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Case study

Integrating geological uncertainty in long-term open pit mine production planning by ant colony optimization

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ABSTRACT

Meeting production targets in terms of ore quantity and quality is critical for a successful mining operation. In-situ grade uncertainty causes both deviations from production targets and general financial deficits. A new stochastic optimization algorithm based on ant colony optimization (ACO) approach is developed herein to integrate geological uncertainty described through a series of the simulated ore bodies. Two different strategies were developed based on a single predefined probability value (*Prob*) and multiple probability values ($Prob_n^t$), respectively in order to improve the initial solutions that created by deterministic ACO procedure. Application at the Sungun copper mine in the northwest of Iran demonstrate the abilities of the stochastic approach to create a single schedule and control the risk of deviating from production targets over time and also increase the project value. A comparison between two strategies and traditional approach illustrates that the multiple probability strategy is able to produce better schedules, however, the single predefined probability is more practical in projects requiring of high flexibility degree.

1. Introduction

The long-term open pit mine production planning is a large combinatorial optimization problem that involves specifying the blocks extraction sequence and their destination during mine life. Mathematical formulation is aimed to maximize the net present value (NPV) of the mining operation subject to a series of operational constraints such as reserve, slope, mining capacity, and milling rate. The operational research techniques, which have been developed to solve long-term production planning since 1960s, could be categorized in two major classes of deterministic and stochastic-based approaches.

All inputs are assumed as fixed value in the deterministic approaches. In early investigations, Dagdelen and Johnson (1986) suggested an approach based on Lagrangian relaxation. Later, a branch-and-cut algorithm was developed by Caccetta and Hill (2003). The major drawback of these methods was their disability in applying on real scale deposits where, typically, include hundreds of thousands to millions of blocks. Several attempts have been spent on reducing the problem size such as Fundamental Trees methodology of Ramazan (2007). Moreover, the other class of researches focused on the heuristic methods (Gershon, 1987), combination of dynamic programming and heuristics (Tolwtnski and Underwood, 1996), and meta-heuristic approach such as genetic algorithm (Denby and Schofield, 1994), particle swarm algorithm (Ferland et al., 2007), and ant colony algorithm (Sattarvand, 2009). A detailed review of the solution approaches could be found in Osanloo et al. (2008).

Ignoring any kind of uncertainty is the common weakness of all deterministic algorithms, which leads to create un-realistic plans in terms of operational requirements. Dimitrakopoulos classifies the uncertainties of mining projects into three major sources as geological, technical, and economical uncertainties (Dimitrakopoulos, 1998).

Grade uncertainty is the major source of deviations from production targets and general financial deficits. Vallee (2000) reported that the average production rate of 60% observed mines in the early years of the mining is 70% less than predicted rates, mainly due to grade uncertainty. Uncertainty-based open pit optimization approaches could be categorized into variance-based and simulation based groups. The first type involves integrating of the grade variance in traditional deterministic algorithms. Albach considering grade variance, developed a linear programming to design a lignite mine (Albach, 1967). A similar approach based on stochastic integer programming model has been suggested by Gangwar (1973). Denby and Schofield (1995) used genetic algorithm to integrate the grade variability in planning process.

The second uncertainty-based approach is based on using alternative scenarios of the ore body called “Realization” that are

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provided by conditional simulation methods. Initially Ravenscroft discussed the risk analysis in mine production planning based on the realizations (Ravenscroft, 1992). Dowd (1994) integrated uncertainties of the commodity price, mining costs, and processing costs in a risk based optimization framework. Dimitrakopoulos and Ramazan (2004) considering grade uncertainty, equipment access, and mobility constraints suggested an LP approach that was based on the expected ore block grades and the probabilities of being above cutoffs. Godoy and Dimitrakopoulos (2004) presented a realization based meta-heuristic approach. They generated production schedules for all realizations and then, using Simulated Annealing algorithm, combined the mining sequences in order to produce a single schedule. Ramazan and Dimitrakopoulos (2004) suggested an MIP model that starts with generating production schedules for each realization and then, calculating the extraction probability of each blocks in a given period. The blocks with probability between zero and one have been used in a new optimization model to generate a schedule. The same research has been reported by Menabde et al. (2004). Dimitrakopoulos and Abdel Sabour (2007) using real options valuation (ROV) method attempted to handle multiple uncertainties such as grade and economic parameters in production planning. Gholamnejad et al. (2008) presented a stochastic programming based model that grade uncertainty is integrated explicitly in the mathematical programming model by applying chance constrained programming approach to approximate it into a linear format. Lamghari and Dimitrakopoulos (2012) considering the metal uncertainty, utilized the tabu search procedure to solve the open pit optimization problem. Two different diversification strategies were used to search the feasible domain in order to generate several initial solutions which will be improved later by the tabu search procedure.

The further researches led to multi-stage modeling methodologies in order to minimize the deviations from production targets in addition to the NPV maximization (Benndrof and Dimitrakopoulos, 2009; Consuegra and Dimitrakopoulos, 2010; Leite and Dimitrakopoulos, 2009; Ramazan and Dimitrakopoulos, 2007; Smith, 2001). Ramazan and Dimitrakopoulos (2007) presented a stochastic integer programing (SIP) model to generate production schedules. The geological risk discounting concept (Dimitrakopoulos and Ramazan, 2004) was used in order to control the risk distribution between production periods and minimize the deviations from targets. Another similar SIP model was developed by Leite and Dimitrakopoulos (2009). Benndorf improved the SIP model by adding a third part to the objective function termed “smooth mining controller” in order to create a safe operational condition (Benndrof and Dimitrakopoulos, 2009). Consuegra and Dimitrakopoulos (2010) developed a SIP model to integrate the grade uncertainty in pushbacks design. Later on, Ramazan and Dimitrakopoulos (2012) established a SIP model to integrate the uncertainty of product supply in the optimization model.

Despite the development of numerous approaches to integrating the geological uncertainty, however, the solving methodologies have been received relatively less attention. It has been shown that the single stage models are unable to integrating the grade uncertainty explicitly and creating an optimal single solution. In fact they are a series of repeated implementations of the traditional approaches on ore body simulations. On the other hand, the multi-stage stochastic models which have to be solved by available mixed integer programming packages, are limited to relatively small size instances.

This paper proposes an efficient solution methodology based on Ant Colony Optimization (ACO) to solve the real scale planning problems in presence of the geological uncertainty. The procedure has the capability to simultaneously optimize the UPL and production scheduling. Paper outlines the modeling procedure, two different strategies and discusses the difference between obtained solutions and provided deterministic solution by traditional approach.

2. Formulation of the long-term production planning

Open pit production planning could be effectively modeled as an Integer Programming (IP) formulation with the objective of NPV maximization subject to a set of technical and operational constrains. It can be expressed as following:

$$maximize\ \ Z = \sum_{n=1}^{N} \sum_{t=1}^{T} \frac{V_n}{(1+d)^t} x_{n,t} \tag{1}$$

Subject to:

$$x_{n,t} \epsilon\ (0, 1), \qquad for\ \ n = 1\ \ to\ \ N\ \ ,\ t = 1\ \ to\ \ T \tag{2}$$

Slope constraint: each block can only be mined if its predecessors are already mined before.

$$x_{n,t} - \sum_{\tau=1}^{t} x_{m,\tau}\ \le 0, \qquad for\ \ m = 1\ \ to\ \ N\ \ , t = 1\ \ to\ \ T \tag{3}$$

where $m\epsilon$ (set of predecessors blocks of block n)

Reserve constraint: a block cannot be mined more than once.

$$\sum_{t=1}^{T} x_{n,t} \le 1, \qquad for\ \ n = 1\ \ to\ \ N \tag{4}$$

Processing capacity: the total ore processed during each period should be within the predefined upper and lower limits.

$$\sum_{n=1}^{N} o_n \times w_n \times x_{n,t} \ge \underline{O}, \qquad for\ \ t = 1\ \ to\ \ T \tag{5}$$

$$\sum_{n=1}^{N} o_n \times w_n \times x_{n,t} \le \bar{O}, \qquad for\ \ t = 1\ \ to\ \ T \tag{6}$$

Mining capacity: the total material mined during each period should be within the predefined upper and lower limits.

$$\sum_{n=1}^{N} w_n \times x_{n,t} \ge \underline{M}, \qquad for\ \ t = 1\ \ to\ \ T \tag{7}$$

$$\sum_{n=1}^{N} w_n \times x_{n,t} \le \bar{M}, \qquad for\ \ t = 1\ \ to\ \ T \tag{8}$$

Average grade constraint: the average grade of material mind during each period should be more than predefined value.

$$\frac{1}{N_t} \sum_{n=1}^{N} g_n x_{n,t} \ge \underline{G}, \qquad for\ \ t = 1\ \ to\ \ T \tag{9}$$

Where

- N, is the total number of blocks,
- n, is the block index,
- T, is number of periods,
- t, is the period index,
- V_n, is value of n^{th} block,
- $x_{n,t}$, is a binary variable associated to n^{th} block that mined in t^{th} period,

$$x_{n,t} = \begin{cases} 1 & if\ \ block\ \ is\ \ mined\ \ in\ \ period\ \ t \\ 0 & otherwise \end{cases}$$

- o_n, is a parameter indicating that the n^{th} block is an ore block or not,

$$o_n = \begin{cases} 1 & if\ \ n^{th}\ \ block\ \ is\ \ an\ \ ore\ \ block \\ 0 & otherwise \end{cases}$$

- w_n, is the weight of n^{th} block,