and gangue content are used as inputs to a self-organizing neural net, which generates order preserving topological maps. The arrangement and shapes of these clusters are coupled to unmilled free gold data to predict gold liberation in milled ores (absolute error: 8.1%). Moreover, the self-organizing maps were diagnostic of the quality of data used, indicating that the relationship between particle size and gangue material content requires further investigation.

Introduction

The grinding of ore to a size that is conducive to the extraction of minerals by leaching or flotation is an essential and expensive component of most mineral processing operations. Identifying correct comminution practices is of major importance since over grinding results in reduced floatability of minerals, while under grinding leads to a product in which minerals have not been exposed, and cannot be leached or floated effectively. Milling control is commonly applied on the basis of producing a product within a narrow size band and at a high through-put[1]. With frequent changes in ore types, benefi-ciation set points that produce optimal liberation are usually poorly determined. Thus, great importance is assumed by models able to give a detailed description of the ore liberation—comminution process. Mineral liberation is discussed extensively in the literature[2–12], although further work is evidently required. Progress in liberation technology is best described by comparing the work of Lynch[13] who expected in 1984 for a mineral liberation monitor to 'become available in the near future', to that by Hales and Ynchausti[14] in 1993, 'it is expected to become commercially available in the future'.

In spite of the attention given to liberation, the practical benefits in industry have not materialized. The drawback of current liberation models rests with the manual, laborious nature of determining model parameters, such as intercept lengths, particle size effects, etc., in order to predict the liberation of the valuable mineral. Even in view of complex mathematical approaches such as stereology[12] which are used to infer volumetric particle properties, the reported advantages are limited. Diagnostic leaching has aided efforts to rationalize these models[9–11], enabling a more 'hands on' approach, but is application specific. The existing gap in our understanding of the liberation phenomenon is further frustrated by poor use of available data or limited quantities of data.

Other techniques such as neural computing have emerged in recent years, demonstrating tremendous application flexibility in the areas of classification, simulation and optimization of non-linear processes. The ability of a neural network to learn complex relationships makes it ideal for mineral processing, in that process disturbances are frequent and commonly the result of a multivariable state space change.

This paper is a continuation of previous work[11] where only the relationship between gold liberation and particle size was considered. The current investigation extends this to include a texture characterization of the ore, which other than size, is a major factor in liberation behaviour. In this investigation a self-organizing neural net with a Kohonen layer was used to generate order-preserving topological maps of gold leaching results for

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both unmilled and milled ore characteristics. The arrangement and shapes of these clusters could then be used to develop simple neural net models which were capable of predicting the degree of gold liberation, i.e. gold leaching results, more accurately than other presently used models.

Artificial neural networks

In parametric modelling, it is necessary to know the mathematical form of the expressions involved. Inherent disadvantages of these parametric methods are that the selected mathematical forms of process expressions are not necessarily valid, that all relevant variables are not necessarily included in the mathematical expressions, and that some related processes are ill-defined to such an extent that defy explicit mathematical representation. Therefore, a non-parametric method such as a neural network is a possible alternative that can relate the various deportment of gold and particle size to the measured leachability of an ore. The main advantage is that no functional form needs to be specified, and there is no restriction to the types of data that can be included as inputs. In the case of mineral liberation, it becomes difficult to estimate independently the significance of the mineralogical makeup on the interrelationship between mineral liberation and leaching behaviour. Neural networks provide a means of assessing important process variables without paying attention to step-wise estimation.

The literature on neural nets is substantial, even in chemical and minerals engineering[15–16], so that only the most basic concepts will be explained. A neural net consists of simple computational elements called neurons or processing elements, which are interconnected, and the collective behaviour of these neurons determines the characteristics of the net. Of the numerous network architectures developed to date the Back Propagation Neural Net (BPNN) remains the most widely used for the modelling of ill-defined process systems. A distinction is made between input, hidden and output layers depending on their relation to the information environment of the net. The nodes in a particular layer are linked to other nodes in successive layers by means of artificial synapses or weighted connections (adjustable numeric values). Back propagation neural nets learn by repeatedly attempting to match sets of input data to corresponding sets of output data or target values. Learning occurs by means of algorithms usually designed to minimize the mean square error between the desired and the actual output of the net through incremental modification of the weight matrix of the net[11].

Self-organizing neural network maps

Self-organizing neural nets are valuable tools for the visualization of complex or clustered process data and can be used to create two-dimensional topological order preserving feature maps of the data. Such a net learns without supervision and typically consists of an input layer that is fully connected to a two-dimensional Kohenen layer. Each process element in the Kohenen layer measures the Euclidean distance of its weights to the input values fed to the layer and competes with its neighbours for assignment of a particular exemplar. The reader is referred to Annandale *et al.*[11], Moolman *et al.*[17] and Laine *et al.*[18] for further technical information.

Experimental data

Seven different ores obtained from South African gold mines were used in the experiments, namely ores from the Beatrix, St. Helena, Unisel, Harmony, Harties, Kinross and Leslie mines (some mine names have changed since the ores have been obtained a few years ago). All the ores were fed directly to autogenous mills. Ore samples were initially screened into three size intervals, viz. +6700 μm, +1500-6700 μm, and -1500 μm. The -1500 μm fraction was classified into six size fractions, viz. -1500+300, -300+150, -150+106, -106+75, -75+53 and -53 μm. This set of samples represents the unmilled ore. Representative samples from the eight size fractions were then fed to a laboratory ball mill with iron balls of different sizes, to produce the milled sample of 70%–75% mm. This milled sample was also screened into the above-mentioned six size fractions.

Diagnostic leaching[10] was performed on each of the particle size fractions for each of the ore types (unmilled and milled). The deportment of gold (free, base metal sulphides, pyrite silicates and carbon) and the gangue content (base metal sulphides, silicates and carbon) are shown in Tables I and II where the pairs of numbers are percentage values for the unmilled and milled ores, respectively.

Data analysis

The percentage of gold deportment (Au_p, Au_s, Au_b, Au_c) and percentage of gangue (G_p, G_s, G_b, G_c) (p-pyrite, s-silicates, b-base metal sulphides and c-carbon) in the various milled and unmilled ore minerals, the percentage of free gold in each of the particle size fractions (Au_o), the head grade (HG), as well as the mass distribution (m) were projected to a two-dimensional topological map with a self-organizing neural net. The eleven inputs, viz. x = { Au_o, Au_p, Au_s, Au_b, Au_c, HG, m, G_p, G_s, G_b, G_c }, were fed to a two-dimensional 10×10 Kohonen layer which yields a two-node output layer (x- and y-coordinates for graphical visualization). Figures 1 and 2 show the maps generated for the unmilled and milled ore samples respectively.

Cluster analysis

A method to quantify the clustering of individual ore data begins with calculating the centres of gravity $C_j(X_j,Y_j)$ of each ore j (j=1,2,...,9), given by

$$C_j\left(X_j,Y_j\right)=\left(\sum\frac{x_{ij}}{n};\sum\frac{y_{ij}}{n}\right) \qquad [1]$$

and the distance D_{ij}^k of the i'th data point in ore j from each of the centres of gravity C_k, given by

$$D_{ij}^k=\left[\left(x_{ik}-X_j\right)^2+\left(y_{ik}-Y_j\right)^2\right]_k^{0.5} \qquad [2]$$

where x_{ik} is the x-coordinate of the i'th data point from the k'th ore, y_{ik} the y-coordinate of the i'th data point from the k'th ore, and X_j and Y_j the x- and y-coordinate of the centre of gravity of the j'th ore respectively. For comparative purposes the Euclidean distances D_{ij}^k were normalized, i.e. d_{ij}^k = $(D_{ij}^k - D_{ij,\min}^k)/(D_{ij,\max}^k - D_{ij,\min}^k)$, so that $0 \le d_{ij}^k \le 1$. If each ore type is perfectly clustered and separated from other ore types, then the distances d_{ij}^k (j=k) can be expected to be smaller than the distances d_{ij}^k (j≠k). A measure for the

Table I

Mineralogical analyses of gold deportment (1. unmilled, 2. milled)

		Head Grade	Free	BMS	Pyrite	Silicate	Carbon
Beatrix	1	7.49	17.40	10.22	9.93	55.30	7.14
	2	7.70	64.05	8.03	8.58	11.45	7.89
St. Helena	1	13.08	23.21	6.31	6.44	53.72	10.31
	2	7.96	68.76	9.97	7.36	8.04	5.88
Unisel	1	8.21	40.73	9.14	16.40	22.41	11.32
	2	9.20	74.09	8.62	10.18	3.65	3.47
Kinross	1	3.76	36.49	13.31	6.93	38.87	4.40
	2	3.61	84.91	3.64	3.84	5.24	2.38
Leslie	1	9.46	32.08	8.25	11.02	46.03	2.62
	2	7.12	75.82	5.08	3.23	13.83	2.04
Harties	1	12.4	45.70	8.30	8.30	37.70	-
	2	12.23	67.40	7.70	4.90	20.00	-
Harmony	1	2.65	18.58	6.47	4.56	36.94	33.45
	2	2.76	89.43	4.81	1.30	1.98	0.54

Table II

Mineralogical analyses of gangue content (1. unmilled/2. milled)

Ore type		BMS	Pyrite	Silicate	Carbon
Beatrix	1	14.93/	7.28/	74.61/	3.17/
	2	16.16	7.02	73.96	2.86
St. Helena	1	3.06/	4.71/	90.99/	1.24/
	2	2.55	4.48	91.82	1.15
Unisel	1	3.47/	4.21/	89.69/	2.62/
	2	5.03	4.78	88.60	1.59
Kinross	1	1.94/	2.17/	92.68/	3.21/
	2	2.82	5.42	90.55	1.22
Leslie	1	15.99/	5.90/	75.90/	2.20/
	2	6.44	4.58	87.17	1.81
Harties	1	4.00/	3.85/	89.80/	2.26/
	2	3.44	4.36	89.85	2.35
Harmony	1	10.39/	10.26/	78.09/	1.25/
	2	3.96	4.62	90.18	1.25

sharpness of separation (dispersion) can be constructed by sorting all d_{ij}^k values for each ore j in ascending order. If the d_{ij}^k value (for j=k) under investigation is one of the six (6 size fractions) closest to the centre of gravity, it is assigned a value of 0, otherwise it is assigned a value, which corresponds to its sorted position. For each ore type (6 size fractions), these values are summed to give the dispersion, M_j, and are subsequently normalized so that unmilled and milled topological maps can be compared. The normalized measure of dispersion is presented in Figure 3 for the unmilled and milled ores respectively.

For the unmilled ores (Figure 1), a reasonable level of clustering is evident. The bottom right quadrant shows the mapping of the largest size fraction for all ore types, indicating particle size dependence for liberation characteristics. The main feature in this SOM is the clusters that are grouped together; for example, Beatrix and Leslie. These two ore types are very similar in both their gold deportment and

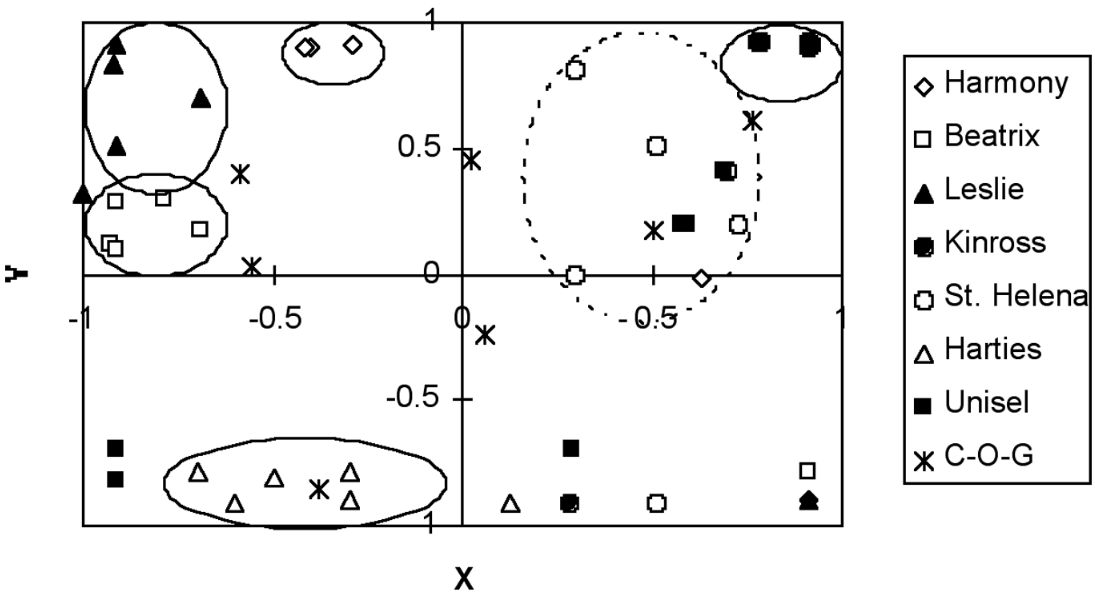

Figure 1— Topological feature map of unmilled gold ores. The clustering of ore type is reasonably defined (except for Unisel)

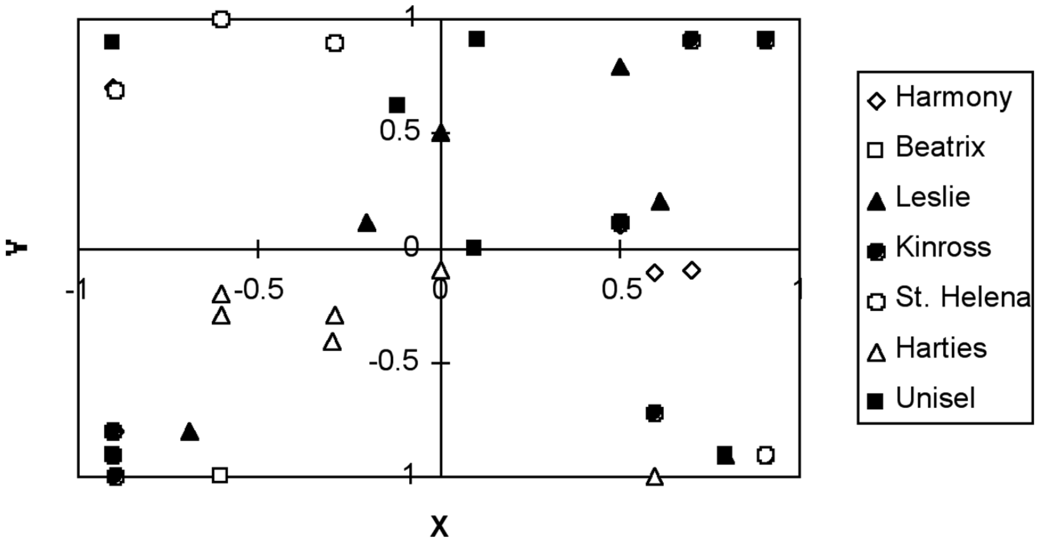

Figure 2—Topological feature map of milled gold ores

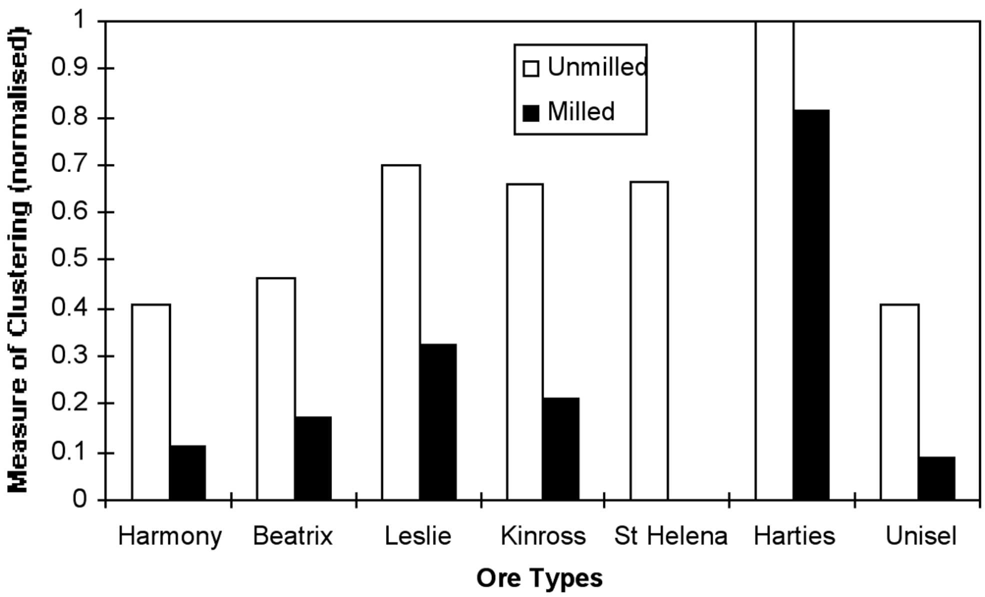

Figure 3—Measure of clustering for unmilled and milled ores

mineralogical content, as shown in Tables I and II. Similarly, the Harmony cluster is also in close proximity, but obviously separated. Data from Tables I and II show that gold deportment for Harmony in the form of free gold and carbon differ to that of Beatrix and Leslie. Analysing Tables I and II can make similar deductions regarding the position of all ore type clusters. The other significant feature in Figure 1 is that a single size fraction (+300 μm) data point from each ore type is located in the bottom right quadrant, and as a consequence, most of the centres-of-gravity (C-O-G) do not lie within close proximity of the majority of the data points for each ore type. For this size fraction for all ore types, the free gold available for leaching is much less; for example, the three largest size fractions for Beatrix (unmilled) yield free gold percentages of 13.4% (+300 μm), 72.3% (-300 μm+150 μm) and 83.5% (-150 μm+106 μm). Clearly, there is a particle size dependency, which is not accounted for in the current set of data. With only 42 exemplars available and a large number of parameters involved, it is difficult to obtain a comprehensive picture of liberation properties.

It would be reasonable to suggest that geographical location of each mine would be strongly related to the relative position of the clusters on the SOM. However, this is not the case, indicating that mineralogical content of an ore is a highly localized phenomenon.

As shown in Figures 2 and 3, the level of clustering in the milled SOM is considerably less than its unmilled counterpart (Figure 1), indicating that the ores behave quite differently when comminuted. The shift in relative positions of the centres-of-gravity is well illustrated in Table III.

For example, Harties maintains its degree of clustering ($1.00_{unmilled}$ - 0.81_{milled}) and only shifts a distance of 0.5. In

Table III

Euclidean distances between the centres-of-gravity of unmilled and milled ores

Ore types	Euclidean distances
Harmony	0.65
Beatrix	1.23
Leslie	0.72
Kinross	1.18
St. Helena	0.91
Harties	0.50
Unisel	0.40

contrast, St. Helena undergoes a dramatic increase in dispersion ($0.67_{unmilled}$–0.00_{milled}) and a significant translation in its centre-of-gravity (0.91). This information gives an indication of the complexity involved in modelling the liberation process. While particle size information is an attractive basis for determining liberation characteristics, as in the case of the King liberation model[7], Figures 1,2 and 3 and Tables I, II and III demonstrate that gold deportment and mineralogical content are the main determinants of liberation.

Neural net modelling

The prediction of free gold liberation resulting from the comminution process is achieved by linking the topological map features (i.e. x- and y- coordinates) in Figure 1 to a simple back propagation neural net. The assumption is that similar ores (i.e. ores projected to the same area of the SOM map) will behave similarly with regard to the liberation of gold during comminution. The neural net is trained using {x, y, $Au_o^{unmilled}$} data as the inputs and {Au_o^{milled} } data are the outputs. The hidden layer is omitted due to a limited number of exemplars. As shown in Figure 4, this single layer neural net model was able to predict the data with an absolute error of 25%. This is significantly better than the 63% achieved by Annandale[11]. As indicated by the highlighted square in Figure 4, the +300 μm data is the most significant contributor to prediction error, a fact that was identified in analysing the unmilled self-organizing map.

Figure 5 represents the neural net predictions of the average liberated free gold. The 8.1% absolute error is a good improvement on the 15% by Annandale[11] and the 19% by the Lorenzen model[19].

Discussion and conclusions

The grinding of ores to a size that is conducive to the optimal extraction of valuable mineral is the single most critical aspect of comminution practices. Although mineral liberation is discussed thoroughly in the literature by various researchers[2–9], there is still much work to be done. In this investigation it was shown that neural net modelling is an excellent tool for understanding the relationship between gold liberation and ore gangue content. In particular, self-organizing maps were used as a diagnostic tool to analyse the significance of gold deportment and mineralogical content in comminution activities. It was found that the relationship between particle size and gangue mineral content needs further investigation, particularly in view of the fact that the proportions of base metal sulphides, silicates, pyrite and carbon are directly responsible for gold liberation. The error of 8.1% in predicting milled free gold belies the complexity of the modelling process, since the quantity of free gold in the larger size fractions was poorly determined.

It is postulated that a larger database will bring clarity to many of these issues. Furthermore, it is expected that an extensive analysis of particle breakage mechanisms will bring to light the role of fracturing in the liberation phenomenon.

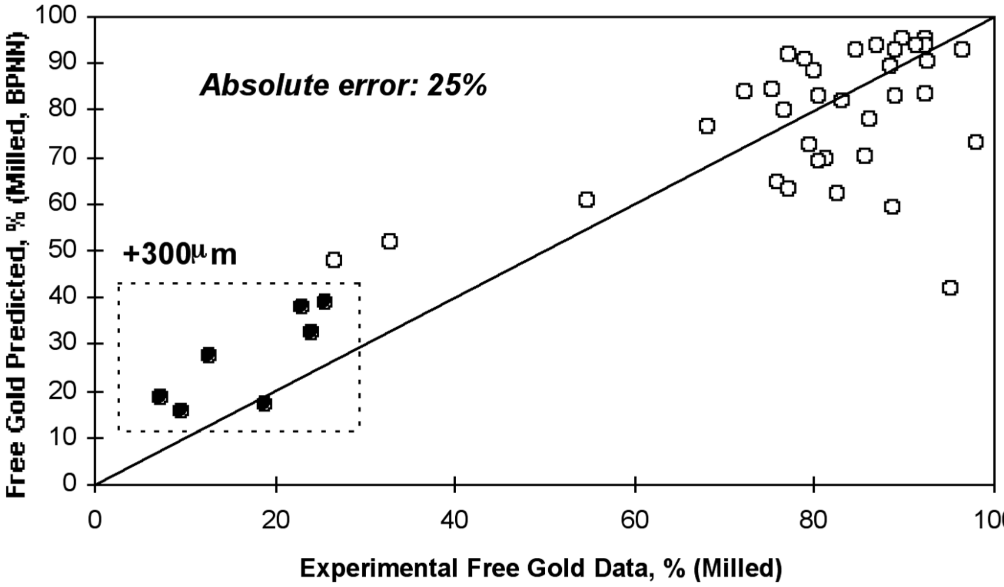

Figure 4—Experimental milled free gold data versus neural net predictions

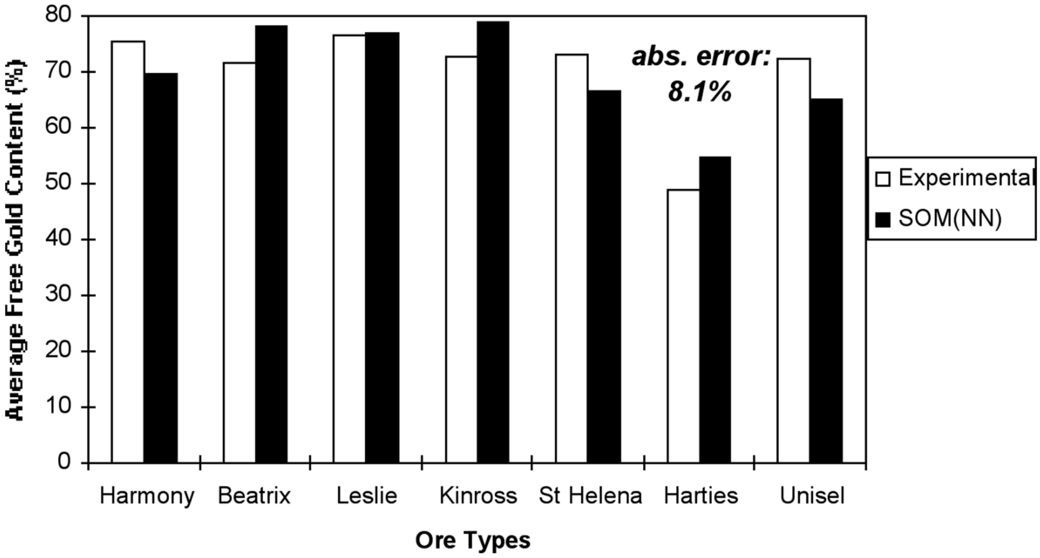

Figure 5—Neural net prediction of the average free gold (milled) for each ore type. Absolute error: 8.1%. The major contributor to error is due to poor prediction of +300 μm size fraction

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