Development of a Maturity Scale for Mining Performance and Maintenance Data Analytics

Ali Soofastaei
VALE

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BY DR ALI SOOFASTAEI, DATA SCIENTIST, VALE, AUSTRALIA; JEREMY DAVIES, ADJUNCT RESEARCH FELLOW AT THE UNIVERSITY OF QUEENSLAND, AUSTRALIA; AND EDSON ANTONIO, DATA SCIENCE PROGRAM LEADER AT VALE, BRAZIL

Data analytics is the science of examining raw data with the goal of discovering useful information, reaching conclusions about the meaning of the data and supporting decision-making. The main opportunity that data analytics presents for mining is its potential to identify, understand and then guide the correction of complex root causes of high costs, poor process performance and adverse maintenance practices. These root causes may be invisible to simple analysis or reporting methods. Data analytics can, therefore, reduce costs and accelerate better

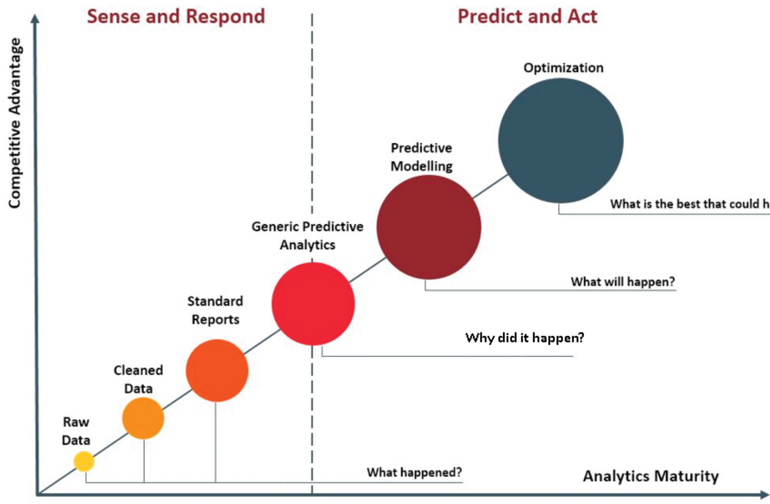

Figure 1. Data analytics maturity levels

decision-making, which ultimately enables new products and services to be developed and delivered, creating added value for all.

The purpose of a maturity model is to provide a guided benchmarking tool for a mining company to assess the development and progression of its own data analytics programs. A self-assessment allows a mine manager, for example, to determine at what level of maturity their organisation is operating – and in what areas and by how much they should progress and improve.

Ultimately, this enables mining companies to improve their data analytics capabilities, and to develop intelligence-led operations and maintenance processes, which will improve their bottom line performance.

In the maturity model presented in this article, six levels for data analytics capabilities have been defined (Figure 1).

In the first level, raw data is simply gathered and saved. The method of storage could be paper or digital. There are no steps to modify the data sets collected at this level of maturity, and the data may be noisy and include errors and gaps. The quality of received data at this level of sophistication is certainly not good enough to enable meaningful analysis to be completed. Therefore, paying very close attention to the quality of data and making sure the reliability of data sources is very high are two essential, base-level tasks required as foundations for increasing the level of data analytics maturity.

In the second level of maturity, datasets collected will be clean – noise in data sets will be reduced, gaps between recorded data will be completed, data will be sorted, and incorrect data will have been deleted. This level of maturity at a mine site provides some critical insights into what capabilities are required of the data collection hardware and software. The prerequisites will soon become evident for the data collection process and technology to provide enough high-quality data to use in data analytics models.

The third level of data analytics maturity brings the capability to identify and capture significant patterns in the data collected. At this level of maturity, all collected and cleaned datasets should be analysed to identify relationships between critical parameters. These investigations are presented in the form of technical and management reports, often based on standard formats. Experts will use the reports to recommend if any further analysis is needed, and will also be able to indicate what the likely benefits of further data analysis will be for the mine assets in question.

Completing a generic predictive analysis capability is possible when the company has reached the fourth level of maturity. This stage represents the level beyond which a transition from a ‘Sense and Respond’ approach to the more proactive ‘Predict and Act’ stage will take place; however, the most valuable insights gained by using data analytics methods at maturity level four will be restricted to answering purely heuristic questions. This maturity level of data analysis does not offer the capability to estimate the value of future critical parameters associated with mining operations or maintenance performance.

The development of predictive models – a maturity level five activity – is one of the most critical phases of data analytics. There is a competition between tier-one mining companies to develop predictive algorithms and applications that can forecast the behaviour of the main parameters in

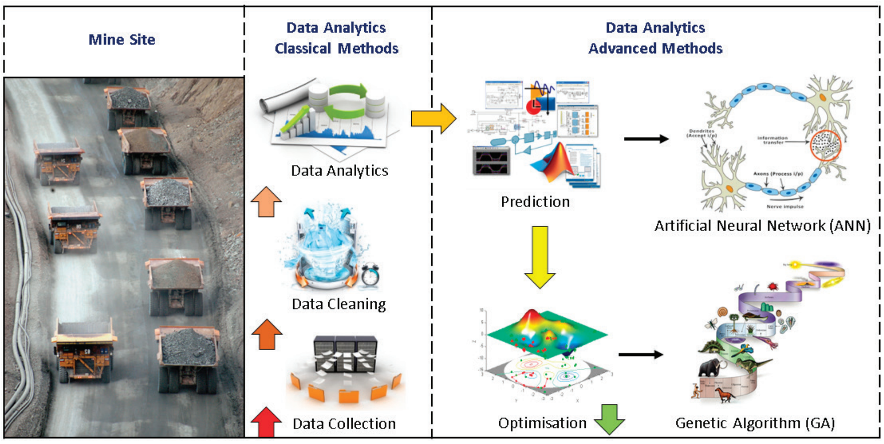

Figure 2. Haul truck fuel consumption simulation and optimisation model

mining operations, such as productivity, fuel consumption, energy efficiency, machine component life and failure behaviour.

Several international mining companies have already installed and are gathering data from hundreds of sensors installed on their mining equipment. Millions of kilometres of fibre optic and conventional cables have been connected between equipment and control rooms to gather data, and relay it to centrally based analysis and reporting systems. There are many different types of wired, wireless and wi-fi-based data transmission systems provided by communication and network specialist companies like Cisco, Weihua, Optus, Telstra and ATT. Huge volumes of data are transferred every second, creating a significant data challenge for mining companies at any level of maturity.

The communication specialist companies have, of course, developed a number of algorithms and applications designed specifically for data cleaning and sorting. Indeed, many providers of proprietary mining equipment – both process plant and mobile OEM equipment providers – have developed technologies and, in some cases, analysis algorithms and analysis services, in competition with the existing data analytics service providers; however, there is still a significant gap between predictive models developed in other industrial sectors and those available to the mining industry. Also, hard-won experience from adjacent sectors – like automotive, aerospace and defence – suggests that mining companies should develop in-house expertise and capabilities before they will be able to successfully 'subcontractor outsource' their business-critical data analysis activities.

Predictive models are critical to helping mining operations and maintenance teams improve their abilities to manage their overall mining operations; however, the ability to make predictions about performance, without a matching capability to optimise the performance, severely limits the value of this type of analytics for mine owners. The main aim of developing a prediction capability is a step to analytics maturity level to level six, the optimisation level.

This highest level of maturity, level six, provides the ability to optimise operations and is currently an aspiration for mining companies (although we see some innovative companies make progress in specific areas of the mining value chain, like material processing). The technology is advancing very quickly, and to a large extent, the mining companies are having to 'run hard to catch up' with other sectors and the optimisation capabilities they have developed.

Figure 1 shows the two dimensions of maturity: a time dimension (over which capability and insights are developed) and a competitive advantage dimension (the value of insights generated). As we've described previously, at the lowest levels, analytics are routinely used to produce reports and alerts. These use simple, very well understood processing and reporting tools, such as pie graphs, top-ten histograms and trending plots. They typically answer the question: 'what happened?' More sophisticated analytical tools operating in real or near-real time, are often used to guide process improvement. These are aimed at informing the user about 'what just happened' and assisting him/her in choosing the next best action to take (or allow the system to automatically make adjustments as a result of the analysis – as in a classic closed-loop control-system environment found in process control). Towards the top end of the comparative advantage scale are predictive models, and ultimately optimisation tools, with the capability to evaluate 'what will happen' and the ability to identify the best available responses – 'what is the best that could happen?'

Figure 2 schematically illustrates work from one of the recent PhD projects at the University of Queensland. The capability developed uses advanced data analytics to not only predict the fuel consumption of haul trucks at surface mines, but also uses artificial intelligence models to optimise other associated critical variables that influence the energy efficiency of hauling operations on the mine – presenting a holistic 'best operating compromise' for the truck-hauling process.

Practical experience in working with mining companies, identifying and analysing the highly complex, coupled operational and business challenges they face, convinces us that increasing the maturity level of data analytics is not an optional plan. We believe it is essential for mining to build the skills and capabilities associated with the higher levels of advanced analytics maturity if they are to simultaneously increase their productivity, and reduce the operational and maintenance cost of their operations. More complex, difficult-to-mine assets with deeper, lower-grade deposits makes the need for better analytics a key business issue, not a 'nice to have'.

The starting point to reach a

position of competitive advantage through the use of advanced analytics is to undertake a self-assessment, to establish where the gaps or shortfalls are in current capabilities.

Figure 3 illustrates a simple assessment tool that can be used to map the level of data analytics maturity across a range of key dimensions.

There are six levels of maturity on the model. Subdividing each level to represent medium or high competence within each level can be helpful, to recognise a range of competencies and that the assessments are never ‘binary’. At its simplest, each dimension is scored from 0 to 6, indicating increasing capability.

We have identified 27 indicators in the model, categorised into four groups: System, Data, People, and Process. Mine managers or consultant companies should score each dimension for each group from 0 to 6 to construct a spider diagram (often called a radar plot) that gives a simple visualisation of where the strengths and weaknesses lie in terms of advanced analytics.

In our experience, using a maturity model (like Figure 1) can be a useful way of engaging with the wide range of stakeholders involved in developing and using advanced analytics capabilities. Using the broad descriptors of Figure 1 as a high-level ‘Analytics Roadmap’, alongside the assessment tool presented in Figure 3, enables discussions with different groups to be conducted in the same way, using the same language, and will create standardised assessments across the organisation.

In future, budget and company investments should be targeted at improving the areas of weakness indicated by a self-assessment, with the objective of moving the spider diagram scores towards a circle, increasingly moving to be located in the green band associated with optimisation capabilities.

Finally, it is worth stressing that the cultural changes associated with introducing advanced analytics capabilities are significant as there are potential impacts across the whole of the operations landscape. Measuring, managing and successfully implementing the cultural and organisational change implied by the introduction of advanced analytics is beyond the scope of this short paper, but will be dealt with in further papers we plan to publish later this year.

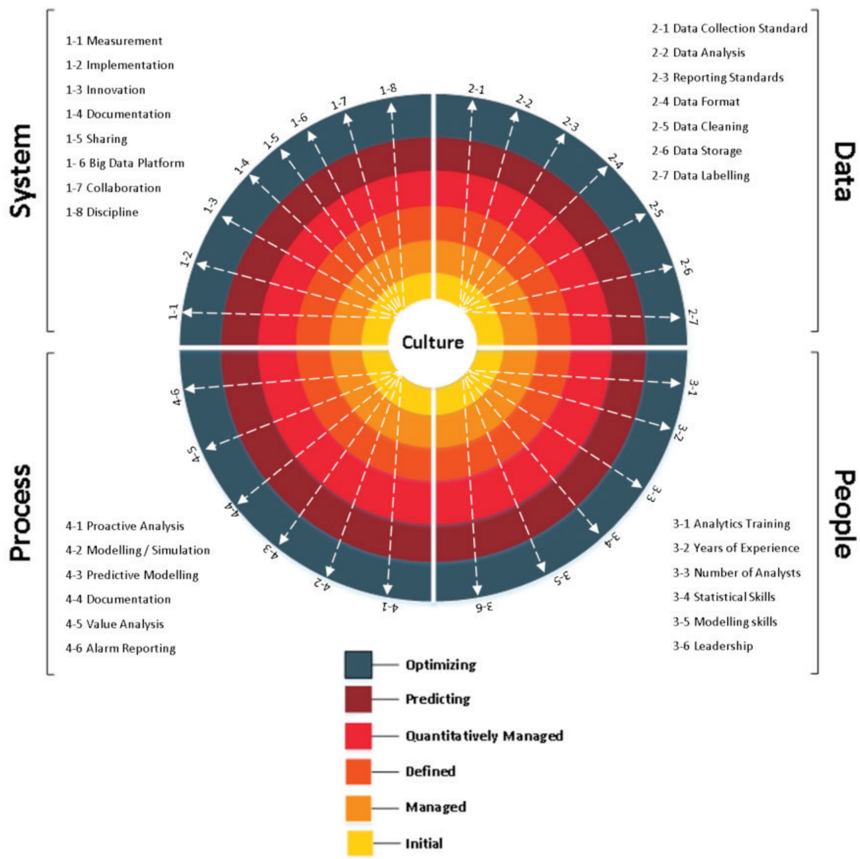

Figure 3. Developed self-assessment model for data analytics maturity scale

In summary, development of a maturity model for mining performance and maintenance data analytics is a valuable aid for mining companies, and may be the difference between success and failure in this field. The next generation of data analytics models must focus on prediction and optimisation projects. Mining companies need a self-assessment system to map their company maturity level in data analytics in a way that can be shared unambiguously with all stakeholders and can be used to drive investment into the most important areas. The models presented in this article can be useful to start an internal discussion and benchmarking process with the aim of improving a mining company’s maturity level, and its ability to develop, deploy and gain value from using advanced data analysis methods.

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