Application of the Metaheuristic Approaches in Open Pit Mine Planning

Javad Sattarvand and Omid Gilani
Sahand University of Technology, Iran

Masoud Soleymani Shishvan
Delft University, Delft, Netherlands

Asif Khan
RWTH Aachen University, Aachen, Germany

ABSTRACT: Production planning of the open pit mines has been one of the challenging mathematical problems for mine engineers in the last decades. It is usually a large optimization model which is impossible for solution in a reasonable period of time even in its simplest formulation. The problem deteriorates by the recent tendencies for incorporation of the existing complexities such as nonlinearities in parameters, uncertainties of the ore grades and doubts about economic and marketing factors. Metaheuristic approaches such as genetic algorithm, simulated annealing, ant colony optimization, particle swarm optimization and tabu search are a set of methodologies that have shown their capabilities in solution of the large and complex problems through severe investigations and numerous researches. The paper summarizes the results of the research studies that have been accomplished by the authors on application of the metaheuristics including genetic algorithm, ant colony optimization and particle swarm optimization in production planning of the open pit mines. It has been proved that metaheuristics could be considered as a new set of open pit optimization methods and their required memory and amount of computations are not as much of mathematical programming. Although the global optimum is not guaranteed in metaheuristics, however, NPV of the mine plans produced by some commercial packages have been improved in most cases from 2 to 8 percent. Procedure of the grade uncertainty incorporation into long-term planning has also been explained and the results have been discussed.

INTRODUCTION

The last three decades have seen a widely-publicized revolution in the application of the computers in the mining industry in order to produce better mine plans on more complicated and often lower grade deposits. Recent researches in the field of open-pit optimization have been focused on developing less complex algorithms that require less computational resources and incorporate the real mining complexities.

The core concept of this complex and large-scale optimization problem is the block model, where the ore body and surrounding rocks are discretized into a three dimensional array of regular blocks and required characteristics are assigned to the each block. The long-term open-pit mine production planning problem can be defined as specifying the sequence in which the blocks should be removed from the mine as a certain material type, in order to maximize the total discounted return from the project subject to a variety of economical and physical constraints.

At late 60s, researchers were only focused on the ultimate pit limit (UPL) problem. Lerchs and Grossmann's algorithm (1965) based on graph theory and Johnson's Max-flow algorithm (1969) based on network flow concept were among the best attempts to solve this problem. Whilst subsequent studies motivated to a more general problem namely the problem of production planning. Gershon (1983) presented a Mixed Integer Linear Programming (MILP) model. Several approaches were developed then to solve this MILP model. Dagdelen and Johnson (1986) and Caccetta et al. (1998) used Lagrangian parameterization in order to relax the mining and milling constraints into the objective function. Later Caccetta and Hill (2003) proposed a branch and bound technique to solve the formulated scheduling problem. Dowd and Onur (1993) and Onur and Dowd (1993) formulated the problem as a dynamic programming model. Ramazan (2007) described the application of fundamental tree algorithm to reconstruct the mining blocks and decrease the number of variables in scheduling problems without reducing the resolution of the model or optimality of the results. Bley et al. (2010) presented an integer programming formulation which was strengthened through adding inequalities derived by combining the precedence and production constraints. The addition of these inequalities decreases the computational requirements to obtain the optimal integer solution. Chicoisne et al. (2012) developed a new algorithm for this problem based on a well-known integer programming formulation which called C-PIT method.

A significant tendency can be seen recently in the application of metaheuristic approaches for open pit production planning. Early studies begun by Denby and Schofield (1994) by application of the genetic algorithm (GA). The main advantage of their method was in its ability to solve the ultimate pit limit and the long-term planning problem simultaneously. Later Denby and Schofield (1995) continued to consider risk assessment in their scheduling process. They also extended the algorithm from 2D to 3D (Denby & Schofield, 1996) and used it for a flexible scheduling operation, Denby et al. (1998). Kumral and Dowd (2002 and 2005) investigated the solution of the open pit mine production scheduling problem by means of the simulated annealing (SA). The main advantage of this routine is that it utilizes a multi-objective function comprised of three minimization components. Godoy and Dimitrakopoulos (2004) used simulated annealing method on the effective management of waste mining and orebody grade uncertainty. Their objective function minimizes the chance of deviation from production target for each period in different scenarios. Recently Lamghari and Dimitrakopoulos (2012) presented a diversified Tabu search (TS) approach for the open-pit mine production scheduling problem in the field of metal uncertainty. They used two different diversification strategies to generate several initial solutions and then optimized these solutions using the TS method. Sattarvand (2009) used ant colony optimization (ACO) for long-term production planning of open pit mines. Shishvan and Sattarvand (2014) extended the ACO approach for a real scale mine design. The current paper reviews some of the methodologies and results of the research studies that have been accomplished by the authors on application of three metaheuristic approaches including ant colony optimization, particle swarm optimization and bee colony optimization in production planning of the open pit mines. These are among the most efficient metaheuristic optimization tools that are not properly examined in the open pit mining scheduling, however, despite their promising results there is no evidence to be the best alternatives for optimization of the open pit mines. Following briefly describes the nominated metaheuristic methods and explains the application methodology. Interested reader would refer to the related publications of the authors for details.

METAHEURISTIC APPROACHES

Metaheuristics could be defined as a series of algorithmic ideas that improve the heuristic methods and make them to be applicable to an extensive range of challenging problems. They are usually inspired by the biology and the nature and their application has expressively improved the capability of the algorithms in finding high quality solutions to very hard combinatorial problems, particularly for large and poorly understood problems.

Ant Colony Optimization (ACO)

ACO, which is inspired by the foraging behavior of the ant colonies, is developed by Dorigo and Stützle (2004). In nature, the ants walk randomly and upon finding food return to their colony while laying down chemical trails called pheromone. The pheromone trail transmits a message to other members of the colony. The other ants are likely to follow the trail instead of randomly traveling. If they eventually find food then reinforce the trail by depositing more pheromone. Over the time the pheromone trail starts to evaporate and reduce its attraction. Obviously, magnitude of the evaporation in longer paths is higher than shorter. Thus, the intensity of laid pheromone on the shortest path, by comparison, gradually increases up to the level that balances with the evaporation rate. This makes the shortest path to be marched and followed by almost all of the ants. The methodology of the ant colony optimization mimics this natural behavior by considering a series of variables representing and continuously updating the pheromone values based on the quality of the found solutions, (Dorigo & Stützle, 2004). It has successfully applied to solve some of the leading engineering optimization problems such as traveling salesman problem.

Particle Swarm Optimization

Particle swarm optimization (PSO) algorithm is a stochastic population based optimization technique first proposed by Kennedy and Eberhart in 1995. PSO is a nature inspired algorithm. It is based on the social interaction of individuals living together in groups, for example, bird flock, fish schools, animal herds, and so forth. PSO algorithm performs the search process by using a population (swarm) of individuals (particles). Each particle is a potential solution to the optimization problem. At the start a random starting position and random velocity are assigned to each particle of the swarm. The velocity and position of the individual particles are then iteratively adjusted for finding better positions in the search space. This is accomplished based on the current fitness of the particle and the distance and fitness of the other direct neighbors and indirect swarm groups. Iteratively swarm groups concentrate on the best parts of the solution domain and best points of each part. Khan and Niemann-Delius (2014) used PSO for long-term open pit optimization.

Bee Colony Optimization (BCO)

BCO is a relatively new metaheuristic that was developed in 2005. It mimics the foraging behavior of the honey bees in nature. It combines a kind of local search with a global search to explore the solution domain. The effectiveness of BCO has been successfully investigated through several engineering optimization problems. This is a population based algorithm which classifies the solutions to three major groups called scouts, followers and inactive based the fitness of the solution.

Information is shared inside colony about the fitness of the each solution that inspired by the waggle dance of the honey bees. The higher the fitness of any solution, the more potential for it to become scout solution and attract more followers. Some of the scout solution re-initialize the local domains to keep global searching and the explorative characteristics of the algorithm. After each iteration the population of the scout bees is updated and process runs into next iteration.

MODELING METHODOLOGY

Application of all three ACO, PSO and BCO on optimization of the open pit mine scheduling problem has been implemented through an almost similar modeling approach. In most cases, the output of a commercial software is utilized as starting point and the metaheuristic approaches applied to perturb and improve it towards a better solution.

Encoding of the Mine Schedules

A given open pit schedule can be considered as the superposition of a series of the pit shells related to the different mining periods, Figure 1. In turn, each pit could be represented by a series of block model columns and defining of the pit-depth in each column, as shown in Figure 1. Consequently, any 3D mine schedule (a solution) can be represented in computer programming by a two dimensional array of integers denoting the depth of the pits in block model columns related to different mining periods.

Objective Function and Operational Constraints

Net present value as the most popular objective is used for the optimization, however, unlike the mathematical modeling methods, operational constraints applied into the model as a set of penalty factors. This methodology which would be one of the strengths of the methodology, enables the approach to go beyond some technical restrictions by paying their extra costs. For example, exceeding the defined mining rate is never possible in mathematical programming after adding the related constraint to the model, however, in reality there is normally the possibility to mine additional masses by employment of the temporary contractors which are usually more expensive than self-operation.

Initial Solution

The experiments showed that sometimes the running time increases using a random initialization. Therefore, a sub-optimal solution for the problem of long-term open-pit scheduling is used. For instance in ACO approach the initial schedule is used to give higher initial pheromone values to those blocks that construct the pit shells of the initial schedule. This prevents the generated solutions from scattering and makes them to be close to the best so far found solutions, therefore, a gradual perturbation is performed to convert the initial solution towards a better one. It has been discovered that BCO and PSO are less sensitive to the configuration of the initial population.

Iterations

During each iteration a set of new schedules are constructed based on the current system status. This is implemented by manipulation of the pit depths. Selection of the new depth (for a certain period in a certain column) is constrained by an upper and lower bound which are the depths related to the largest possible pit and the shape of the earlier periods configuration (or initial topography)

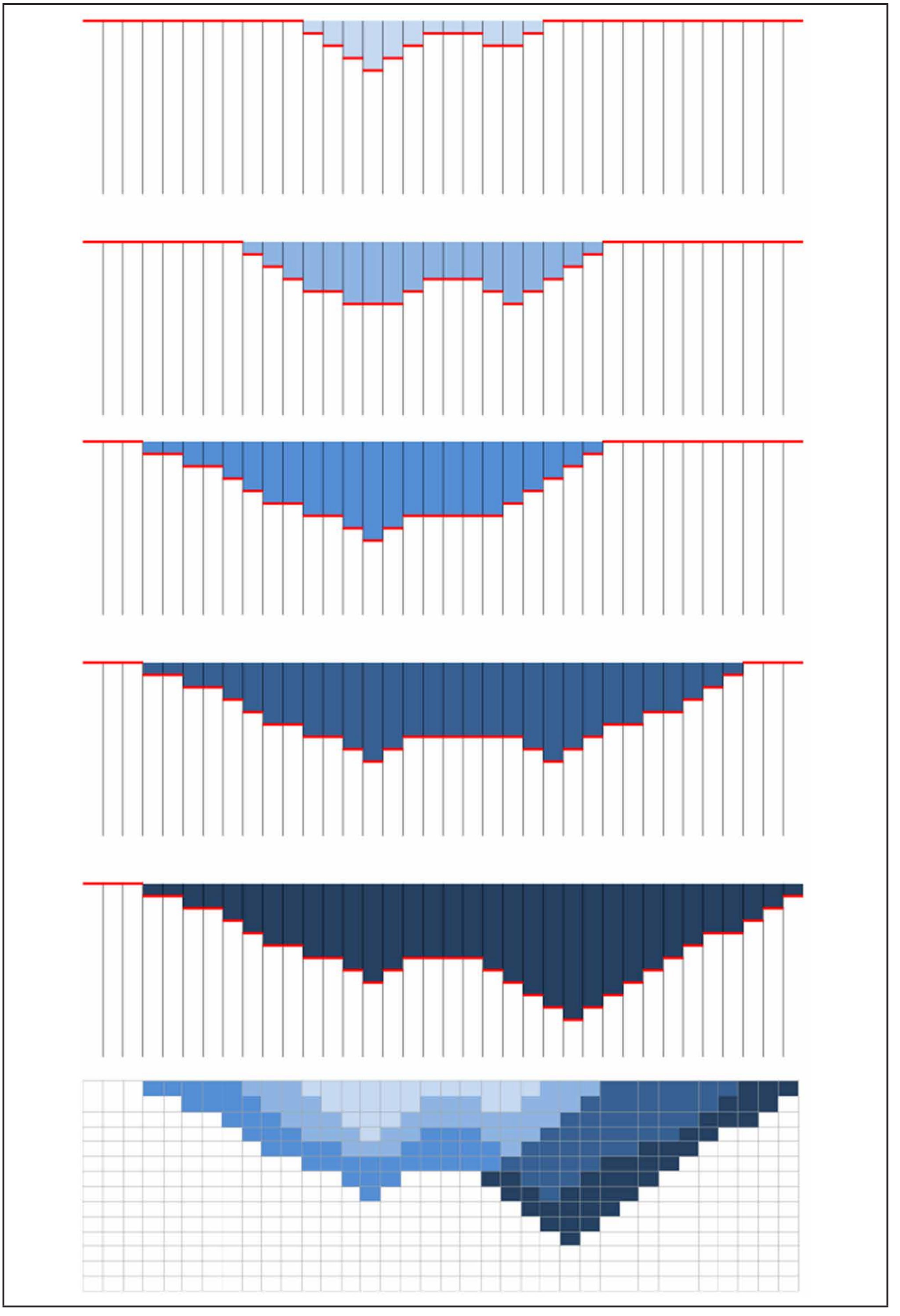

Figure 1. Combination of the single pits to generate a mine schedule

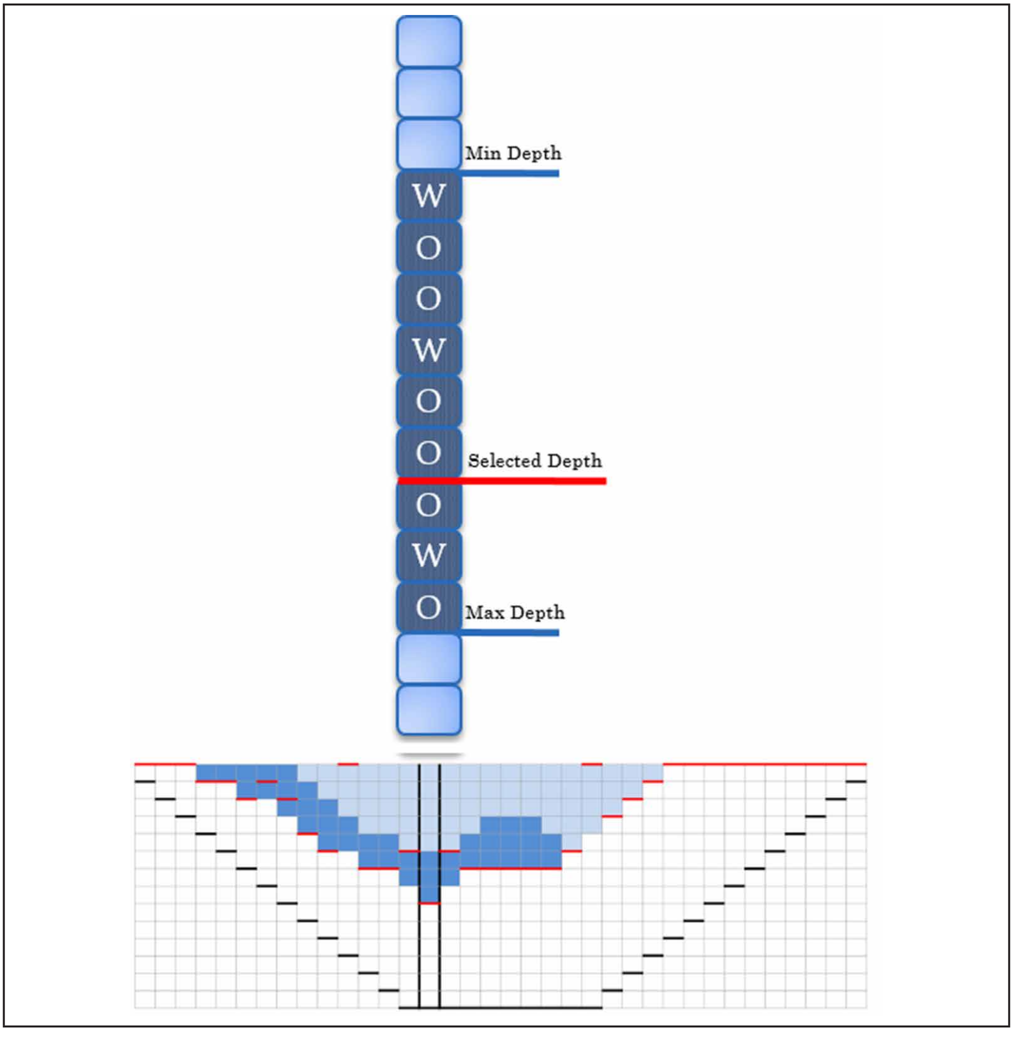

Figure 2. Perturbation of the depths in each iteration

respectively, Figure 2. For example, the chosen depth for the second period in a specific column could not be above the depth of period one. The largest possible pit is the biggest pit that can be constructed in the block model without violation of the slope angles. Clearly the block model should be large enough to allow the whole deposit to be mined. Recent investigations showed that perturbation of the depths in a series of randomly selected columns (instead of all columns) could increase the efficiency of the algorithm. The best so far solution is the potential optimized schedule which could differ from the best of the last iteration.

In fact, depth determination process is the core of each metaheuristic methodology. Figure 3a, b and c show the general flowchart of the ACO, PSO and BCO approaches for open pit optimization respectively. ACO considers a set of variables (pheromone values) for each block of the block model representing the attractiveness of that block for being the deepest point of the pits in optimal solution. These values are initialized by assigning of higher pheromones to a few numbers of the

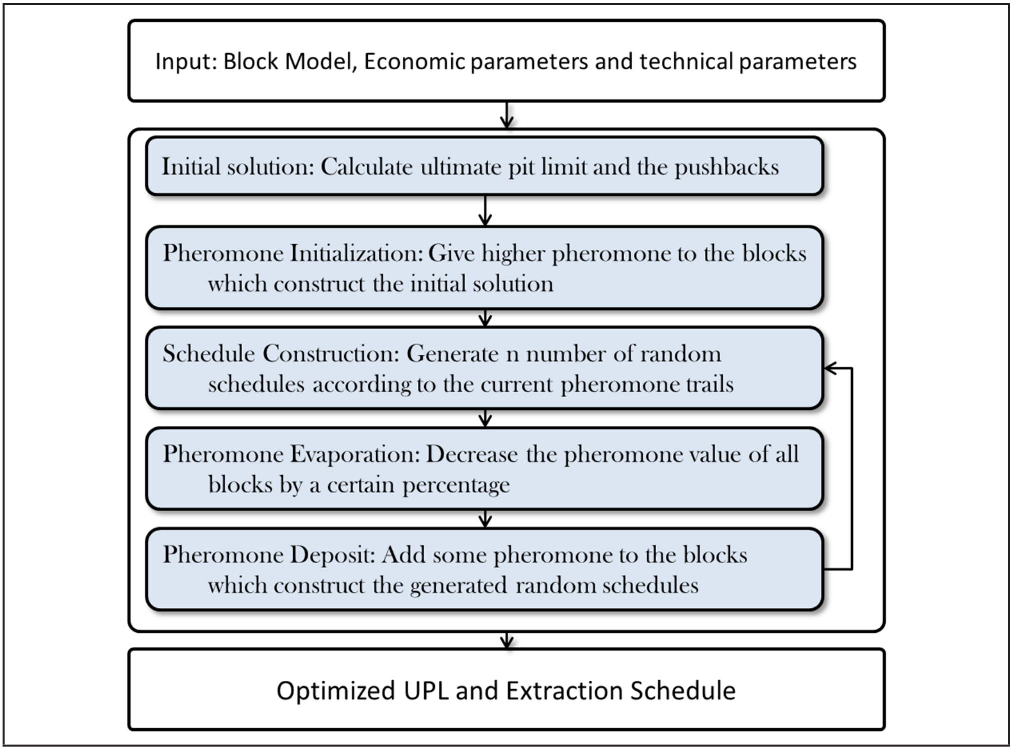

Figure 3a. ACO approch for open pit optimization

blocks around the sub-optimal initial pit depth and then updated to new values after each iteration based on the quality of the found solutions. The update process consists of two steps. The first step, called pheromone evaporation, involves in a uniform reduction in the value of all the pheromones in order to help the ACO model disregard the bad solutions. The next step, pheromone deposition, consists of adding additional pheromone to the blocks which have contributed to the construction of the schedules. Different strategies of pheromone update such as ant system, elitist ant system, ranked based ant system, max-min ant system and ant colony system (ACS) have been investigated, Sattarvand (2009). They differ in the manner of the selection of the blocks for pheromone update and the amount of added pheromones. Results showed that only the last two variants are applicable on real scale models whereas min-max is the most explorative and ACS is the fastest method. Dissimilarly, during each iteration of PSO, a new depth is calculated for the column based on the fitness of the current solution and that of the other neighboring schedules in that column as well as that of best-so-far solution. Accordingly, a particle velocity is calculated for the depths and the new depth is calculated by applying the current position and the velocity. Finally, each iteration of BCO consists of constructing a new population of the schedules which are classified into three scout, inactive and follower categories according to their corresponding schedule's fitness respectively in descending order. The selection of the depth is implemented based on an effective factor which is calculated for each block of the column according to its undiscounted economic value and distance from the best-so-far solution.

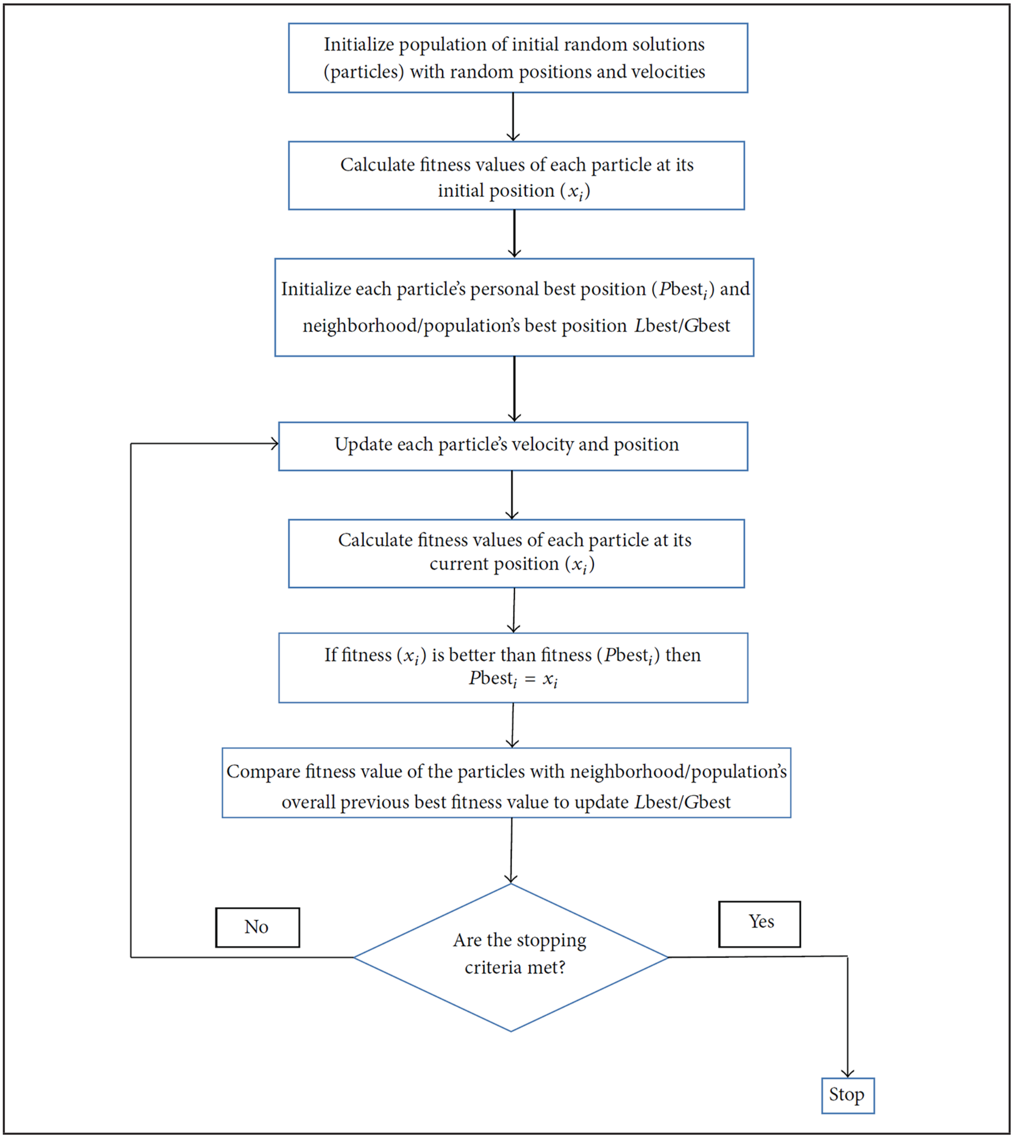

Figure 3b. PSO approach for open pit optimization

Normalization

The consequence of independent depth determination in each column is not always feasible due to the required slope angles. Therefore, a normalization stage based on the selected depths is necessary in order to generate a feasible pit shape. Several normalization procedures have been tested by authors according to different strategies such as construction of the largest pit (Figure 4) or based on random columns.

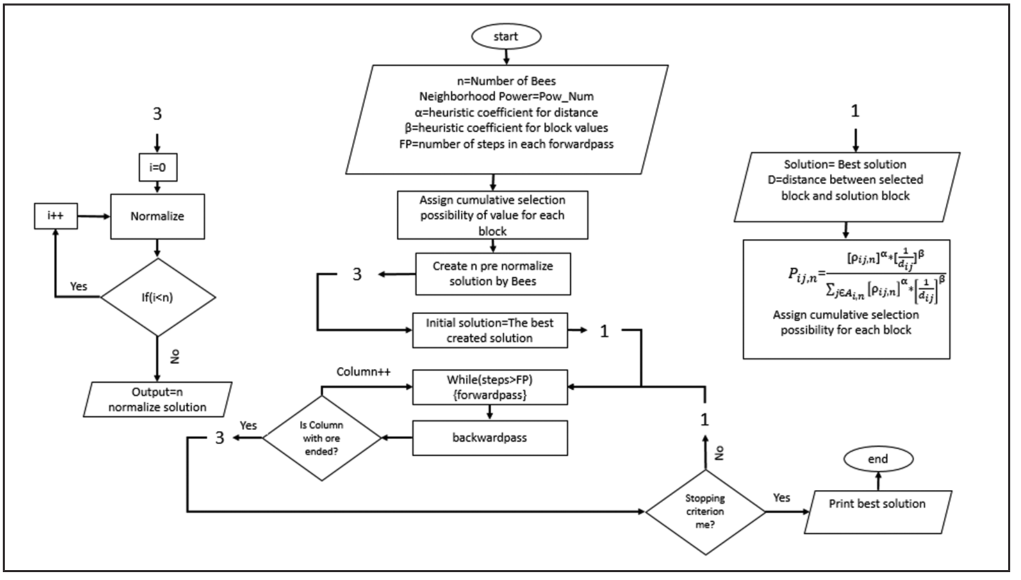

Figure 3c. BCO approach for open pit optimization

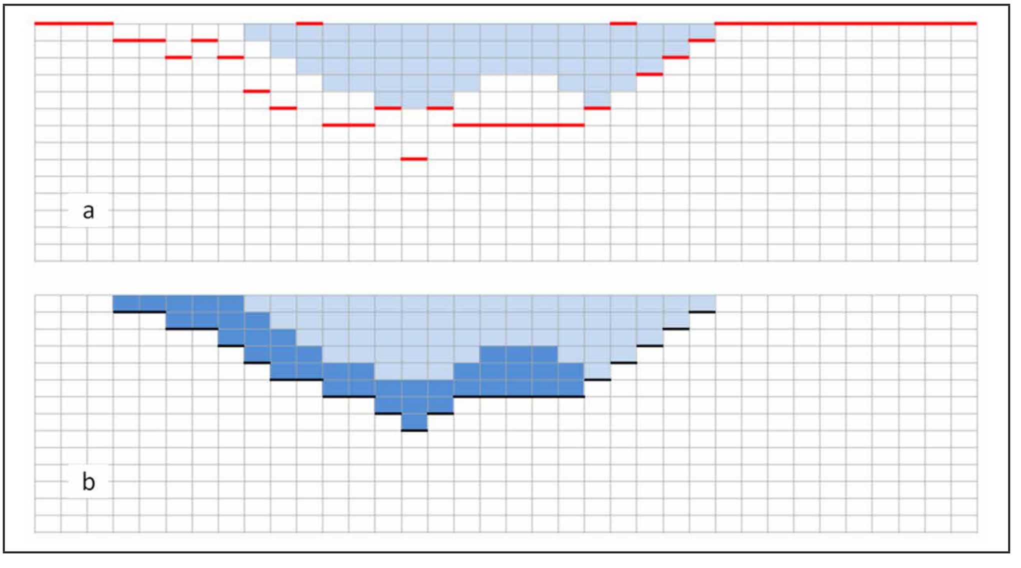

Figure 4. Normalization with the largest pit creation strategy

Termination of the Algorithms

Algorithms set to terminate after a certain number of iterations or when it does not catch any improvement. Each metaheuristic approach utilizes a specific routine to distinguish between stagnation and termination.

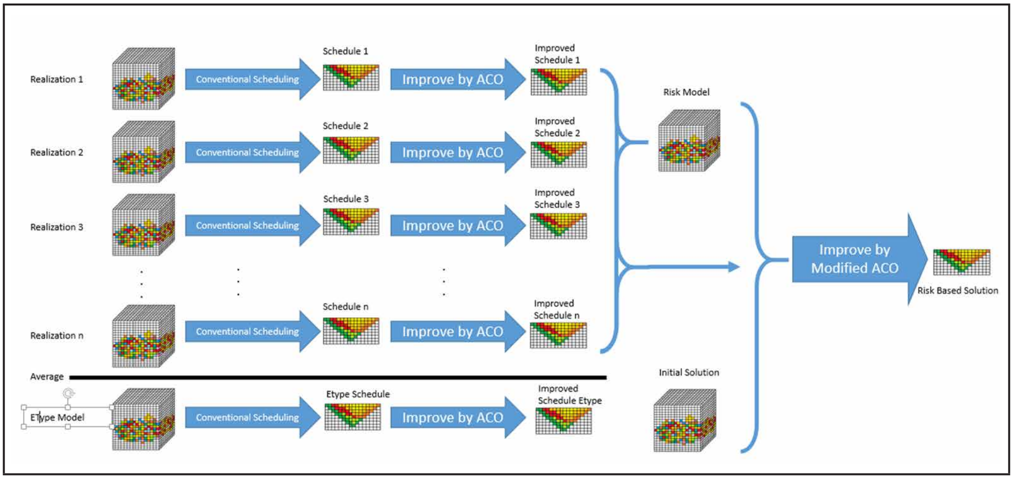

Figure 5. Flowchart of the grade uncertainty incorporation in ACO pit optimizer

Modeling of the Uncertainties

The main sources of the uncertainties in a mining projects which are geological, technical and economical can differ in concept. For example commodity price is a variable that its exact forecasting is not possible for the future years. In contrast, grade of the ore body is a variable that its uncertainty would be diminished by extension of the exploratory studies which needs time and money. Figure 5 outlines the process of methodology developed for investigation of the grade uncertainty effects on mine planning. The routine involves in creation of several realization of the deposit and solving of each model by ACO approach. A risk factor is then calculated for the blocks based on the number of the times which that block has fallen in a certain planning period. The calculated risk factor is added to the objective function in the next step and algorithm tends to consider not only the high grade ore blocks to the early years of mining but also those blocks with lower risks get more attraction too.

CONCLUSION

Metaheuristics have shown their capability to get near optimal solutions for large scale engineering problems. The study has presented the some metaheuristic approaches developed for long-term open pit production planning. The analysis revealed that they can successfully improve the value of the initial mining schedule generated by the conventional algorithms in a reasonable computational time. The other advantages are the ability to consider any kind of objective functions, the capability of considering variable slopes, the less sensitive computation time to the size of the model and the acceptable amount of required computational resources. However, no guarantee to reach the global optimum, and being sensitive to the settings of the parameters are drawbacks.

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