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Application of predictive data mining to create mine plan flexibility in the face of geological uncertainty

Ajak Duany Ajak^{a,*}, Eric Lilford^b, Erkan Topal^c

^a Mining Engineering Department, WASM, Curtin University, Kalgoorlie Campus, Australia

^b Department of Mineral and Energy Economics, CGSB, Curtin University, 78 Murray Street Campus, Australia

^c School of Mining and Geosciences, Nazarbayev University, Astana, Kazakhstan

A B S T R A C T

Geological uncertainty represents an inherent threat for all mining projects. Mining operations utilise resource block models as a primary source of data in planning and in decision making. However, such operational decisions are not free from risk and uncertainty. For the majority of iron ore mines, as an example, uncertainties such as clay pods and variability in grades and tonnages can have dramatic impacts on projects' viability. However, a paradigm shift on how uncertainty is treated and a willingness to invest in areas that create operational flexibility can mitigate potential losses. Data analytics is touted as one of the major disruptions in the 21st century and operations that properly utilise data can create real opportunities in the face of an uncertain future. Since organisations have abundant definite geological data, a combination of data mining and real options can provide a competitive advantage. In the present study, predictive data mining algorithms were applied to a real case mine operation to predict the probability of encountering problematic ore in a mining schedule. The data mining model outputs were used to generate possible real options that the operations could exercise to deal with clay uncertainty. The most suitable data mining algorithm chosen for this task was the classification tree, which predicted the occurrence of clay with 78.6% precision. Poisson distribution and Monte Carlo simulations were applied to analyse various real options. The research revealed that operations could minimise unscheduled losses in the processing plant and could increase a project's present value by between 12% and 21% if the predictive data mining algorithm was applied to create real options.

1. Introduction

Understanding the ore body and operational uncertainty are crucial for every mining project as these parameters affect the ultimate delivery of the planned targets. Geological uncertainty is an inherent threat that all mining operations have to manage. However, managing risks posed by the lack of adequate ore body knowledge is a major challenge to mine planning engineers, geologists and operational managers who are under constant pressure to produce mine plans and deliver the required tonnes of ore at specified grades to satisfy their executives and the market. Mine geologists and planning engineers have a reasonable level of information obtained from the resource model regarding ore boundaries, tonnages, geochemical grades, lithological units and geometallurgical characteristics such as ore strength, response to crushing, grinding and floatation processes (La Rosa et al., 2014), which are necessary to undertake proper planning and to warrant mining of the deposit (Cornah, 2013; U.S. Bureau of Mines and The U.S. Geological Survey, 1980). However, there is still geological

information that is either 'known unknowns' or 'unknown unknowns' (Brown and Innocent, 2012; Brammer and Smithson, 2008). Known unknown is the availability of the information needed to work out the unknown variable while unknown is the existence of a variable that is not yet explored with no realisation that something is missing (Brown and Innocent, 2012; Brammer and Smithson, 2008). Geological processes that lead to ore formation tend to be very complex and not every parameter can be easily estimated (Spalla et al., 2010, p. 208). Therefore, geological models contain uncertainties which require quantification (Wellmann and Regenauer-Lieb, 2012). It has been proven that most mining investment decisions are commonly made based on either incomplete or inaccurate information (Haque et al., 2016).

For most iron ore deposits, uncertainties such as the presence of fibre material and clay pods are seldom modelled into Ore Block Models (OBMs). These are the known unknowns to the majority of the iron ore operations whose production can be interrupted by the unexpected appearance of the unwanted material. Clay pods shock the processing circuit if unknowingly fed into the crusher and can cause a significant

* Corresponding author.

E-mail addresses: ajak.ajak@postgrad.curtin.edu.au (A.D. Ajak), E.Lilford@curtin.edu.au (E. Lilford), erkan.topal@nu.edu.kz (E. Topal).

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amount of downtime and reduction in productivity in the plant ([The Australian Journal of Mining AJM, 2011](#)). Clay material accounts for approximately 15% of the feed for fine iron ore deposits and it is generally sent to the tailings dam ([Clout, 2013](#)). However, for balanced iron ore operations, the clay proportion in the plant feed can range between 6% and 11% but constitutes between 23% and 46% of product in the wet process. Thus, its potential overall impact on individual operations should never be ignored during the mine planning process.

In operations where the ore body has a high clay content which is modelled into the ore body, a desand process has usually been implemented. This is a two-stage process that is a combination of the traditional wet processing plant and a desand circuit. Desand plants are very expensive to build and operate at a high cost. Apart from the Fortescue Metals Group Limited (FMG) Cloudbreak Mine, these plants are sparingly used in the Pilbara region in Australia as they require a constant supply of clean water that must be supplied in large volumes to operate. In addition, they are not commonly built as there is usually very limited data on the prevalence of the clay material in the ore deposit to justify the inclusion of a desand plant, which is capital intensive. Therefore, most operations in the Pilbara use wet plants that integrate either one- or two-stage hydrocyclone circuits due to their ability to upgrade products ([Clout, 2013](#)). However, these circuits are not intended to process clay material. For mining operations that operate one or two production pits or those that utilise a single processing plant, any downtime caused by clay material feed can cumulatively translate into significant financial losses, which are published at the end of each reporting period.

Big Data is touted as one of the major disruptions in the 21st century ([Deloitte, 2016](#)) and has recently been the focus of many big firms. Data are expected to grow as technology improves and business units within operations become more connected. Companies that use and treat data as an important asset can create value through predictive analytics. Underground patterns can be visualised easily and relationships to the available information can be revealed, as well as options created and utilised to avoid or mitigate losses. However, mining operations are not making full use of this abundant data. Regardless of the reluctance to adopt data mining, it remains a superior method for obtaining knowledge of what is hidden inside the messier real-world data than the standard statistical techniques that are commonly applied ([Berson et al., 1999](#)).

Considering there is already plenty of data available for improving decision making, especially for mining operations, a literature search returned limited cases of the application of predictive data mining in solving clay material geological uncertainty in mining operations, particularly in the creation of managerial flexibility. It is important to highlight that there is a disconnect between technical personnel such as mine planning engineers and data managers who focus on analysing activities that are geared to improve productivity and efficiencies rather than creating flexibility that should be considered at the early stages of mine planning and design. Therefore, the problem that this study is aiming to address is how to use data mining methodologies for creating real options, particularly when dealing with internal uncertainty that results in operational risks.

2. Methodology

In the present study, the predictive data mining algorithms such as decision tree classification or the ID3 machine learning model will be utilised for predicting the occurrence of the problematic ore in mine schedules. The outputs will then be applied for the purpose of creating and analysing real options in a real-world case study. Orange ([Demsar et al., 2013](#)) and [RapidMiner \(2017\)](#) software programs that combine both statistical and machine learning capabilities will be applied to create both the training and machine learning models for predicting clay pod occurrences.

Once the model is confirmed, it will then be applied to an already

generated mine plan that has utilised OBM data to predict any problematic ore via qualitative classification of the risks in each block that has been scheduled for mining during each period. The results of the analysis will then be utilised to create various real options that provide managerial flexibility in the running of their respective mining operations.

2.1. Predictive data mining with ID3 decision tree classification

Predictive analytics is the process of applying various mathematical formulae to discover the best decision for a given situation and to eliminate guess work about the future ([Mishra et al., 2010](#)). There is a large number of algorithms that can be used to perform predictive data mining (PDM). This data mining activity aims to quantify the probability of intercepting a problematic ore including clay pods during the planning of the real case mine study. This will assist in the creation of real options for managing geological uncertainty as the predictive model will be generated and applied to create the necessary managerial flexibility to reduce plant downtimes and unnecessary maintenance. A decision tree classification, which is also known as the ID3 algorithm, will be utilised to demonstrate how data mining can be applied to create real options analysis. In the next sections, the ID3 algorithm will be explained through examples. Since the field of data mining is a specialised area of study, it is beyond the scope of this research to explore the presented theories in detail. Instead, the research will focus on the chosen techniques among other classes of data mining summarised in [Fig. 1](#). This is because the use of geological data including structure, lithology and mineralogy, ore types and associated elements, geophysical and geochemical data of an ore deposit is considered to be the fundamental method in descriptive models which were suggested and consequently developed by [Cox and Singer \(1986\)](#). These models have major disadvantages including:

- The geological uncertainty is not observed (visual assessment) with these methods while the geological uncertainty is an obvious and salient feature which has to be always predicted for mining scheduling ([Yasrebi et al., 2013](#)).
Data Mining has proved its superiority to the classical statistical and conventional geological methods as follow:
- In classical statistics, frequency distributions of a desired attribute in an intended area must adhere to a normal distribution. To do this, different populations based on the mean and standard deviation (SD) should be carried out with normalised data. This is not met in data.
- In addition, local neighbourhood statistics can provide less statistical information which is less biased than that of global statistics, such as mean and SD because the utilised data generally satisfy non-normal distributions and contain outliers ([Agterberg et al., 1993](#); [Zhang et al., 2007](#); [Yasrebi, 2014](#)).

2.2. Modelling clay uncertainty in a mining operation using decision tree classification

Decision trees are a class of regression models that have been re-structured in the form of a tree that is more visual than conventional statistical regression models. Thus, it is a form of machine learning that analyses the past data and uses it to predict future events of similar characteristics. The input data, which is also referred to as the predictor, is broken down into smaller units and the model continues to break down the data until the target variable is predicted. The theory behind decision tree classification is based on the ID3 algorithm. This algorithm deploys what is referred to as “greedy search” where all the possible branches are explored in the probability space without back-tracking. This algorithm uses entropy and information gain (also referred to as gain ratio) in the [RapidMiner \(2017\)](#) and Orange ([Demsar et al., 2013](#)) software programs ([Sayad, 2017](#)). These will be utilised in

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