Resources Policy 38 (2013) 591–597

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

A heuristic approach to stochastic cutoff grade optimization for open pit mining complexes with multiple processing streams

Mohammad Waqar Ali Asad [a,1,*], Roussos Dimitrakopoulos [b]

[a] Department of Mining Engineering, Western Australian School of Mines, Faculty of Science and Engineering, Curtin University, Australia
[b] COSMO Stochastic Mine Planning Laboratory, Department of Mining and Materials Engineering, McGill University, Canada

ARTICLE INFO

Article history:
Received 6 December 2012
Received in revised form
11 September 2013
Accepted 19 September 2013
Available online 18 October 2013

JEL classification:
Q

Keywords:
Stochastic optimization
Cutoff grade
Heuristic algorithms
Open pit mine planning

ABSTRACT

Cutoff grade specifies the available supply of metallic ore from an open pit mine to the multiple processing streams of an open pit mining complex. An optimal cutoff grade strategy maximizes the net present value (NPV) of an open pit mining operation subject to the mining, processing, and marketing/refining capacity constraints. Even though, the quantities of material flowing from the mine to the market are influenced by the expected variation in the available metal content or inherent uncertainty in the supply of ore, the majority of cutoff grade optimization models not only disregard this aspect and may lead to unrealistic cash flows, but also they are limited in application to an open pit mining operation with single processing facility. The model proposed herein determines the optimal cutoff grade policy based on a stochastic framework that accounts for uncertainty in supply of ore to the multiple ore processing streams. An application on a large-scale open pit mining operation develops a unique cutoff grade policy along with a portfolio of mining, processing, and marketing/refining rates. Owing to the geological uncertainty, the approach addresses risk by showing a difference of 14% between the minimum and maximum production rates, cash flows and NPV.

Introduction

In an open pit mining complex, a typical open pit produces material of various categories, which is transported to the appropriate processing streams for recovering metal as a valuable product. Knowing the ultimate pit limit, i.e., the size or extent of an open pit mine, the supply of material in terms of grade–tonnage curves is established (Hustrulid and Kuchta, 2006), that is the available quality (grade categories) and quantity (tonnes within these categories) of material within the pit limit. The grade–tonnage curves along with the economic parameters such as price of metal, operating costs, metallurgical recovery, and discount rate become the basic input to determine the optimal cutoff grade policy.

Cutoff grade policy defines the amount of ore and waste in a given period during the life of an operation. While waste is hauled to the waste dumps, ore being valuable material is sent to the processing streams for crushing, grinding, and upgrading to produce concentrate, which, in turn, may be upgraded further by refining to produce a final marketable product (Lane, 1964; Taylor, 1972). Cutoff grade policy maximizes NPV of an open pit mining complex subject to the mining, processing, and marketing/refining capacity constraints (Rendu, 2008; King, 2011). Given that multiple ore processing options exist, cutoff grade for a particular processing option is defined from the known economic parameters and grade–tonnage curves, and depending upon the quality of ores described in grade–tonnage curves, it is sent to the most economic processing stream (Dagdelen and Kawahata, 2008).

While, mine is a source of supplying ore to a number of processes that convert raw ore to a profitable product, expected variation in metal content throughout the extent of the orebody defines the inherent uncertainty in supply of ore. Taking the limited exploratory drill-hole information as an input, the geostatistical technique of conditional stochastic simulation (Goovaerts, 1997; Boucher and Dimitrakopoulos, 2012; Machuca-Mory and Deutsch, 2013) is used to characterize this geological uncertainty, resulting in a set of equally probable simulated realizations of the orebody, showing the variation of the metal content and corresponding tonnages from one realization to the next. Thus, as opposed to a traditional procedure that calculates or derives a single grade–tonnage curve from a single (or constant and known) estimated orebody realization, the stochastic procedures derive multiple or equally probable grade–tonnage curves from a set of conditionally simulated or equally probable realizations of the orebody. As a result, each simulated realization of the orebody is translated into grade categories and corresponding tonnages within these grade categories to

* Corresponding author. Tel.: +61 8 9088 6139.
E-mail addresses: waqar.asad@curtin.edu.au, mwaasad@gmail.com (M.W.A. Asad), roussos.dimitrakopoulos@mcgill.ca (R. Dimitrakopoulos).

[1] Previously (12/2009 to 06/2012) Research Associate at COSMO Stochastic Mine Planning Laboratory, McGill University, Canada.

0301-4207/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.resourpol.2013.09.008

create a grade–tonnage curve. Consequently, being derived from simulated or equally probable realizations of the orebody, each grade–tonnage curve in the set of simulated grade–tonnage curves becomes equally probable, i.e., at the time of actual mining, the probability of supplying material from (or corresponding to) a particular grade–tonnage curve remains the same. Given this fundamental difference between the traditional and stochastic procedures, it is well-established that the geological uncertainty impacts the ore and metal production targets (Elkington and Durham, 2011). For instance, Baker and Giacomo (1998) validate that owing to the discrepancies came from the poor description of the orebody, out of 48 mining projects in Australasia, 13 revealed 20% more than projected reserves, and 9 realized 20% less than the originally forecasted reserves. Similarly, a World Bank survey in Canada and USA shows that 73% of mining projects were closed prematurely due to problems in their ore reserve estimates, and led to severe losses in capital investment (Vallee, 2000). Consequently, recognizing the importance of incorporating geological uncertainty, it is imperative to adopt a stochastic framework for making a strategic decision on cutoff grade policy. Owing to the variation in metal content (grade) and corresponding tonnages from one grade–tonnage curve to the next, the stochastic framework honors the fact that given a defined cutoff grade, there is a possibility that the same material may be identified as ore in one grade–tonnage curve and waste in another grade–tonnage curve (Godoy and Dimitrakopoulos, 2011). Thus, as opposed to the traditional approaches that ignore the geological uncertainty by considering a single (or constant and known) grade–tonnage curve, a stochastic framework jointly considers multiple simulated or equally probable grade–tonnage curves and addresses the risk of not having enough ore to feed the processing streams under geological uncertainty (Satybaldiev and Freidin, 2006; Dimitrakopoulos and Abdel Sabour, 2007; Elkington and Durham, 2011).

Lane proposed a heuristic approach to cutoff grade optimization (Lane, 1964, 1988) that not only considers a constant grade–tonnage curve, but also limited in application to open pit mining operations with mine feeding ore to a single processing plant. Lane's theory has been modified in a number of traditional cutoff grade optimization models (Dagdelen, 1992, 1993; King, 2001; Asad, 2002; Cetin and Dowd, 2002; Ataei and Osanloo, 2004; Asad, 2005, 2007; Bascetin and Nieto, 2007; Osanloo et al., 2008; He et al., 2009; King, 2011). Dagdelen (1992, 1993) and Asad (2002) propose the steps of the algorithm that implements Lane's approach. King (2001) includes variations in ore type throughput in cutoff grade optimization models for multi-element mineralization. Cetin and Dowd (2002) suggest a genetic algorithm for multi-mineral cutoff grade optimization. Ataei and Osanloo (2004) recommend a combination of genetic algorithm and grid search technique to determine cutoff grades for multi-metal deposits. Asad (2005) incorporates stockpiles into the cutoff grade optimization model for multi-mineral deposits. Asad (2007) looks into the impact of metal price and cost escalation on cutoff grade optimization. Bascetin and Nieto (2007) suggest an NPV maximization model through an optimization factor to determine cutoff grades. Osanloo et al. (2008) incorporate environmental issues into cutoff grade optimization model. He et al. (2009) share a genetic algorithm and neural network based strategy to simulate a complex mining system for calculating the optimal cutoff grade. King (2011) explains the intricacies of Lane's approach giving details of various policies to consider operating and administrative costs. Dagdelen and Kawahata (2008) present a linear programming based cutoff grade optimization model that considers constant grade–tonnage curve with multiple processing options. Rendu (2008) covers the procedural aspects of considering multiple processing options in a cutoff grade optimization model. While constant grade–tonnage curve as an input is the common feature of these studies, majority of them do not attempt to look into the combined impact of considering a set of simulated or equally probable grade–tonnage curves derived from simulated or equally probable orebody realizations and multiple processing options.

Unlike previous studies, realizing the importance of acknowledging geological risk to open pit mine planning, we propose an extension in Lane's theory herein, such that, it is applicable in a stochastic framework that not only takes into account multiple simulated or equally probable grade–tonnage curves generated from a set of simulated or equally probable orebody realizations (Boucher and Dimitrakopoulos, 2012; Horta and Amilcar, 2010), but also considers supply of ore to multiple ore processing destinations in an open pit mining complex. The proposed cutoff grade optimization model (i) maximizes NPV of future cash flows; (ii) satisfies the mining, processing, and marketing/refining capacities constraints; (iii) develops a unique and optimal cutoff grade policy for the life of operation by simultaneously utilizing all available equally probable realizations of the grade–tonnage curves; and (iv) addresses risk by developing a portfolio of possible mining, processing, and marketing/refining rates that correspond to the optimal cutoff grade policy.

In the following sections, we discuss the stochastic cutoff grade optimization model, describe the heuristic procedure for calculating optimum cutoff grade, present the steps to implement the heuristic approach, and demonstrate the benefits of the proposed model in a case study followed by conclusions.

Stochastic cutoff grade optimization model

The stochastic optimization model is limited in application to an open pit mining complex that consists of a single material source (mine), multiple material destinations (processing streams and waste dump), and a market/refinery receiving concentrate from these processing streams. Also, it is assumed that an optimal ultimate pit limit has been established and the available reserves (in terms of multiple simulated or equally probable grade–tonnage curves) within the pit limit are known (Asad and Dimitrakopoulos, 2013). However, the model jointly accounts for a set of simulated or equally probable grade–tonnage curves and multiple processes for defining the cutoff grade policy. The uniqueness of the model lies in simultaneous utilization of a set of simulated or equally probable grade–tonnage curves for developing an exclusive cutoff grade policy. The following parameters (Lane, 1964; Hustrulid and Kuchta, 2006; Asad and Dimitrakopoulos, 2012) facilitate description of the model:

t	period (year) indicator;
T	life of operation (years);
p	process indicator;
ω	grade–tonnage curve indicator;
n	grade categories indicator;
N	number of grade categories in a particular grade–tonnage curve;
$\varphi_{\omega t}$	cash flow for grade–tonnage curve ω during period t ($/year);
S	selling price of metal ($/tonne of metal);
r	marketing/refining cost ($/tonne of metal);
m	mining cost ($/tonne of material);
c_p	processing cost of process p ($/tonne of ore);
f	administrative or fixed cost ($/year);
M	mining capacity (tonnes/year);
C_p	processing capacity of process p (tonnes/year);
R	marketing/refining capacity (tonnes/year);
$Qm_{\omega t}$	quantity of material mined for grade–tonnage curve ω during period t (tonnes of material);