

APPLICATION AT OK TEDI MINING OF A NEURAL NETWORK MODEL WITHIN THE EXPERT SYSTEM FOR SAG MILL CONTROL

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ABSTRACT

An expert system applied to the control of mineral process unit operations is, by its nature, the site best operating practice, having been designed by the local experts in conjunction with consulting metallurgists. The “common sense” layer in a MET (MinnovEX Expert Technology) solution determines an appropriate action for the current operating conditions through a developed heuristic model of the process (expert system). The magnitude of the setpoint change that is made is proportional to the confidence that the system has in its interpretation of the current conditions (fuzzy logic). The solution is always striving to take the process to a constraint and thereby optimise the operation. An accepted limitation of the solution is that the only way the system can determine if a constraint has been reached is to exceed it and then withdraw – essentially “experimenting” with the process. By leveraging a model, which can accurately “simulate” the process, this restriction can be circumvented by pre-testing the set point change through a “what if” analysis and then modifying the solution as appropriate.

At Ok Tedi, the introduction in 1999 of a MET expert system for SAG milling resulted in significant improvement in circuit throughput. Yet, with the additional inclusion of an accurate model of the process there was still more that could be achieved. Hence, in 2002 a MET Neural Network model was developed and deployed to enhance the existing expert system solution. The principal objective of this model was predicting the effect that changes in SAG tonnage and density would have on the power draw of the mill - essentially a power predictor. The results have seen a decrease in process variance with an associated increase in average circuit performance.

This paper describes the methodology by which the Neural Network model was implemented, the considerations and limitations when applying this technology and ultimately the results that were achieved..

INTRODUCTION

Ok Tedi Mining Limited (OTML) is located in the Star Mountains in the remote Western Province of Papua New Guinea. OTML began operation in 1984 as a gold producer and now operates an open pit mine and concentrator which produces about 600,000 tpa of high grade copper and gold concentrate for Asian and European markets. Concentrate production commenced in tandem with gold production in late 1987, and gold production ceased in 1988. Production is achieved via conventional SAG grinding and flotation technology. The grinding line at Ok Tedi consists of two SAG mills, each feeding a pair of ball mills. The SAG mills are 9.6 m diameter by 4.3 m long and each have about 6,800 kW installed

power (slightly different power levels on the two mills). The mills operate in closed circuit with 10 mm vibrating screens, with a typical circulating load of about 15 % (and no pebble crushing). Flash flotation cells are installed in the ball mill circuit. The copper concentrate is transported 156 km by pipeline from the mill to the filter and drying plant. Dried concentrate is transported by barge 850 km to a silo vessel located in the Fly River delta for storage and shipment.

Over the life of the plant, the ore characteristics have changed significantly. This provides a challenge for any advanced control system; it must be able to perform adequately without relying upon fixed attributes of the ore.

ORE TYPE AND FEED SIZE DISTRIBUTION

The ore body consists of many different ore types. These range from fast milling monzonite porphyries, oxide skarns and oxide porphyries, to medium and slow milling monzodiorites, siltstones and skarns. Ore hardness and size distribution of the SAG feed both vary widely. In describing ore hardness, the SPI (SAG Power Index) varies from 10

to 130 minutes, which translates to a SAG specific power range of about 3 to 9 kWh/t for this site. The design of the ore stockpiling and conveying system contributes to fluctuating size distribution with significant short-term segregation occurring under certain operating situations. Depending on ore type and feed size distribution, each SAG mill will process between 700 and 3000 tph. The budgeted average total throughput is 88,000 tpd.

THE OK TEDI ADVANCED CONTROL SYSTEM IMPLEMENTATION

The SAG expert system at Ok Tedi was completed in 1999, described previously by McCaffery, Katom, and Craven (2001). It runs within the MET (MinnovEX Expert Technology) toolkit based on a Gensym G2 platform. This provides an object oriented, real time environment, which is ideal for this type of application. The system is installed on two mid-range Intel PC's (P3 500MHz, 256 MB) with Windows 2000 operating systems. One computer is required to run the complete system; the other provides a redundant standby backup capability. An OPC server connected to the Bailey DCS and an OPC client running on the MET computers provide communication between the Bailey DCS and the system.

Gensym provides a layered product, GDA, built on the G2 platform that provides a large library of objects for graphical description of logic and statistical functions. MinnovEX has further extended the GDA library within its MET toolkit. MET provides an additional comprehensive library of objects and procedures that enable the easy design and rapid deployment of real-time expert systems for process control in processing plants. Objects from the MET/G2/GDA libraries are used to represent the SAG milling environment schematically. This approach results in a straightforward and flexible system with fast and simple connection to data sources.

The attributes of the Ok Tedi SAG mills that are used by the expert system are power draw, lift pressure, motor temperature and recycle tonnage. Fresh feed tonnage and feed density are the

manipulated variables. Set point changes in tonnage or SAG mill feed density are returned to the DCS PID controllers.

Fuzzy sets are defined for all the measured parameters. Each attribute is normalised, and its span divided into fuzzy belief values. A typical example is the SAG Mill 1 Bearing pressure (described later in Figure 3). These fuzzy belief values are used as inputs to 80 rules, which describe the knowledge of the mill's control strategy. In addition to the attributes used by the expert system, the neural network also uses real-time size data obtained from cameras located over the mill feed conveyor and analysed by a Split-On-Line vision system.

The paper is organized into two parts. Part 1 reviews the concepts and issues for implementing expert systems and Neural Networks. Part 2 then describes the execution of the Neural Network project on the SAG mill at Ok Tedi.

PART 1. EXPERT SYSTEMS, FUZZY SYSTEMS AND NEURAL NETWORKS

WHY ARTIFICIAL INTELLIGENCE?

Methods, targets, and equipment settings for normal steady-state operations are well understood. Most plants have software and instrumentation that handle this quite nicely. Outside of normal operating conditions,

however, control system efficiency may deteriorate rapidly as alarms can cascade into uncontrollable system breakdown. Sometimes algorithms and equation-based software solutions can handle these abnormal situations. But as systems become more complex and interconnected, artificial intelligence techniques are used increasingly to predict failures before they occur, and to deal with process upsets before consequential problems can occur.

If process conditions could always be determined and modelled in advance, then normal equation-based modelling and software techniques would be sufficient. However, process disturbances and abnormal situations often entail a certain degree of unpredictability. It is the unknowns and unpredictable behaviour of processes operating in combination with one another that call for advanced techniques known collectively as artificial intelligence (and SAG milling circuits clearly exhibit unknown feed properties and unpredictable behavior). The areas of artificial intelligence are summarized in Figure 1.

The goal for an expert system is to capture the thinking of a human expert in a computer program so that a non-expert can benefit from the expert's problem-solving skills. The program can react to situations by providing advice or taking direct action in the same manner

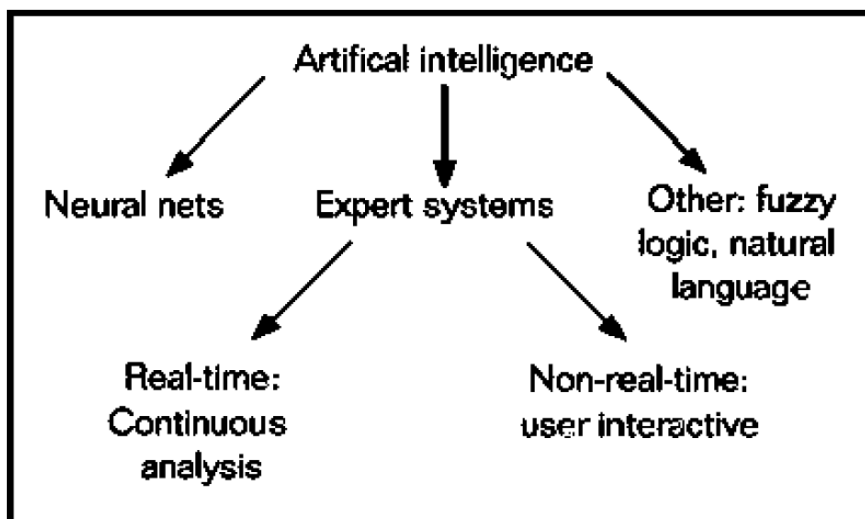


Figure 1. Areas of Artificial Intelligence

as the human expert. Real-time expert systems have dynamic databases that continuously update with current process information.

Expert System inference engines interpret the contents of their knowledge base in order to solve problems. They act as rule selectors, choosing which rules in the knowledge base apply to the problem at hand. Their primary task is the invocation of a key precept of an expert system - the concept of logic before data. An expert system, in order to emulate the decision making process, should "chain" through its logic prior to making a judgement - this is what sets these systems apart from a simple rule based "linear" system.

At a certain level of complexity, the expert system will be called upon to deal with imprecise information. At this point a methodology is required to deal with descriptive states, such as "too wet", "too coarse" and many similar descriptive attributes.

Neural Networks are often used to classify complex data, and the formalism of Fuzzy logic¹ is used to manipulate the information.

Fuzzy logic is based on the way the brain deals with inexact information, while neural networks are modelled after the physical architecture of the brain. Although the fundamental inspirations for these two fields are quite different, there are a number of parallels that point out their similarities. Fuzzy systems and neural networks are both numerical model-free estimators and dynamic systems. They share the common ability to improve the intelligence of systems working in an uncertain, imprecise, and noisy environment. Both fuzzy systems and neural networks have been shown to have the capability of modelling complex non-linear processes to arbitrary degrees of accuracy. MinnovEX has successfully applied both techniques to a variety of mineral processing and metallurgical control systems and scheduling applications.

Fuzzy systems start from highly formalized insights about the structure of categories found in the real world and then articulate fuzzy IF-THEN rules as a kind of expert knowledge. Fuzzy systems combine fuzzy sets with fuzzy rules to produce overall complex non-linear behaviour. Neural networks, on the other hand, are trainable dynamic systems whose learning, noise tolerance, and generalization abilities grow out of their connectionist structures, their dynamics, and their distributed data representation. Neural networks have a large number of highly interconnected processing elements (nodes) which demonstrate the ability to learn and generalize from training patterns or data; these simple processing elements also collectively produce complex non-linear behaviour.

In light of their similarities and differences, fuzzy systems and neural networks are suitable for solving many of the same problems and achieving some degree of machine intelligence. Their differences have prompted a recent surge of interest in merging or combining them into a functional system to overcome their individual weaknesses. This concept realises the benefits of both fuzzy systems and neural networks. That is, neural networks provide fuzzy systems with learning abilities, and fuzzy systems provide neural networks with a structural framework with high-level fuzzy IF-THEN rule thinking and reasoning. Consequently, the two technologies can complement each other, with neural networks supplying the brute force necessary to accommodate and interpret large amounts of sensory data, and fuzzy logic providing a structural framework that utilizes and exploits these low-level results. Most neural-fuzzy applications are fuzzy rule-based systems in which neural network techniques are used for learning and/or adaptation.

Further details on Neural Networks are provided in an Appendix to the paper.

MET IMPLEMENTATION

MinnovEX has implemented the technologies described in a graphical programming environment, which is intended to enable the site technical and operating personnel to enhance and modify the control space so that it accurately reflects current best practice. This feature is very important since it allows evolutionary operation and similar quality systems to be applied throughout the life cycle, to improve the operation of the process while having a "standard operating procedure" that reflects current best practice. Four key components of the implementation process, discussed further here, are:

- (a) knowledge capture,
- (b) fuzzification of process variables,
- (c) generation of fuzzy rules, and
- (d) tuning of fuzzy sets and rules.

(a) Knowledge Capture

The quality of the knowledge base is the key to an expert system's success. An expert system's performance will only be as good as the information captured within its code. This requires more than just careful creation. The system must evolve as the operating practice develops. The integration process is the first step in this development but the system itself is the greatest driver towards the continual improvement. By definition the system is pushing the unit operation(s) to their bottlenecks and identifying where they exist. The obvious next step is to find a way around those limitations and it is this process that results in modified and improved "standard" operating practice. Hence an expert system is thought of as a 'living entity'; it must evolve with changes in operations personnel and the process.

The MET methodology for expert system development is based upon exhaustive interviews of all the stakeholders in the process operation. This includes all the operating and technical personnel combined with the metallurgical experience and benchmarking that the MinnovEX team brings to the project. The operating procedures that are determined from this process are then reconciled into a single set of operating practices. These are represented graphically, much as they will finally be

¹The ability to judge degrees of truth as opposed to absolute truth – items can be 60% sure as opposed to conventional crisp logic, which is true or false.

implemented. Any differences between individuals are resolved through a “change management” process that encourages participation, discussion and conflict resolution.

The resulting document is used to build the initial knowledge base, which is then refined into an ultimate “site” best operating practice.

The on-going maintenance of the rules is more straightforward since rules tend to be changed singly (or at least within an independent “chain”) and evaluated in isolation. The modified knowledge base can then be tested off-line in parallel with the existing system as an initial “standard”. Once the logic has been debugged, and if it shows promise, it can then be tried online. At that stage the logic either becomes part of the permanent system or the original knowledge base is reinstated.

(b) Fuzzification of Process Variables

The normalised process variables are fed through the Fuzzifier (see Figures 2 and 3). This section determines the confidence of membership of the process variable for each of the classifications. The x-axis of Figure 3 is normalized bearing pressure, defined

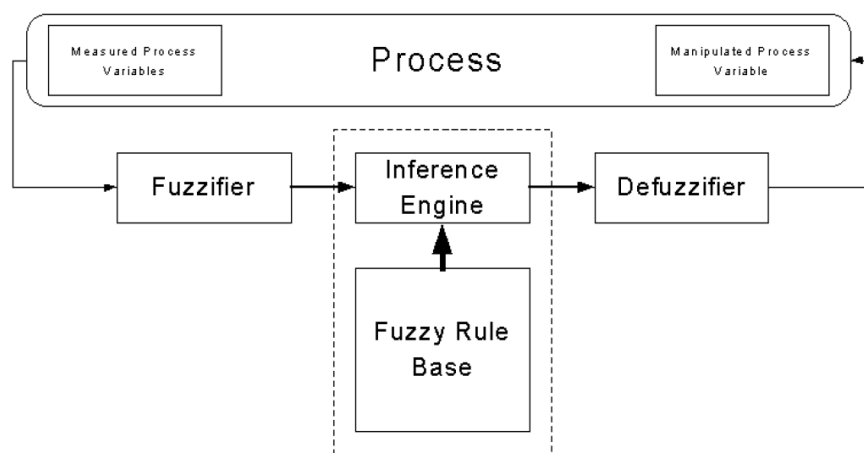


Figure 2. Fuzzy Logic Controller

as [(very high pressure – measured pressure) / (very high pressure – low pressure)]. A mid range pressure (which would normally be ‘pressure OK’) would have a normalized value of about 0.5. In the case referenced here of normalised bearing pressure, at a normalised value of 0.3, there is a 50% possibility that the pressure is low and a 50% possibility that the pressure is OK. At a value of about 0.8, there is a 50% possibility that the pressure is OK and a 50% possibility that the pressure is High. Similar construction continues through to a normalised value of 1.0 where there is a 50 possibility that the value is very high

and 50% possibility that the pressure is extreme. At 1.1 the pressure is definitely extreme. If we look at the low end, where the values are a bit better spaced, if the value was about 0.2, then there would be about a 30% possibility that the pressure was OK and about a 70% possibility that the pressure was low.

(c) Generation of Fuzzy Rules

A typical rule is shown in Figure 4. All the inputs to the rule, shown on the left are fuzzy beliefs. The output from the rule is a belief value that an action should occur. The stronger the belief, the larger is the change that is made to the setpoint of

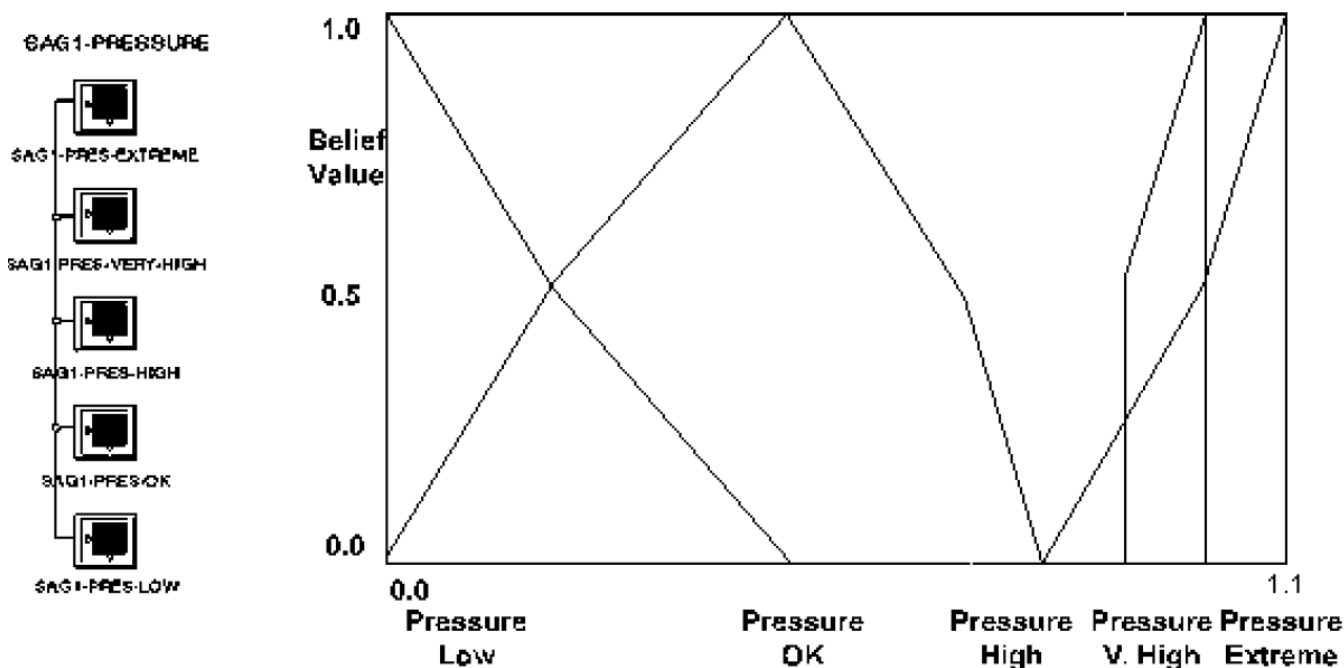


Figure 3. Fuzzifier and Fuzzy Class Membership

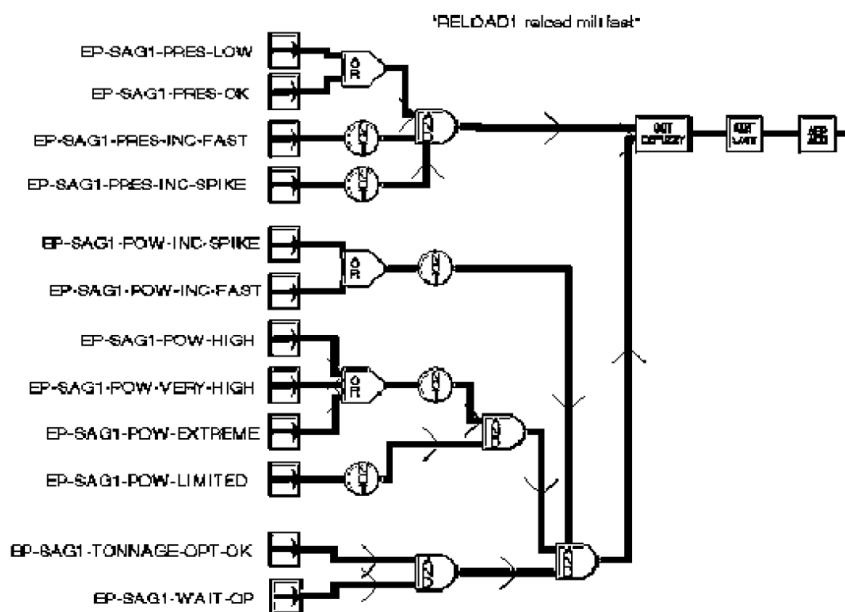


Figure 4. Graphical Fuzzy Rule and Defuzzifier

the appropriate variable. If the belief value is 1.0, then the maximum value appropriate for that condition is taken. If the belief value is 0.6 (a little greater than 'don't know'), a much smaller action will be taken. The system then waits for the process to respond to the change, and re-evaluates its actions. In this way, if an error is made, the consequences are small, and would increase the likelihood that the correct action is taken at the next evaluation.

(d) Tuning of Fuzzy sets and Rules

There is additional information that is required for the successful implementation of a Fuzzy Logic Expert System. The membership function for each of the variables needs to be carefully chosen. The decision about what constitutes "TOO HIGH" and what is "EXTREME" requires careful analysis. Both the magnitude of the setpoint changes that correspond to a given condition and the time that must elapse before the effect of a setpoint change can be evaluated must be considered on a case-by-case basis. Effective tuning requires a significant investment of on-site time, especially for the tuning of variables that are rates-of-change.

COMPARISON OF EXPERT SYSTEMS AND NEURAL NETWORKS

The two forms of artificial intelligence used in the Ok Tedi Control system now

have been described. The MET expert system solution contains knowledge derived from human operators and technical experts. It is, essentially, fixed in its response to its stimuli. Although the MET design makes it easy for metallurgists or operating personnel to modify its behaviour, it does require human intervention to change. It has the advantage that it can respond to events, which at the time of design were hypothetical. This allows the expert system to be designed to control events that will not necessarily ever happen, such as overloads and failures. The Neural Network on the other hand, has no prior knowledge of the process. All of its knowledge of the process comes from observing the process responses to stimuli. This limits its usefulness to operating in the process envelope near points that have occurred previously. This is a significant limitation when the intention is to operate the process at the limits of the operating envelope, i.e. at the constraints.

The conventional approach would be to invert the Neural Network into a controller (NN controller) and use the expert system to define the regions in which the NN controller may operate and provide defined behaviour outside that region. This approach works well when the Neural Network is being used for optimising the process. The expert

system would shift the process into the vicinity of the optimal operating point, then transfer control to the NN controller. If there were a significant process disturbance, the expert system would inhibit the Neural Network and manage the disturbance.

However, this approach is not appropriate when the objective is to run the process against constraints. The approach that MinnovEX has used in this situation is almost the opposite of this strategy. The normal control is provided by the expert system, with the Neural Network modifying the behaviour of the expert system near the constraints. The Neural Network model operates in simulator mode with the expert system using it in a "what if" capacity. The expert system defines a desired change and tests the results in the model. The model then predicts the outcome expected by the set point manipulations. The logic around the Neural Network estimates the confidence of the prediction of the network, and if the confidence in the prediction of the network is high, then the Neural Network modifies the behaviour of the expert system as appropriate.

When the system starts off, with no history, or when there has been a significant change in the ore properties, then the confidence of the neural network's prediction is low. Over time, it learns the behaviour of the process, and the confidence of its predictions increase.

OPERATION AGAINST CONSTRAINTS

Unlike when a process is operated manually or with PID control, an expert system will continue to manipulate the setpoints until the process is operating against a constraint. This has two consequences. The first is that, given that the control system is correctly designed, the process is always operating close to optimum conditions. The second is that the true operating constraints are always identified. This information becomes invaluable when trying to improve the plant operation.

PART 2. THE OK TEDI NEURAL NETWORK FOR SAG MILLING

The SAG expert system installed in 1999 produced significant improvement in the mill operation. The metric that Ok Tedi chose to measure the performance of the system was the power draw of the SAG mills. This is commonly used at Ok Tedi as a key performance indicator, due to the highly variable nature of the ore and the difficulty in benchmarking. It is an appropriate indicator, as the grind is kept relatively constant and the mill is power limited. Ok Tedi uses a formula by which this can be directly translated into throughput. After installation of the MET expert system SAG2 demonstrated a 5.3% increase in throughput (McCaffery, Katom, and Craven, 2001).

The system was well accepted by the operators, and was controlling the mills for greater than 95% of the time. The next step in the controller evolution was to attempt to use a higher percentage of the installed capacity. Analysis showed that there was variability in the power draw when operating close to the limiting power. The reason for this was that the expert system would add tonnes in an appropriate manner, and a short time later it would detect that the mill was beginning to overload. It would then decrease the feed tonnes, to prevent the mill going into overload. It is inevitable that an expert system will cycle around its operating point as it continually tries to push to the constraint (in this case overload), so this behaviour was not entirely unexpected (it was still significantly improved upon the original installed system). The problem was exacerbated when a change in the ore properties occurred.

Options that were considered included detuning the expert system - this would increase the risk when a genuine rapid response was required. What was required was gain scheduling based upon a moving target, the point at which overload was likely to occur. A neural network is an ideal tool for this task, but there were some constraints on the complexity that the network could have due to the variability of the feed. It was found that the maximum time that

the mill process could be considered stationary was of the order of two hours. The minimum sampling time over which most of the variables could be considered to be reasonably uncorrelated was approximately one minute. This meant that the maximum number of reasonably independent samples that could be used for training the network was of 120.

The challenge was to modify the controller so that it had prior knowledge of when an overload was likely to occur, and to moderate the actions of the expert system when this occurred. The structure had to be such that it could be reasonably well trained with 120 data samples. Due to the variability of the ore, it could not be assumed that the model applied at a given time would be applicable a few minutes later; therefore, on-going validation of the network predictions were essential.

The final design of the network had three components: a trainer, a validation network and a predictor.

The Neural Network operates in two distinct time frames simultaneously. In the first instance, it operates three minutes behind real time. In this case, it should be accurately predicting the current process operating environment, except for the effects of any setpoint changes made during the last three minutes. A first order approximation is made to the current process variables to allow for setpoint changes that have been made in that time, and the corrected process variables are compared with the predictions from

the neural network. This neural network model is used to determine the validity of the model at the present time and is necessary because the system is operating on the limits of the training domain of the neural network - there will always be doubt about the validity of the model in this regime.

In the second time frame, the NN operates in real time and predicts the tonnage and density setpoints required to achieve the target mill power three minutes into the future. A z-score is calculated for the prediction based on the standard deviation and the mean of the prediction error for the current value and the setpoint deviation predicted by the NN. An inverse normal curve is used to provide the probability that the new setpoint prediction is not due to measurement variability.

The inputs to the network are shown in Table 1. There are a total of 24 input variables based upon the following variables.

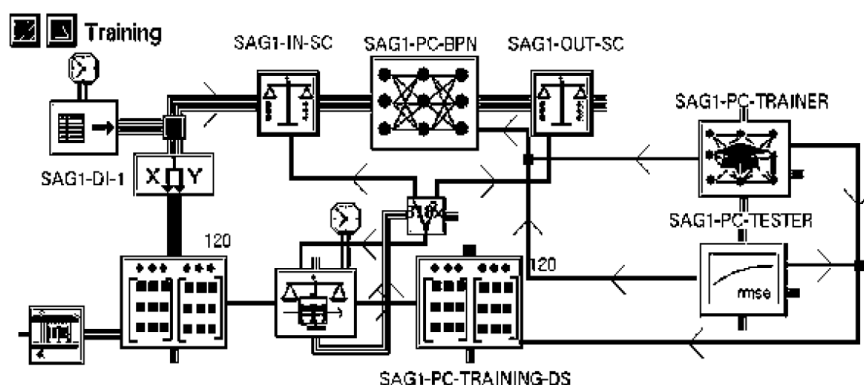


Figure 5. Training Neural Network

Table 1. Inputs to the Training Network

SOURCE
Bearing Pressure
SAG Mill Power
SAG Mill Motor Temperature
Recycle tph
Fresh Feed tph
P ₁₀₀ of the Mill Feed
P ₈₀ of the Mill Feed
P ₅₀ of the Mill Feed
P ₂₀ of the Mill Feed
Stockpile Level
Target Power
Feed Density
<i>Corrected Feed Tonnage</i>
<i>Feed Density</i>

The last two rows are the desired outputs: the predicted tonnage and feed density at the current time, to be calculated based upon values from a minimum of three minutes ago. The structure of the training network is shown in Figure 5.

The network configured from this data is then used to predict the current values of mill feed rate and density. The values obtained from this network are used to develop a confidence interval, which in turn will be used to assess the reliability of the predictions, based on current data, of the mill feed rate and density, in three minutes time. If the predictions are close to the standard deviation of the prediction error, then there is little confidence that the value is not solely a result of prediction error. If the value predicted is well outside the error band, then there is a high level of confidence that the prediction is real. This intuitive concept is handled formally by applying a t-test.

The results obtained from the NN predictor are used to calculate the predicted slope of the feedrate / power curve in three minutes. These predictions are then used as inputs to a fuzzy set. Finally the confidence of the prediction is used to modify the expert system decisions as appropriate. For example; if the expert system decides that a 10 tph increase is justified, then this

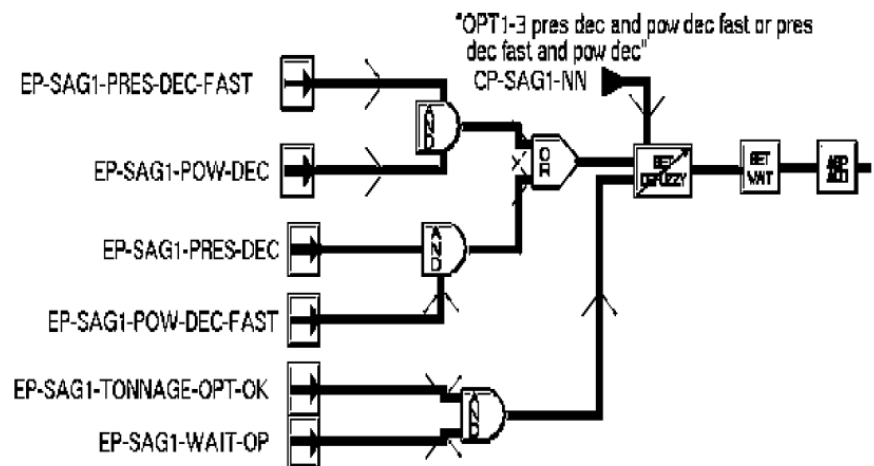


Figure 6. An Expert System Rule Modified by the NN

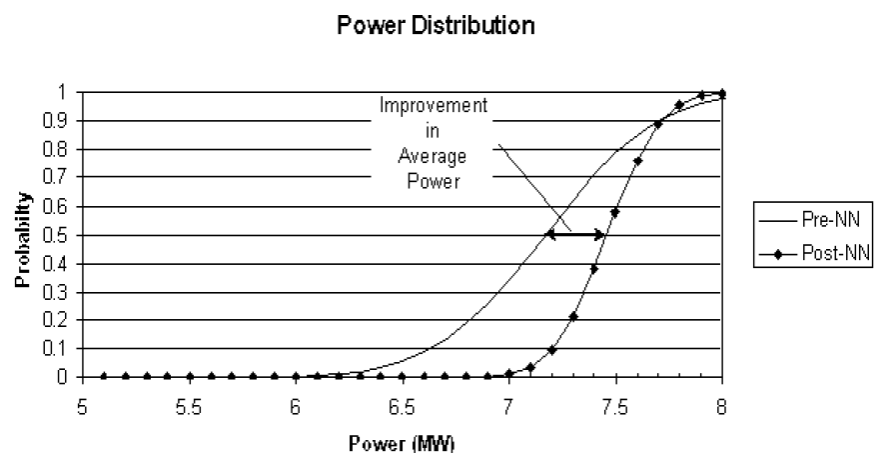


Figure 7. Improvement in Power Draw

value is inserted into the NN simulator. The simulator will then determine the impact of the change and report the findings back to the expert system with a confidence factor. If the outcome is that the simulator determines that the increase will push the mill into overload with a 70% degree of certainty then the expert system setpoint change is modified to 3 tph (change * (100 - certainty)). If the model is 60% sure then the change would be 4 tph and if it is 90% sure the change is 1 tph. A typical expert system rule is shown in Figure 6.

RESULTS

The mean power draw increased from 7.35 MW to 7.48 MW. Equally significantly, the standard deviation of the power draw decreased from 0.38 MW to 0.20 MW. This corresponds to a 35% increase over the increase obtained with the MET expert system

alone which represents (based on Ok Tedi relationships) approximately another 2% increase in throughput, with less variation in tonnage and the resulting benefits to downstream processes (Figure 7). The economic impact of the improved control can be evaluated from the increased throughput, and the increased recovery from a more stable flotation feed.

FURTHER OPPORTUNITIES

The work to date has focussed on managing the grinding circuit to cope with disturbances in the mill feed, and minimise the variability in flotation feed contributed by the grinding circuit. Recent improvements to the process control communication provides the opportunity to manipulate the mill feed, based upon the grinding characteristics of the ore, to reduce the shortterm

variability in the flotation feed. The long-term variability still will be determined by the mine plan.

The next step is to link the mine plan to the control solution, by tracking and following the variability from the ore body to the mill through the incorporation of CEET (Comminution Economic Evaluation Tool) and FLEET (Flotation Economic Evaluation Tool) models. This will provide true "feed forward" control allowing the system to anticipate changes in circuit behavior before these changes occur and then regulate the changes with traditional responsive feed back control. This process has already begun with the incorporation of stockpile information in the system and the measurement of SPI values on the ore body. With better knowledge of what is coming into the process the system will be able to optimise for the specific opportunities that exist. This may include adjusting the load balance between the SAG and Ball Mills or adjusting a target grind to assist in flotation.

CONCLUSION

The application of neural network modelling has been successfully applied to SAG mill control at Ok Tedi. The improvement in the mill power draw is 35% over the already substantial improvement realised with traditional fuzzy expert control alone. This resulted in an additional 2% calculated throughput on top of the 5.3% quoted in an earlier paper. An important supplementary benefit of this technology was the reduction in variability, which ultimately benefits flotation - although this benefit has not been quantified. The Neural Network has shown itself to be robust even under extremely difficult conditions.

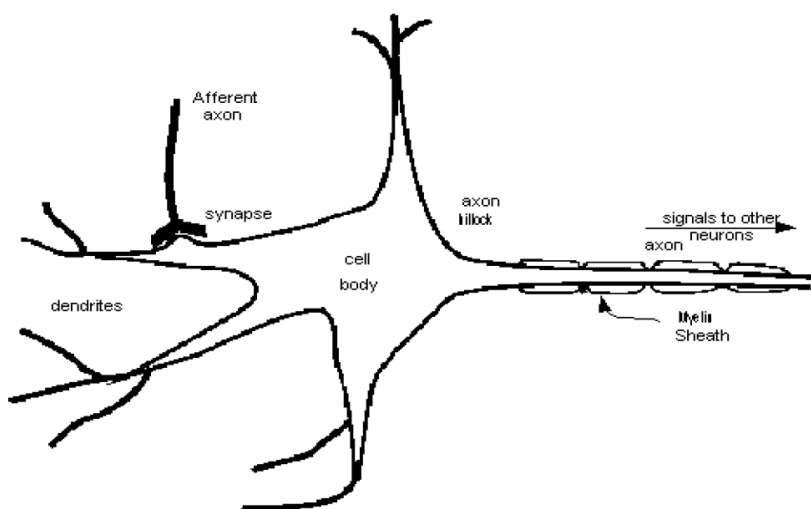


Figure 8. Biological neuron

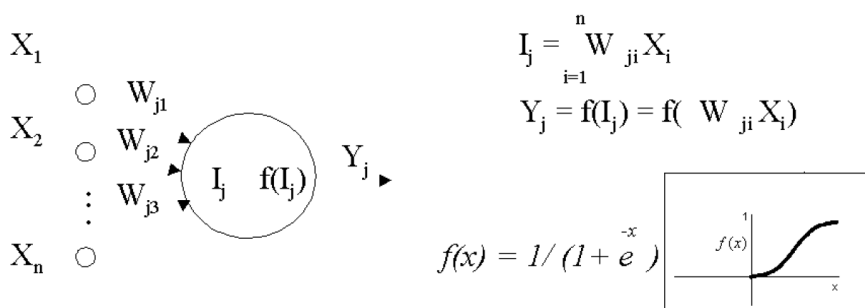


Figure 9. Artificial Neuron

ACKNOWLEDGEMENTS

Any project that pushes the boundaries of conventional technology requires several ingredients for success. The authors would like to acknowledge Rob Sloan (Manager of the Process Control Group at MinnovEX Technologies) for his support, and the technical management at Ok Tedi for their confidence in the project and the provision of the resources necessary for the project.

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APPENDIX - OVERVIEW OF NEURAL NETWORKS

A Neural Network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron (see Figure 8). The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns. The models are often referred to as "data driven" as they are empirical models that are developed using data alone and frequently have the ability to continually "evolve" (retrain/calibrate) based on real time data.

In an animal neuron, electrical pulses travelling along the axon transmit

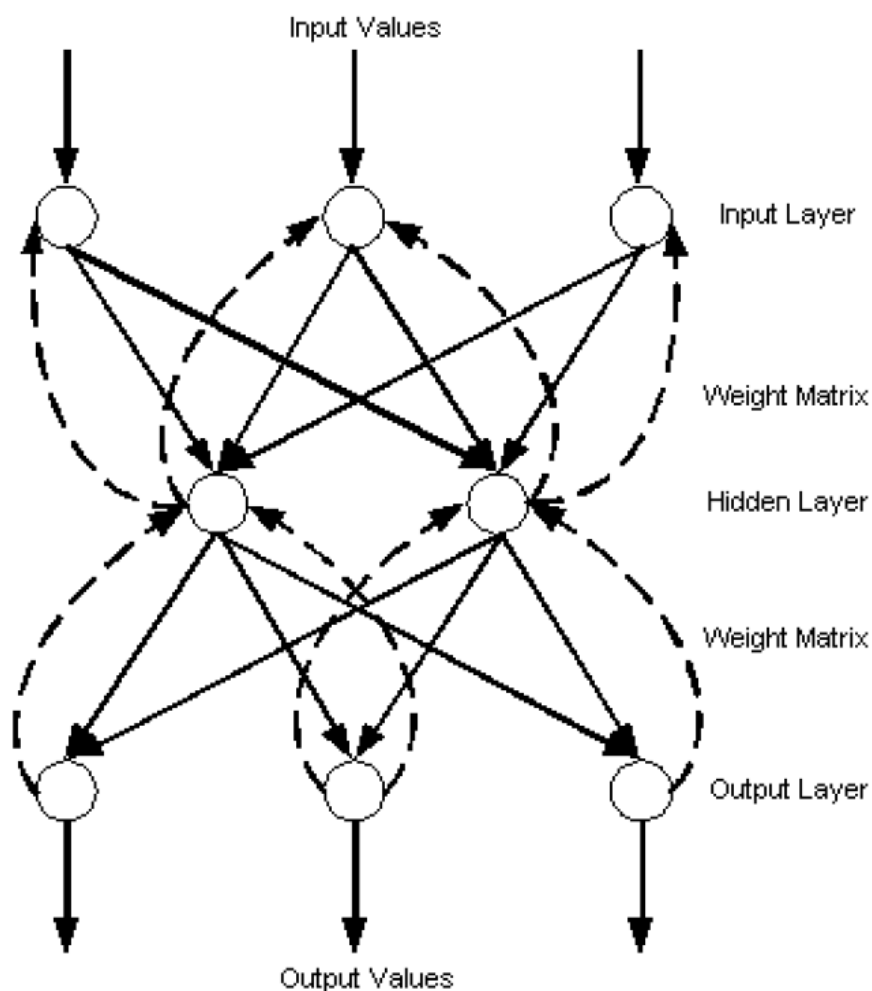


Figure 10. Three layer Back-propagation Network

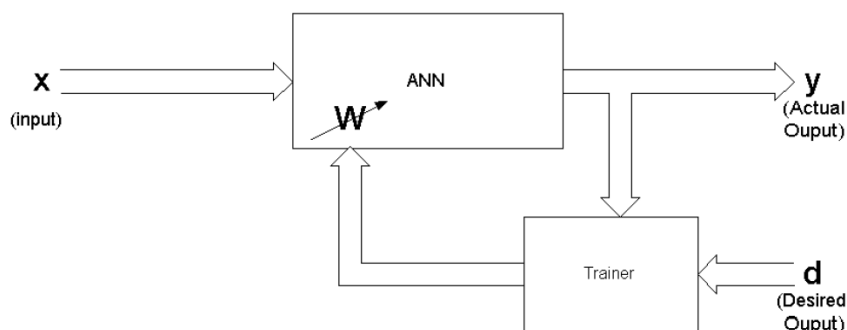


Figure 11. Supervised learning

signals. These pulses impinge on the neuron at terminals called synapses. The neuron sums or integrates the effects of thousands of such pulses over its dendritic tree and over time. If the integrated potential at the axon-hillock exceeds a threshold, the cell 'fires' and generates an action potential or spike which starts to travel along its axon. This then initiates the whole sequence of events again in neurons contained in the efferent pathway (Gurney, 1997).

It is generally accepted that, in real neurons, information is encoded in terms of the frequency of firing rather than merely the presence or absence of a pulse. Phase information may also be important but the nature of this mechanism is less certain.

A common artificial realisation of the neuron is shown in Figure 9.

For this type of artificial neuron, all the inputs, multiplied by the weights are summed. This sum is then the input to an activation function. One that is commonly used is a sigmoid function. The sigmoid function produces an output that closely approximates a cumulative normal distribution. In the form used here, if the sum of the inputs is 0.0, then

the output is 0.0, and if the sum of the inputs is ∞ then the output is 1.0.

Much like an animal brain, many neurons are interconnected to produce an artificial neural network. The neural networks used at Ok Tedi consist of approximately 50 neurons. By comparison with any natural neural network, they are very small.

The type of network that is used at Ok Tedi is a back propagation network. Back propagation refers to the way the network is trained. A simple 3 input, 3 output with 1 hidden layer network is shown in Figure 10.

For neural networks to be useful, they must be trained to produce the desired output. There are three general classes of learning: unsupervised, reinforcement and supervised. In unsupervised learning, there is no teacher to provide any feedback information. The network must discover patterns, features, regularities, correlations, or categories in the input data and code for them in the output by itself. This type of network is used for identifying patterns in a set of data.

In supervised learning, it is assumed that the correct "target" output values are known for each input pattern. But in some situations only less detailed information is available. For example, the NN may only be told that its current actual output is "too high" or "50% correct."

In reinforcement learning the network still receives some feedback from its environment. But the feedback (i.e., the reinforcement signal) is only evaluative rather than instructive. That is, it just says how good or how bad a particular output is and provides no hint as to what the right answer should be (Lin and Lee, 1995).

At Ok Tedi, supervised learning was used, so that the trainer had available to it actual response data. The system is shown schematically in Figure 11. In other words the model had both the inputs as well as the outputs against which it could be verified and validated.

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