The art of making intelligent decisions: the next revolution in the mining industry

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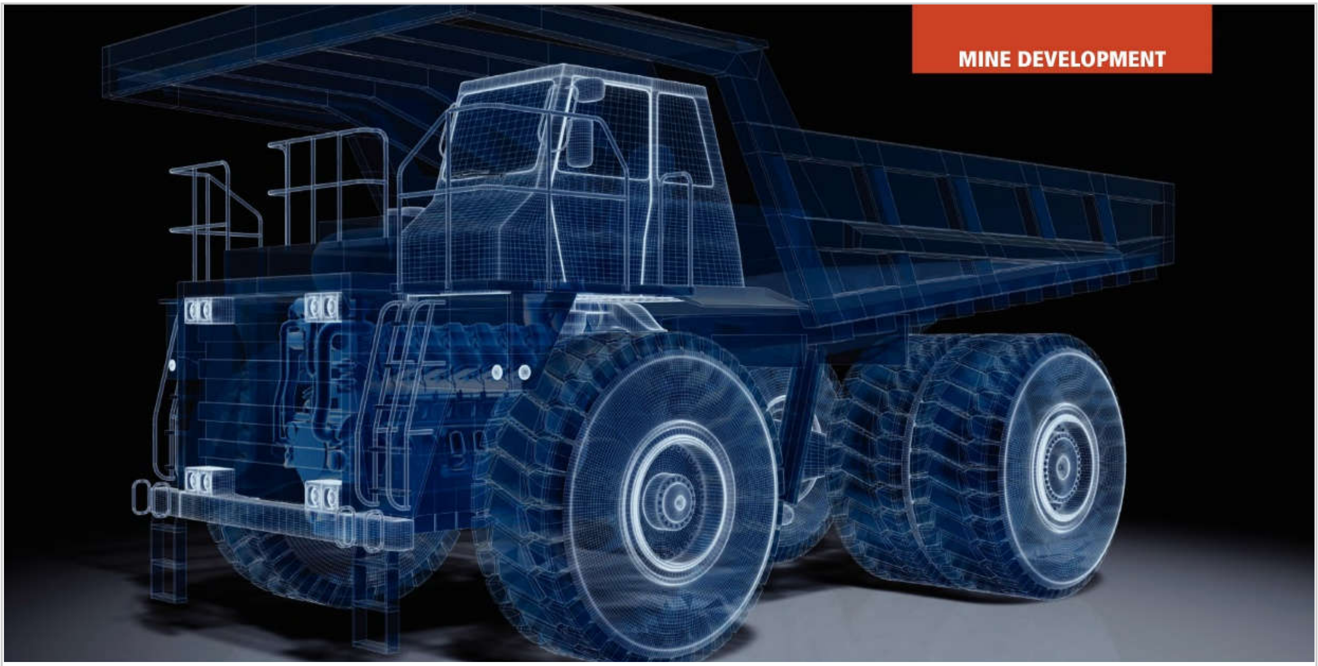
Making a decision is a bridge between business problems and their hidden answers in data.



Big data, global connectivity and pervasive real-time analytics are changing the way that companies manage their business. Today, the general goal of most business intelligence systems is to access data from a variety of different sources; transform that data into information, and then into knowledge; and provide an easy-to-use, graphical interface to display this knowledge. In other words, a business intelligence system is responsible for collecting, digesting and presenting data in a friendly way.

Many mining companies assume that knowledge is the final objective – after all, knowledge is an essential component of any decision-making process – but it is important that businesses understand that knowledge is no longer enough for making decisions in today's competitive global market. A mining company may 'know' a lot about the operation and maintenance systems – it may have thousands of graphs, tables and charts – but management may still be insecure about making a decision! And this is the difference between 'decision support' and 'decision-making'. The saying goes: 'All the knowledge in the world will not guarantee the right or best decision'. More knowledge is equal to more confidence, but it does not improve the accuracy of decisions.

Today, most mine managers realise that a gap exists between having the right knowledge and making the right decision. This gap affects management's ability to answer business questions. The future of mining intelligence lies in systems that can provide answers and recommendations, rather than mounds of knowledge in the form of reports. This will be the next revolution in the mining industry: making intelligent decisions.

In addition to performing the role of traditional data analysis in the mining industry (transforming data into knowledge), new mining intelligence also includes the decision-making process, which is based on prediction and optimisation. This innovative method can help mine managers to select the best-made decisions as chosen by an artificial intelligence system that increases safety, efficiency, productivity and competitiveness.

The recent studies identify opportunities valued at a billion dollars annually in the greater adaptation of data analytics across the mining industry. These opportunities relate to the deeper understanding of the resource base; optimisation of material and equipment flow; increased mechanisation and automation; improved anticipation of failures; and monitoring of real-time performance versus planned performance.

The actual value of analytics relies on the data management maturity level (Figure 1). Analytics can be defined as the use of analysis, data and systematic reasoning to make decisions. Organisations will need to answer the fundamental questions about their business that are drawn from the analytics value pyramid (Figure 1). The value pyramid is a structured, simple and logical approach to breaking down problems to determine the most relevant

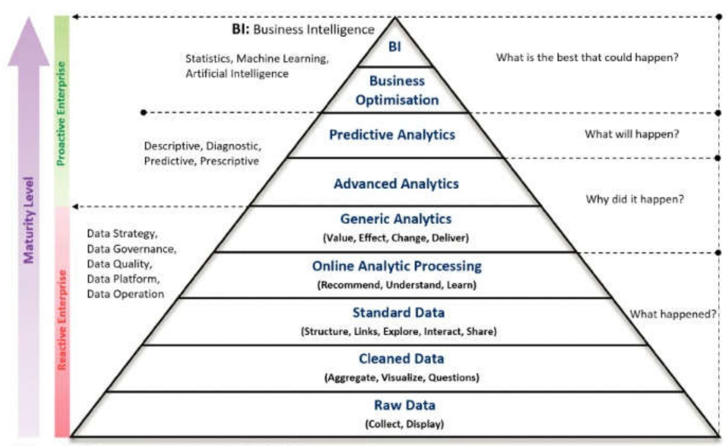


Figure 1. Data management maturity levels

mining industry analytics needed.

The realm of process analytics in the mining industry covers both performance and maintenance analytics. Performance analytics looks to identify sources of delay, rate and quality losses, as well as focusing on efficiency measures, such as energy and fuel efficiency. Maintenance analytics encompasses machine-health monitoring, prediction of remaining useful life and root-cause analysis. There are many approaches to data analytics, including hypothesis testing, predictive modelling, optimisation and data mining.

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Hypothesis testing, as its name suggests, involves the formulation of a hypothesis. In this approach, data must be captured using a defined protocol and then collected in order to test the hypothesis. Predictive modelling uses historical data to develop models such as state-space models or artificial neural networks that are capable of predicting short-term results. Optimisation models attempt to establish optimal system input parameters in order to optimise an objective function. Data-mining algorithms make no a priori assumptions of relationships between data. Instead, multiple data streams are coded into such algorithms in an attempt to form relationships between parameters and derive the relative strengths of relationships that might indicate correlations.

A case study

Approximately 40 per cent of the total energy used in surface mines is related to the consumption of diesel fuel; truck haulage is responsible for the majority of this. Research conducted by the University of Queensland identified three principal, controllable factors influencing truck fuel consumption. These are truck payload, speed and total rolling resistance (Figure 2).

Using truck performance data collected from five surface mines in Australia, Canada and the United States, a model was constructed using an artificial neural network (ANN) consisting of a single-layer perceptron to predict fuel consumption given the identified factor inputs. The model was validated with reference to a sample of the data that was set aside and not used in training the ANN.

Having constructed and validated the predictive analytical model, a genetic algorithm (GA) was used to optimise the input parameters controlling fuel consumption. This optimisation algorithm was applied to the haulage fleets in each of the five mines, in order to determine optimal payload, speed and rolling resistance parameters. This information was then used to provide target values for the mines to control payload and speed variance, and hence reduce the consumption of diesel fuel and associated emissions.

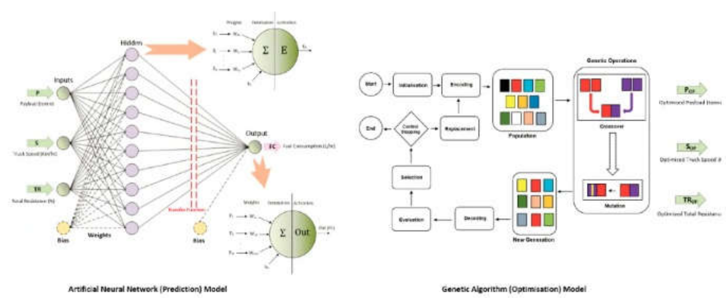

Figure 2. An example of developed and validated prediction-and-optimisation model based on artficial intelligence methods to improve energy efficiency in surface mines

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