Improving Real-time Expert Control Systems through Deep Data Mining of Plant Data

Lynn B. Hales
Michael L. Hales
KnowledgeScape, Salt Lake City, Utah USA

Abstract

Expert control of grinding and flotation plants has been successfully used in the minerals industry since the 1970's.

The earliest of these systems were written in a hard-coded fashion in FORTRAN, BASIC or Pascal. Second generation systems were built using the first experimental expert system shells that were being developed in the artificial intelligence community. Later systems were deployed in systems designed for real-time processing plants that also include the ability to model the process with neural network models and optimize setpoint selection through the use of genetic algorithms.

Significant performance increases have been achieved using these systems but in general they suffer from the static nature of their rules and to a degree the process models. There is an opportunity to further increase system performance by systematically taking advantage of the tremendous amount of data produced by the expert system to improve the design, the heuristic rules, the model topologies and the use of the models.

"Data mining refers to extracting or mining knowledge from large amounts of data." "The objective is to automatically analyze the data, automatically classify it, automatically summarize it to automatically discover and characterize trends in it and to automatically flag anomalies." [1]

Clearly, modern process control systems used in the minerals industry are capable of collecting vast amounts of data. Without a doubt, these data contain important information on the operation of our plants and their ultimate optimization. Coupling the information mined from these data with Expert Control Systems should produce more effective control and greater knowledge of the grinding process and the flotation process.

Introduction to Data Mining

Data mining is all about extracting useful business information from large databases. The key word here is "large." If the database was small discovery technologies is not really needed. In large databases are, such as those we can create in minerals plants tools are absolutely needed to discover and extract patterns and relationships that can be exploited to improve plant performance and profitability. In effect we are seeking to gain knowledge from data. This knowledge discovery can be represented as a process as is shown in Figure 1.

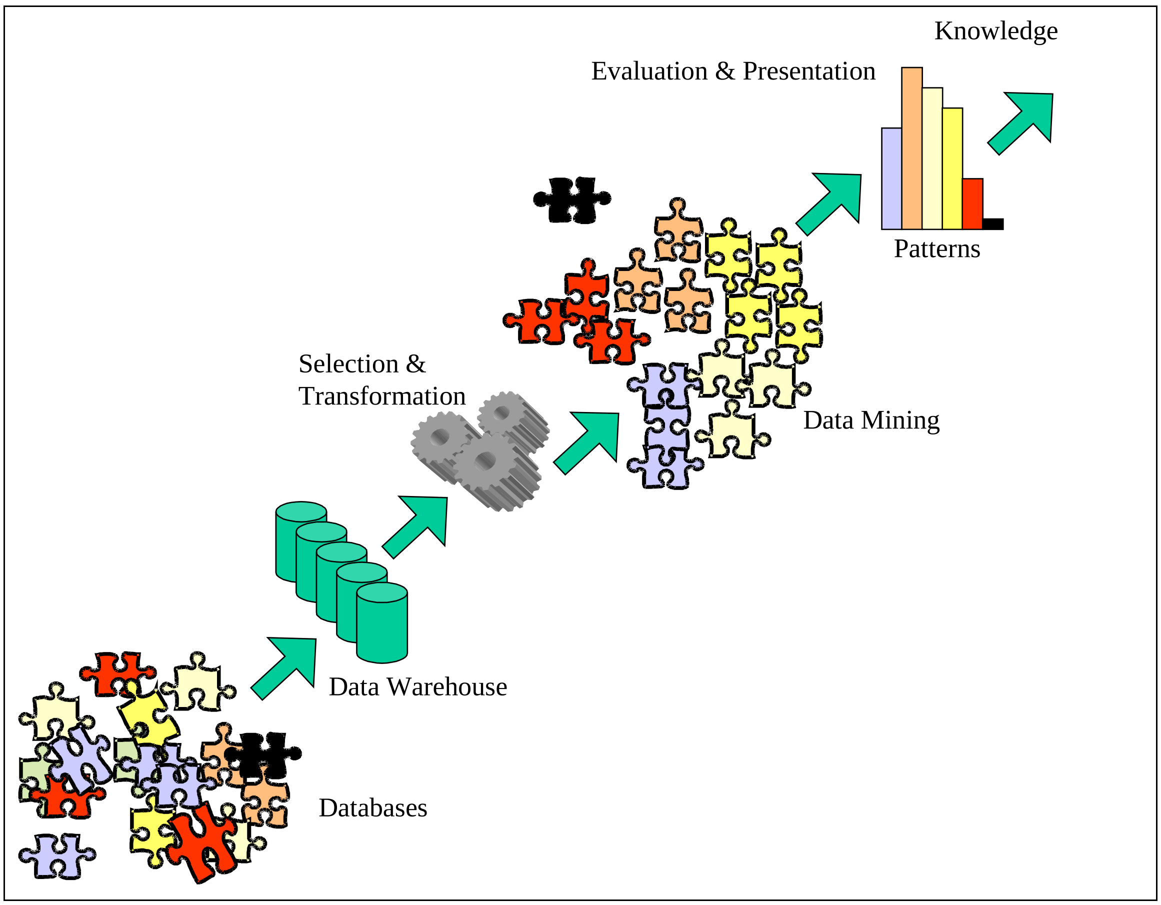

Figure 1. Data Mining is but one step in the process of knowledge discovery.

The steps and processes include:

Data cleaning - removing noise, inconsistent data, outliers
Data integration - combine data from multiple sources in a time-unifying manner
Data transformation – changing according to rules that unify the data or make it suitable for data mining operations

Data mining – the process of applying intelligent methods to the data to extract meaningful data patterns
Pattern evaluation – sorting through the discovered patterns to identify those that represent knowledge of the underlying processes
Knowledge presentation – visualization processes to present the mined knowledge to the user

Data Mining A Sag Mill Circuit

The writer and philosopher, George Santayana, said, “Those who cannot remember the past are condemned to repeat it.” Another axiom that is subtly relevant is “If you don’t measure it, you can’t improve it.” What makes both of these statements interesting is that we measure everything but don’t necessarily improve anything. This seems to be a pretty good description of what goes on in a grinding circuit since throughput rate goes up and goes down as does all the other process variables but what is lacking in general is the definitive relationship between all of process variables and how we can use this information to maximize plant performance.

Universal Question

The following universal question is the question that drives all set point changes in minerals plants regardless of the technologies being used to determine new set points.

> *Given the current physical and mechanical state of the grinding mill, the current process state of the mill, the current feed conditions what set point changes can I make to the independent process variables that will improve my performance five minutes from now. The first need in answering this question is to define what the definition of performance is.*

It is this question that expert rules and predictive models are used to answer. Experience has shown that the modern expert control system is capable of improving plant performance on average day-in-day-out, therefore the universal question is being answered to some degree. It is not known, however, how effective the answers are and whether or not additional improvements are possible.

Discovery vs. Prediction

Data mining is a process that has at least two aims. They are:

> *1) Discovery – tell me something I don’t already know*
> *2) Prediction – the use of a discovery to predict the future*

Over the years the mathematics of statistical analysis has been applied to the masses of data that have been collected from grinding plants. These analyses have included linear and non-linear step-wise regression, auto-regressive moving averages (ARMA), analysis of variance etc., and correlation analysis in many different forms.

Those who have attempted to, or performed these analysis know how time consuming and difficult the task is. The question of “what is the difference between statistical analysis and data mining” is a good one. The answer is that data mining is statistical analysis that is highly automated and rigorously applied to all available data in an completely exhaustively manner.

Some of the components of data mining, as they apply to real-time expert control are discussed next.

Cluster Analysis

The process of grouping a set of physical or abstract objects into classes of similar objects is called clustering. Inherent is a cluster is the similarity of objects within the cluster and the dissimilarity to objects in other clusters. Analysis within clusters and between clusters is the focal point once clustering is complete.

Clustering, in formal or informal ways is inherent is expert control systems. Rules are often partitioned based on ore types or control objectives. Because of this the success of the system becomes dependent upon the understanding of these groups of conditions, their completeness and the degree of co-mingling of conditions and objectives.

In grinding, this formal or informal clustering is present all the time. Plant performance is discussed in terms of 1) ore type, 2) mineralogy, 3) liner life etc. Discussions including these concepts center on explaining performance and how to improve it. By formalizing the processing of clustering performance in the context of objectives and plant conditions then it may be possible to increase understanding and performance.

Two elements of clustering, then, are 1) discovery of what the clusters are and how they differ from common wisdom and 2) how control within each cluster space can be improved. It is easy to understand that better process models, which is another way of saying process understanding, can be developed from data sets that are not corrupted by data that belong to another set of conditions or clusters. Ultimately the desire is to be able to cluster objects together where each cluster can be modeled effectively and independently from the other clusters.

Visually, the following two figures introduce the concepts in a simple way. The first 3D figure shows data that falls within a cube. Each data point is randomly colored. The second figure shows the same data after it has been clustered into 8 clusters and then each cluster is colored a unique color. The clustering results are not surprising and show that the clustering mathematics does indeed have the ability to sift through data and group it into groups of similarity and dissimilarity. In this dataset similarity is based upon the simple position in a 3D space.

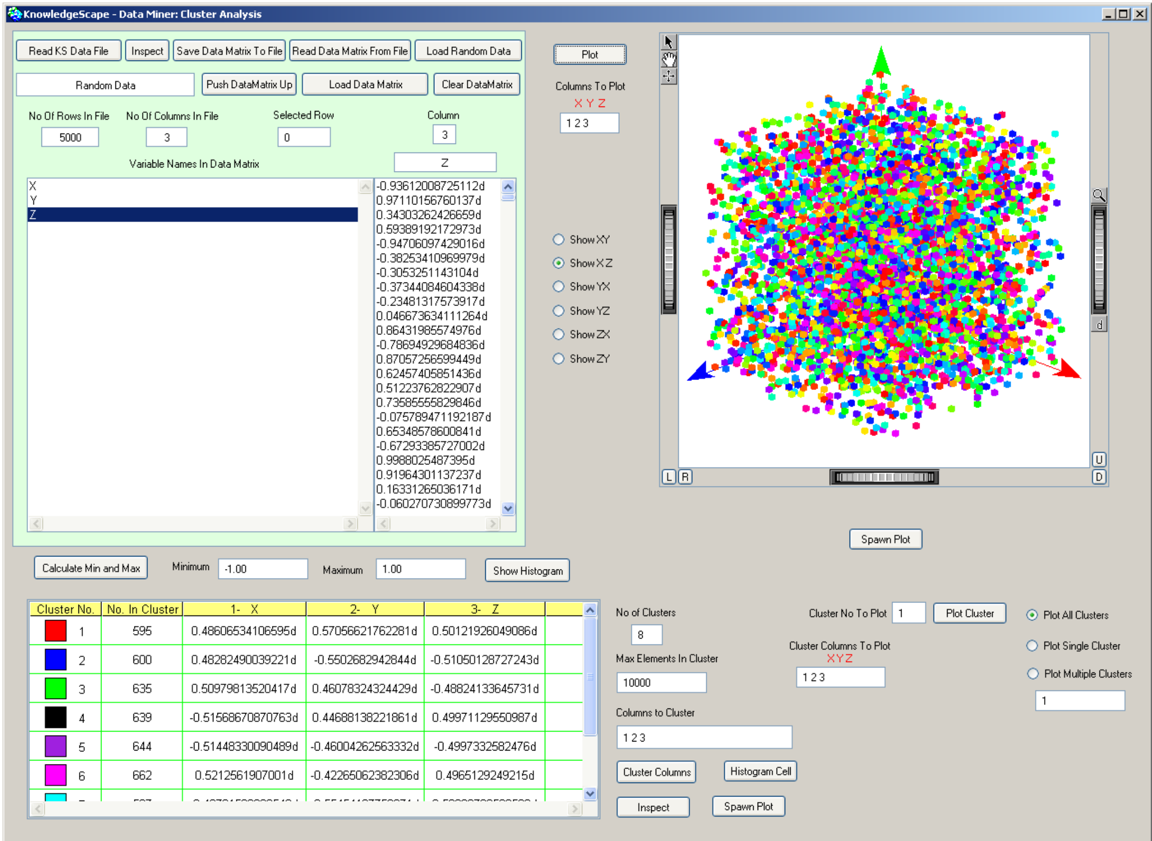

Figure 2. A Simple Representation of data within a 3D space represented by a cube.

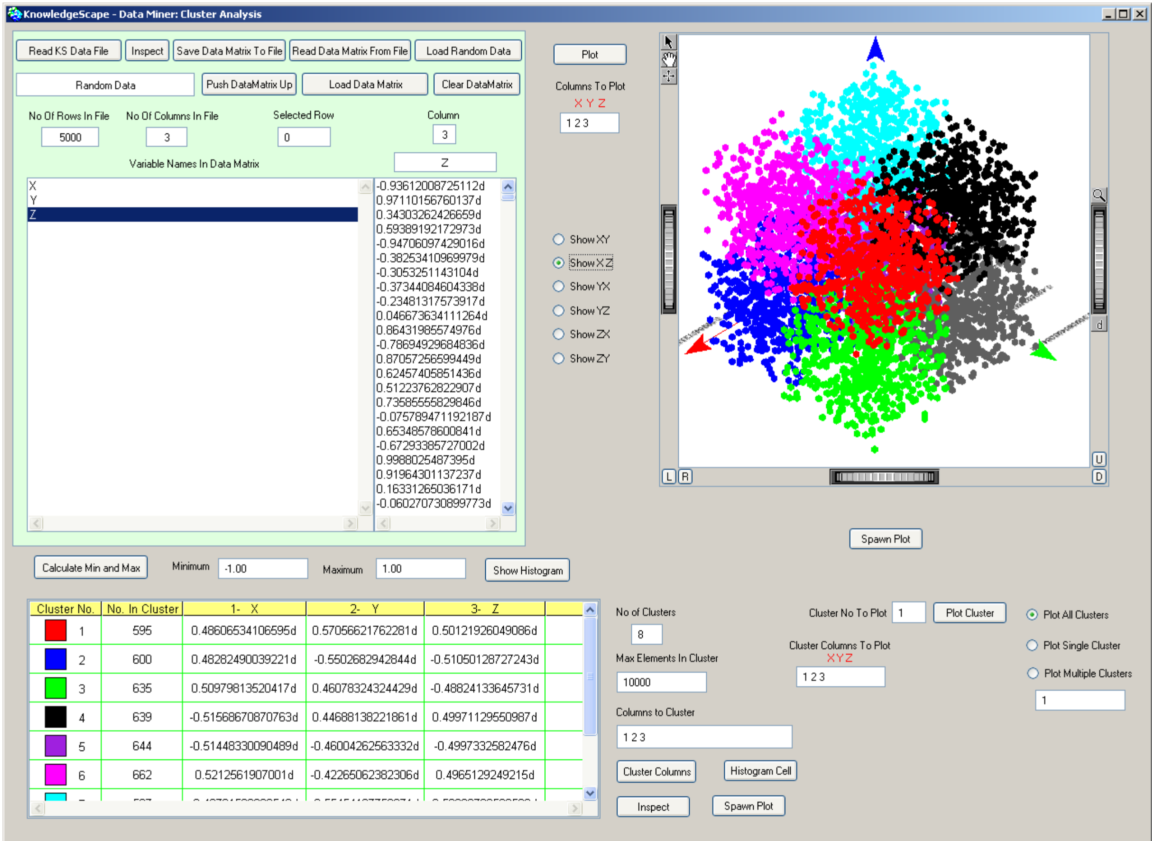

Figure 3. The Same Dataset shown in Figure 2 after Clustering into Eight Clusters

Grinding plants are very complex and many factors contribute to performance. This is no problem for cluster analysis even though it presents a visualization problem for us. To illustrate clustering concepts further data was collected from an operating expert control system from a typical SAG mill/Ball mill grinding plant for a 3-month period. Process variables extracted for cluster analysis included:

1) Feed rate,
2) Sag mill speed,
3) New feed water addition rate,
4) Bearing pressure,
5) Power draw,
6) Current,
7) Sound,
8) Feed size, and
9) Feed color

Now, instead of a simple 3D analysis we are looking at 9 dimensions from either a 2D or 3D perspective. For this analysis we are interested in analyzing clusters of performance that are primarily focused on feed rate.

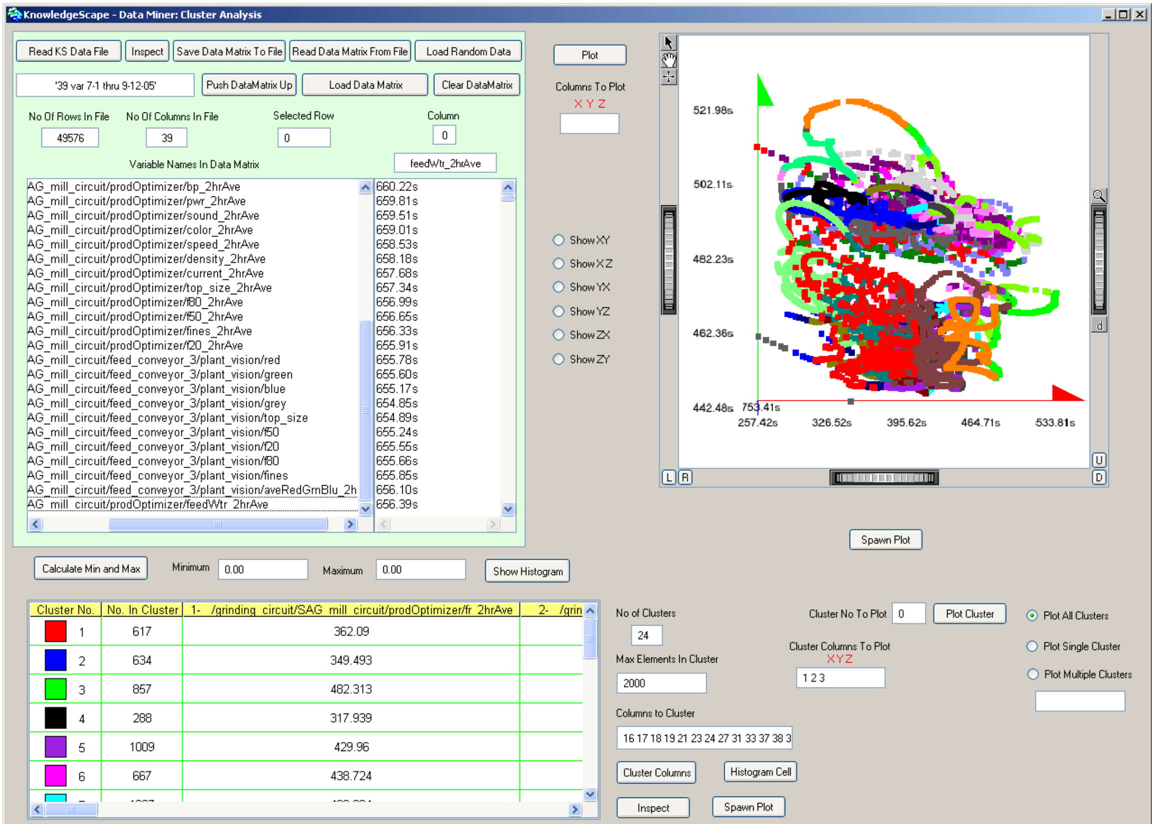

Figure 4. Cluster Analysis of Sag Mill Data

The 3D plot shown from the perspective of the x and y 2D dimensions shows quite a cloud of data. Each cluster is represented by a unique color. The x-axis is feed rate and the y-axis is bearing pressure. One very general trend that is discernable is that the highest throughput rates are not achieved at the highest bearing pressures.

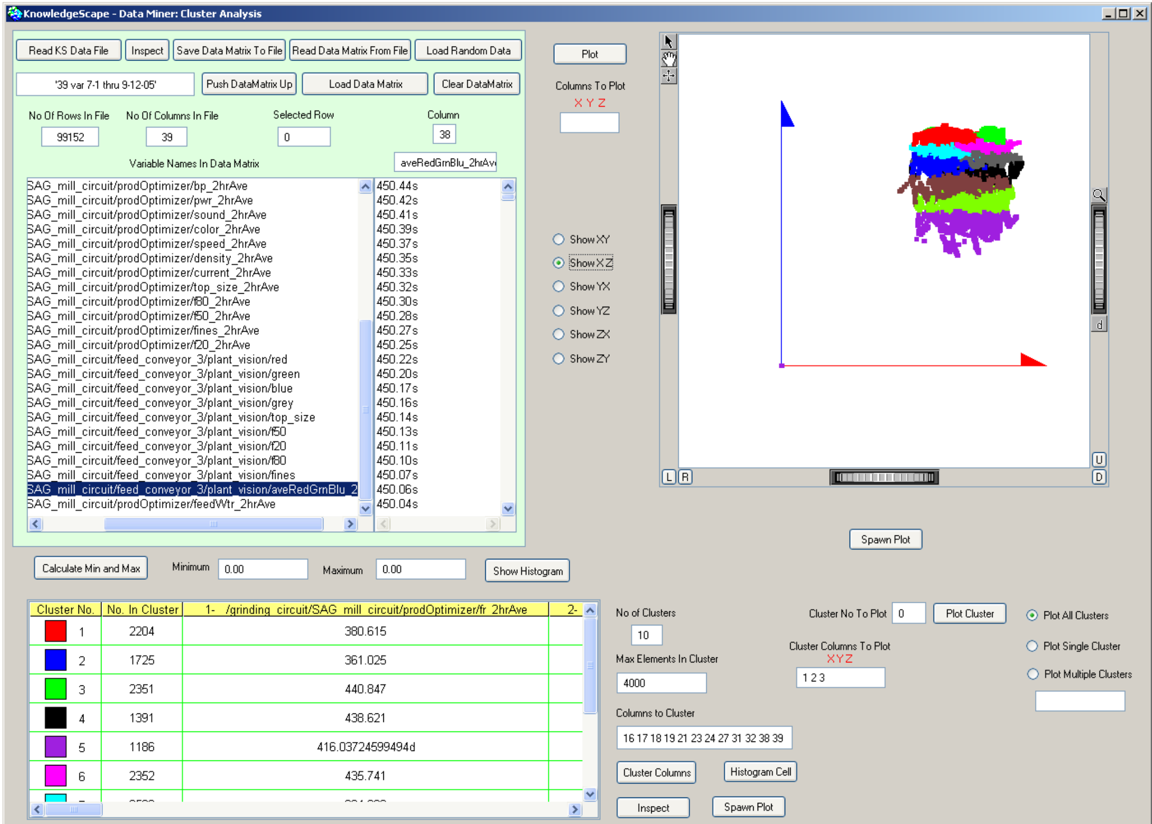

Figure 5. The same Clusters Viewed from the XZ Perspective

In this figure we look at the original cloud of cluster from yet another perspective, the xz side. We now see a lot more order in between the different clusters when we look at them from with the x-axis being feed rate again but the y axis, or the previous invisible z-axis, being mill power. We can conclude from this view that the same throughput rate can be achieved, over a wide range, at a widely varying power. This suggests that as ore conditions change there are enough degrees of latitude, or freedom, to stabilize the throughput rate, minimizing its variance. It also shows that it is not done perhaps as well as it could be.

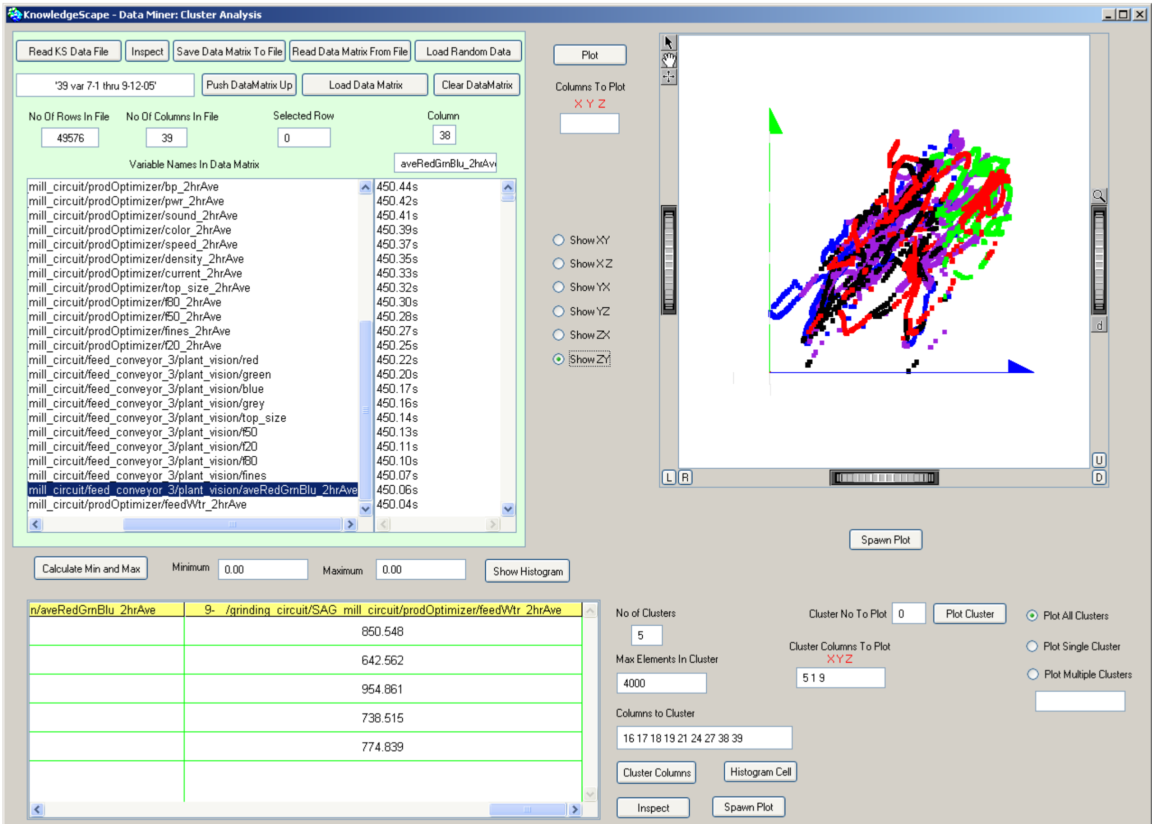

Figure 6. Cluster Analysis Showing the General relationship of Increasing Feed Water and Increase Feed Rate

Figure 6 shows the feed water rate on the x-axis and feed rate on the y-axis. Obviously, as water increases so does the feed rate. What is not known however, from this plot or the cluster analysis is whether the relationship is causal or not. Different data mining techniques need to be run to determine is causality actually exists.

Neural Network Topology Analysis

Neural networks are certainly the most talked about modeling technique in minerals these days. Twenty plus years ago population balance models were invented and have been used also for on-line grinding modeling but their complexity has limited their utility somewhat. Neural networks, are a general modeling methodology, that are effective in predicting future system states in non-linear and complex systems when there is sufficient cause and effect information contained in the datasets being modeled.

Modeling Sag mills has long been the target of this modeling technology. Figure 7 shows the generalized concepts of a neural model.

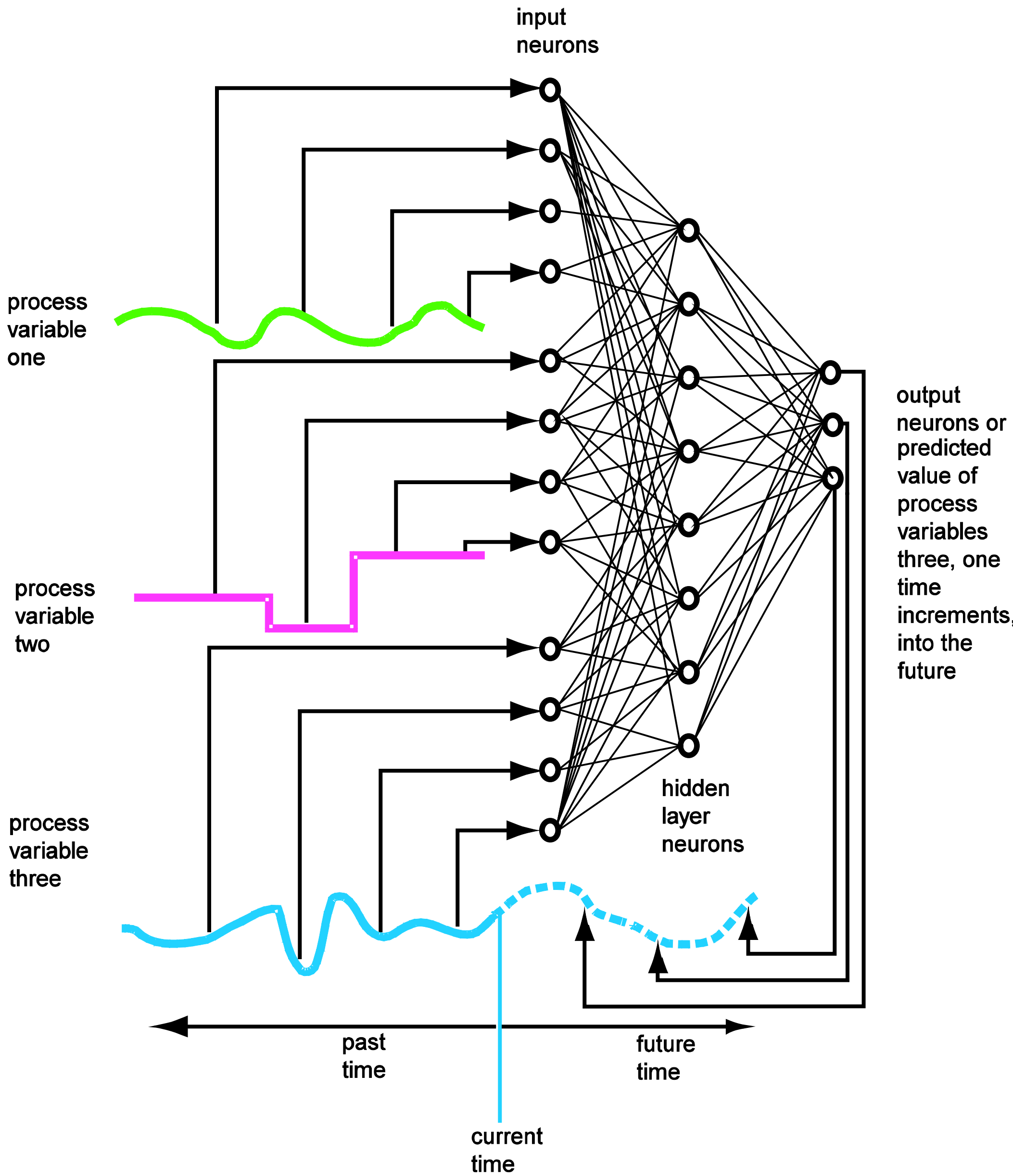

Figure 7. General Neural Network Topology and Input-Output Concepts

Looking at Figure 7 above certainly suggests that neural network models can be configured in an infinite number of ways. One objective of data mining then, is the discovery of the best topologies. Figure 8 below shows a data mining process where a genetic algorithm is used to analyze model topologies.

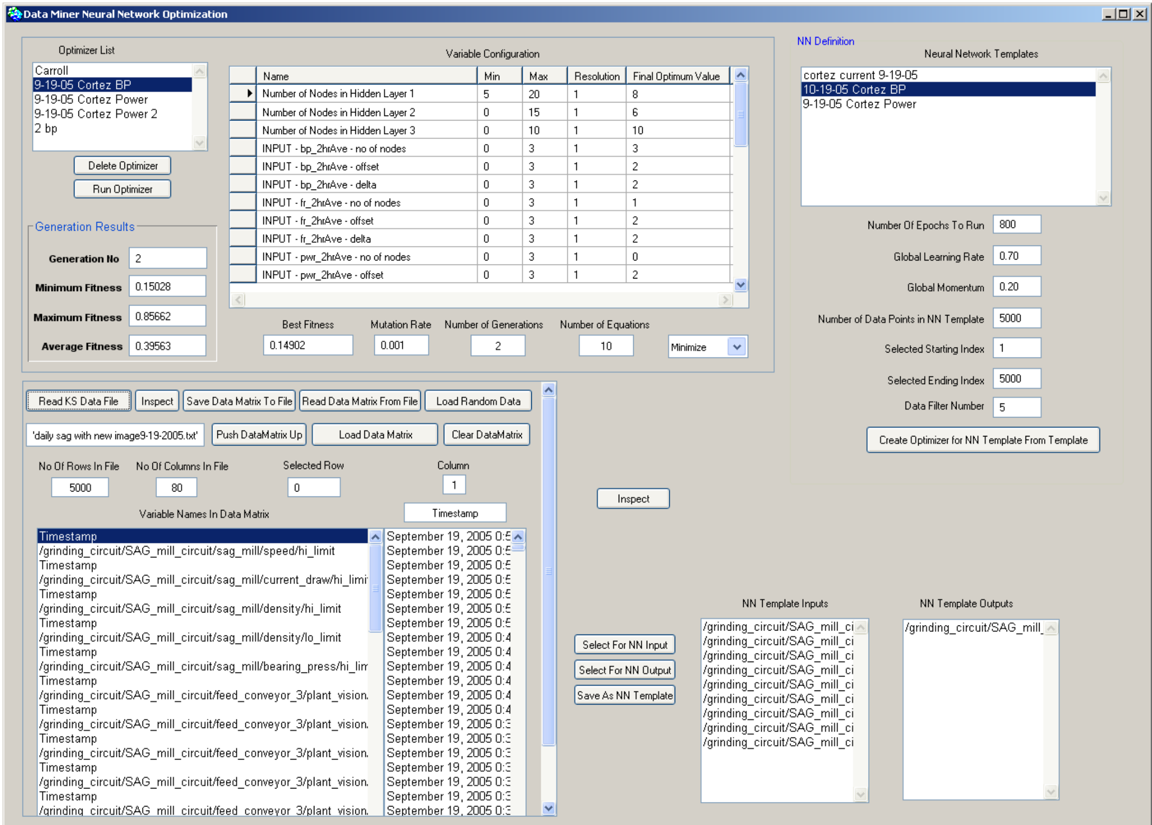

Figure 8. Neural Network Topology Optimization by Genetic Algorithms

The following three figures show the results of the mining effort: first the topology, second the training prediction errors and third the bearing pressure data verses the predicted bearing pressure.

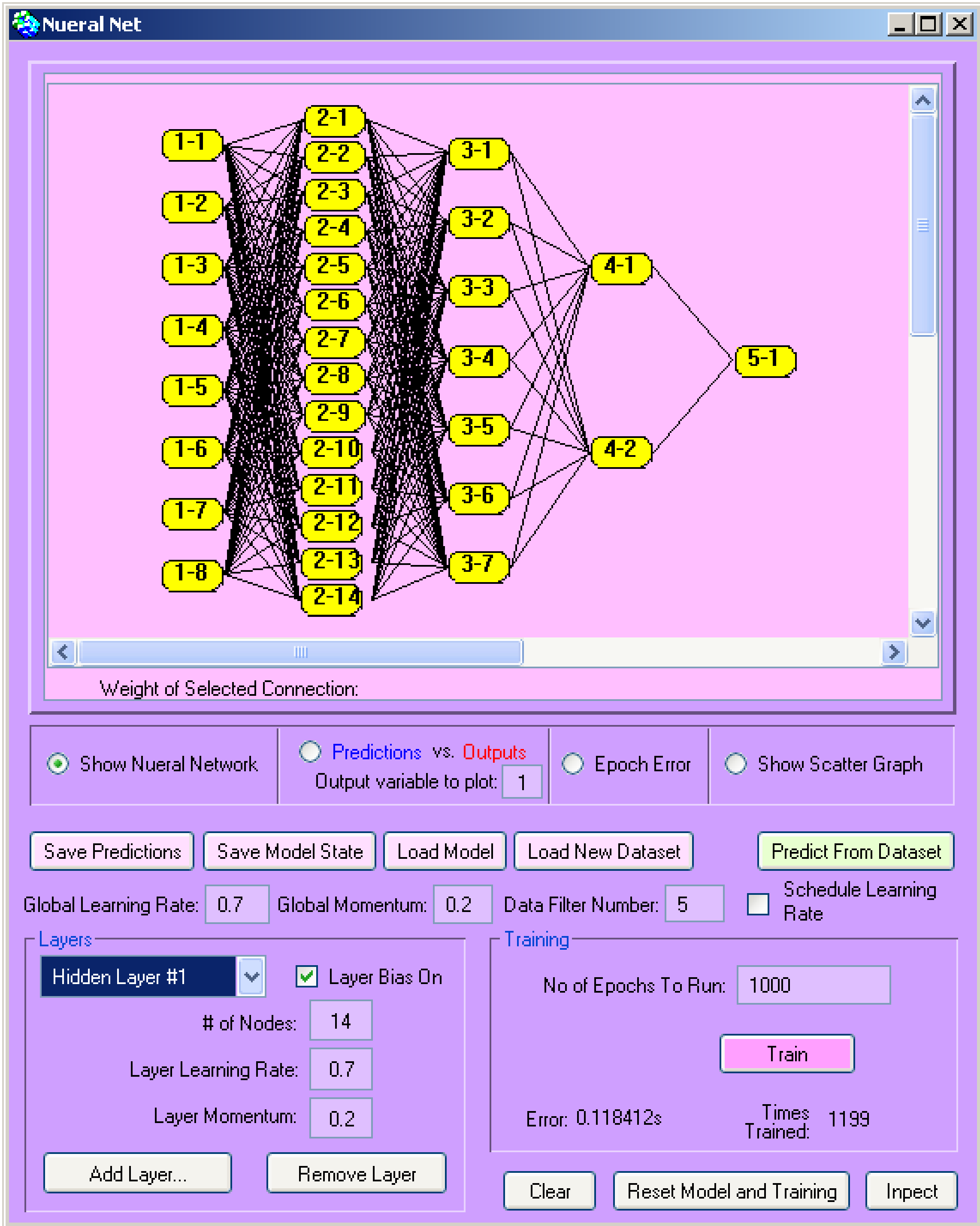

Figure 9. Neural Network Topology

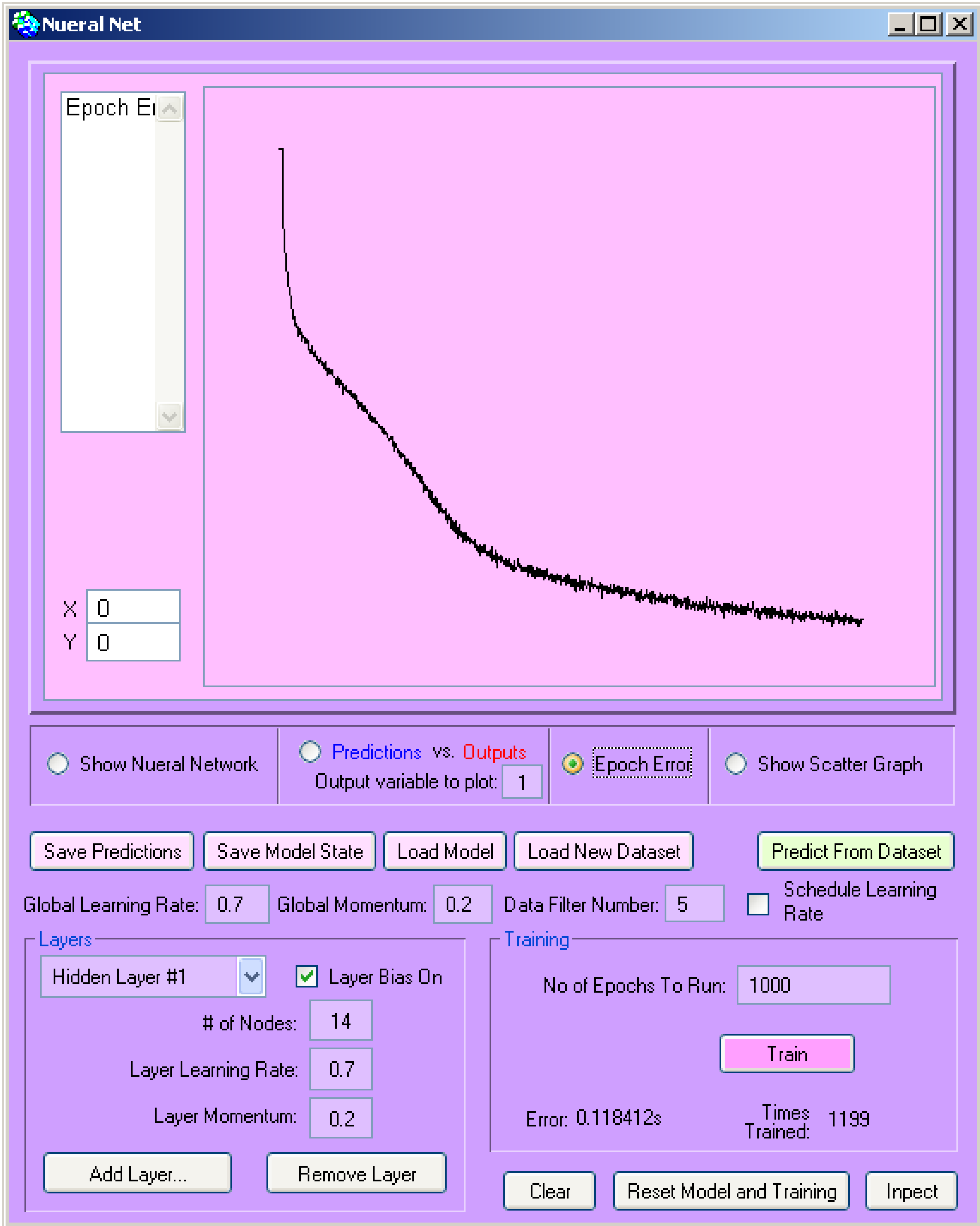

Figure 10. Neural Network Prediction Errors

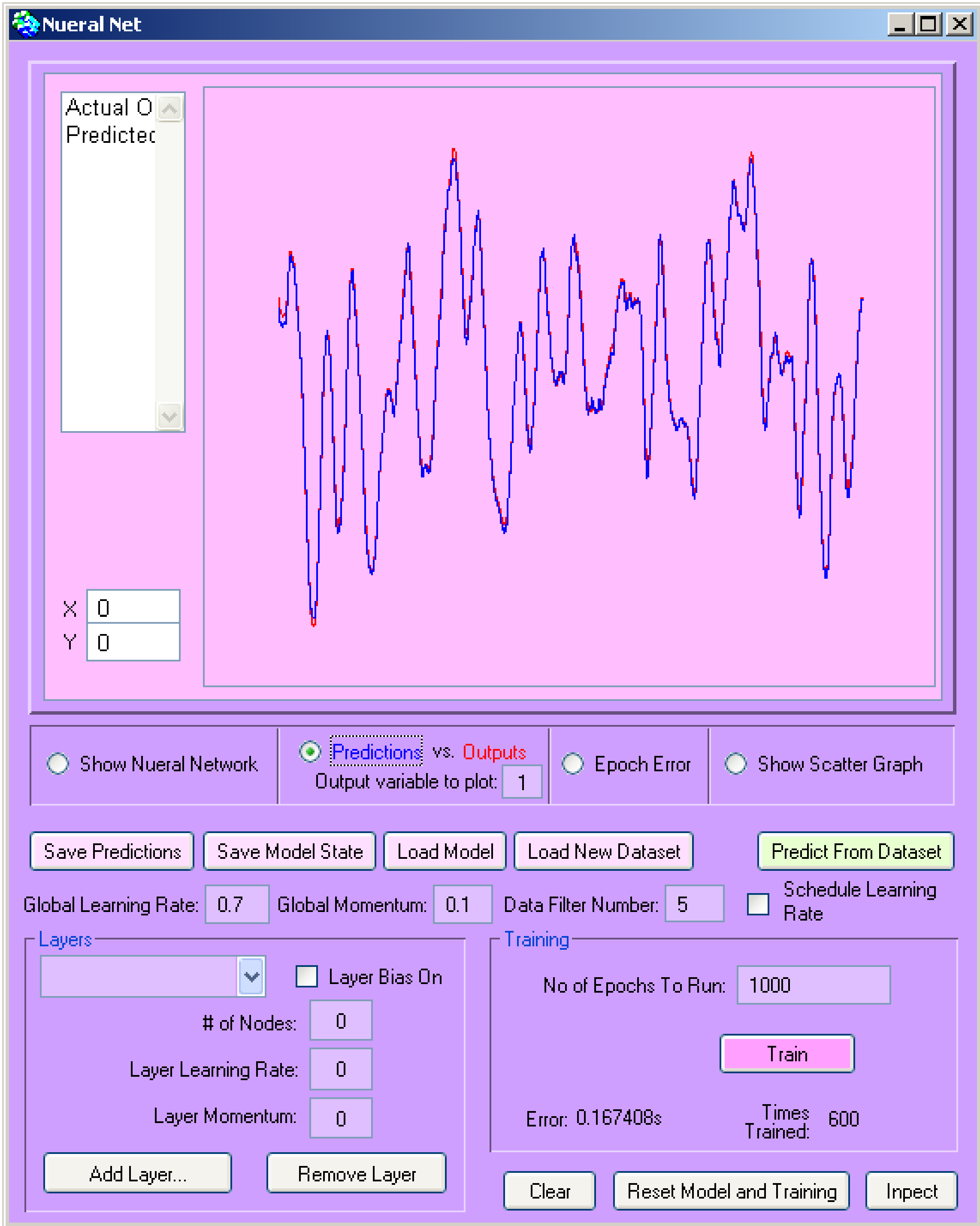

Figure 11. Predictions of Mill Bearing Pressure versus Actual Bearing Pressure

The next figure shows the how well the neural network, which was trained on data collected over a five day period performs when predicting bearing pressure of another entirely different five day period two weeks later. No additional training took place.

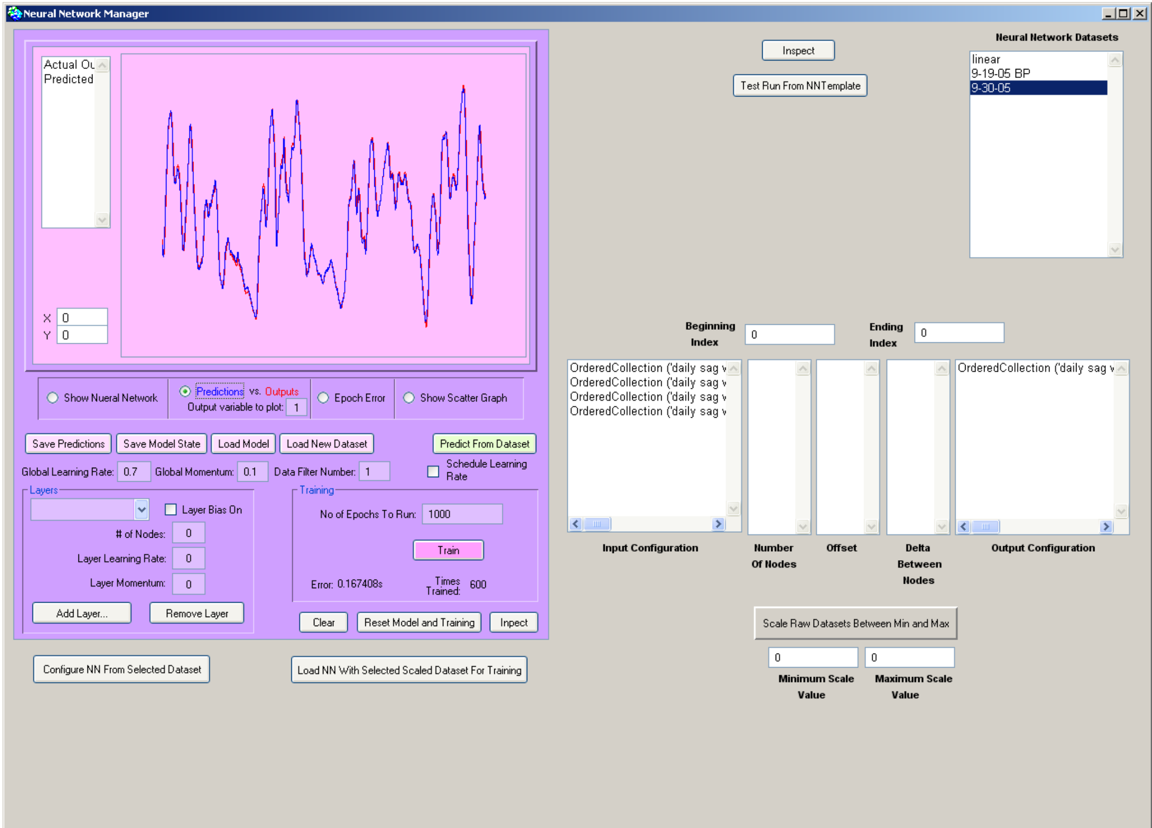

Figure 12. Neural Network Predictions of Totally New Plant Data

As figure 12 shows the predictions are really very good which confirms the validity of the model topology that was determined by the data mining technique.

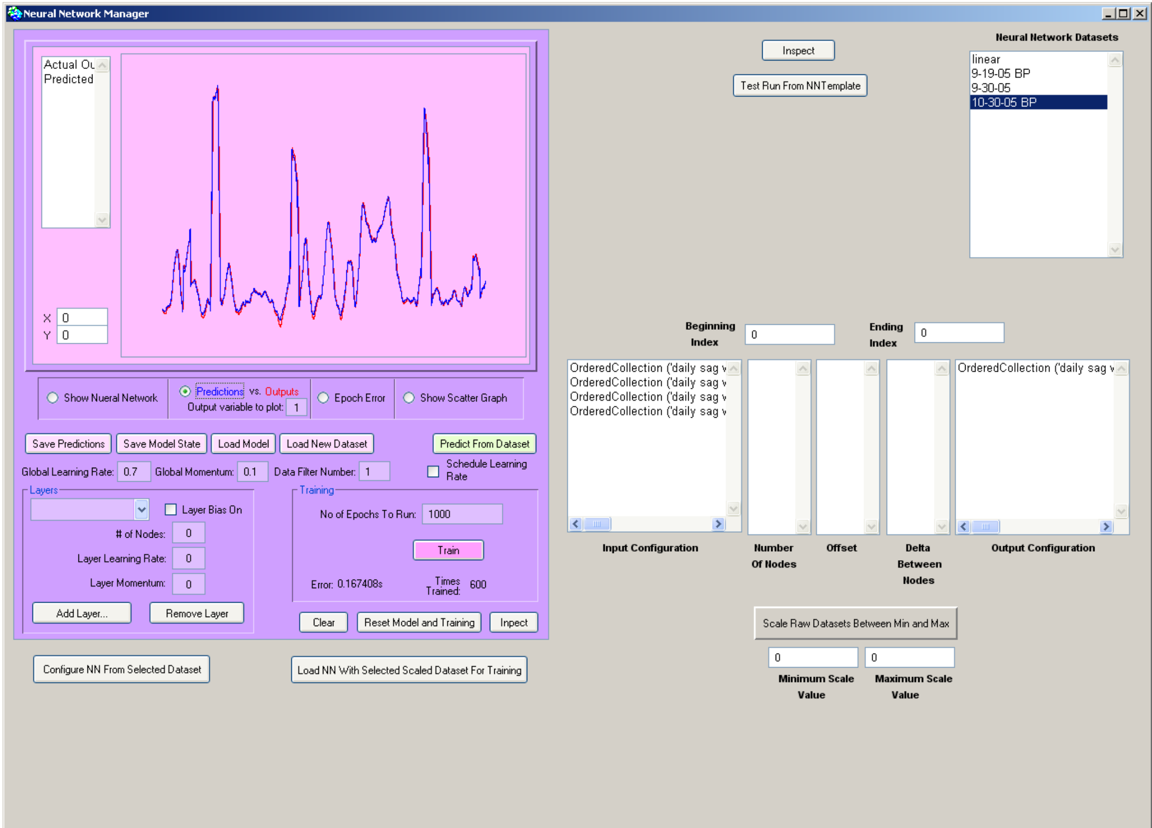

Figure 13. Model Predictions of Five Days of Plant Data One Month Later

Because mill liners are always wearing and changing as is the volumetric ball charge and ball size distribution it has long been known that model parameter adaptation needs to be an ongoing process. This is suggested subtly in the Figure 13 above where the exact same model, that so effectively predicted mill-bearing pressure during two different 5-day periods in one month, predicted the bearing pressure 30 days latter. Here we see that the model predictions are no longer quite as good although, they are still very good. This problem is completely eliminated by simply retaining the existing model topology for a few hundred more epochs.

Rule Induction

One of the greatest improvements that data mining might bring to expert control in the minerals industry is in the area of rule induction. Presently, expert systems typically have several hundred rules that are normally designed to assess the current state of the mill and make set point changes to improve performance in the near term. These rules are often talked about as being heuristic rules, or rules of thumb that have been developed by knowledgeable and experienced people over a long period of time.

What is important to note is that there is little evolution of these rules in the average expert system once the original installation is complete.

A simple example of a typical heuristic rule might be:

> *If the mill bearing pressure has been rising slowly and now is above 800 and the mill power has been decreasing and is now below 2700 then increase the water addition a little and decrease the throughput rate a little*.

Buried in the historical database collected by the expert system is untold numbers of these conditions and actions. Rule induction might be able to discover the supporting data for this rule in terms of:

> *When the throughput rate is decreased a little and the feed water is reduced a little when the mill bearing pressure has been increasing a little and was over 800 and the mill power had been decreasing a little and was below 2700 the mill throughput rate was 2 percent higher a hour later.*

This simple example is actually very complex but it is a good example of the type of knowledge that may be lie hidden in the database.

What is difficult for rule induction systems are discovering patterns in the data that are useful, that is identify facts, or knowledge, that wasn't previously known or understood. Most rule induction systems are known as unsupervised learning algorithms. This means they are looking for patterns or relationships that are accurate and consistent. This means how often they are correct and how often they occur. Rules that only occur infrequently and always aren't correct are of little value; however patterns that are accurate when they occur may be of real value.

The basic format of the patterns uncovered by rule induction is:

If Condition-Then Conclusion, or in the terms of data miners, If Antecedent then Consequent. Of course it is also possible that many conditions or many antecedents can be combined into more complex and interesting rules.

Incorporating Data Mining With Expert Control

There are only a few known case studies where rule induction has been researched in the minerals industry. In spite of this, data mining using rule induction appears to be of potential value in improving the expert rules that are in use throughout grinding plants. Perhaps the next generation of grinding plant expert systems will be improved by some of the data mining technologies reported here.

Areas of collaboration, between expert control and data mining, include:

1) Neural network model topologies,
2) Data clustering and rule and model refinement within the clusters, creating a formalize portioning and specialization of the expert system into parts that make up an improved whole,
3) Rule discovery through rule induction schemes, and
4) The discovery of facts about grinding and mineral processing in general that were not previous understood or known.

Conclusions

Because of the vast amounts of data produced by expert control systems and the fact that they are somewhat static once they are defined, installed and started-up tightly integrated data mining of the data produced will likely be one of the next advancements explored within our industry. Just as expert control promised improved grinding and minerals plant performance twenty years ago tightly integrated and focused data mining enhancements to present expert system technologies promise further improvements in the years to come.

References

[1] Data Mining Concepts and Techniques. Jiawei Han, Micheline Kamber