Multiobjective Evolutionary Algorithms for Operational Planning Problems in Open-Pit Mining

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ABSTRACT

This paper addresses the problem of planning and allocation of trucks in open-pit mines in terms of three conflicting objectives, and adapts three algorithms for its solution: NSGA-II, SPEA2, and a variant of the Pareto Iterated Local Search using Reduced Variable Neighborhood Search as its local exploration mechanism. Results on four different mining scenarios are also reported and compared.

CCS CONCEPTS

•**Applied computing** → **Engineering; Multi-criterion optimization and decision-making;** •**Theory of computation** → *Optimization with randomized search heuristics;*

KEYWORDS

Multiobjective evolutionary algorithms, Open-Pit Mine, Dispatch

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1 INTRODUCTION

This work extends previous developments on the *Multiobjective Open-Pit Mining Operational Planning Problem* (MOPMOPP) [1]. Its formulation is redefined to include the maximization of the working (as opposed to idle) time of the shovels as a third objective. The occurrence of queues for truck loading operations and different speeds between loaded and empty trucks are also included in the simulation model. Two multiobjective evolutionary algorithms are adapted for the solution of this problem, as well as a metaheuristic based on the *Pareto Iterated Local Search.* The full description of the problem and its mathematical model, as well as a review of related works, are available from [1].

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2 PROBLEM DEFINITION

A first version of the MOPMOPP, defined with two objectives (maximization of production and minimization of fleet size), was originally introduced in [1]. In this work we consider an extended model for the Open-Pit Mining Operational Planning Problem, from the perspective of three objectives: maximization of total production, minimization of fleet size (in terms of number of trucks and their carrying capacity), and maximization of total working time of the shovels used for loading the trucks, which can be seen as the minimization of total idle time, mainly due to time wasted by trucks on queues. The model also includes constraints related to limits on chemical quality deviations, to pit productivity, to shovel-truck compatibility, and to valid values for the problems variables. The full definition of the problem can be accessed in the online Support Materials [2].

In this work each candidate solution, $\widetilde{S}$, is encoded as $\widetilde{S} = [\overline{V}|\widetilde{M}]$, where $\overline{V}$ is a column vector of size $|T|$, and $\widetilde{M}$ a $|T| \times j$ matrix, with $|T|$ and j representing the number of trucks and the number of dispatches, respectively. $\overline{V} \in \{0, 1\}^{|T|}$ is a vector with its t^{th} position (v_t) indicating whether the truck is in operation or not. Each cell m_{tj} of dispatch matrix ($\widetilde{M}$) represents the identifier number of the j^{th} destination of the t^{th} truck. See [2] for details.

3 OPTIMIZATION ALGORITHMS

We employ two multiobjective evolutionary algorithsm (MOEAs) to tackle the MOPMOPP, namely the NSGA-II and the SPEA2 [3]. These methods are adapted for the representation and specificities of the problem under consideration, by changing the solution-generation and variation procedures used, as detailed below.

A constructive heuristic was used to ensure feasibility, with regard to dispatches for valid locations, of the candidate solutions in the initial population, as illustrated in Algorithm 1. All trucks begin operation in any of the crushers available for the scenario.

Both MOEAs use a cutoff crossover defined as follows: based on two existing candidate solutions $\widetilde{S}^1$ and $\widetilde{S}^2$ (each a $I_g \times J_g$ matrix), a random odd integer $p \in [1, J_g]$ is used to generate two new solutions: $\widetilde{S}^3$, by combining the first p columns from $\widetilde{S}^1$ and the final $J_g - p$ columns of $\widetilde{S}^2$; and $\widetilde{S}^4$, by combining the first p columns from $\widetilde{S}^2$ and the final $J_g - p$ columns of $\widetilde{S}^1$.

The mutation operator is applied as follows. Vector V is mutated using a simple bit flip mutation, which randomly flips elements from this vector with a certain probability. Matrix M is subject

Algorithm 1: Constructive Heuristic

```
Input: #desired solutions (nSol); scenario (Mine); #dispatches (J)
Output: P: initial population
P ← ∅
nT ← getNumberTrucks(Mine)      // number of available trucks
for k=1 to nSol do                   // Generate nSol solutions
    for t = 1 to nT do                         // For each truck
        s^k_t1 ← randBinary()         // sample random binary value
        curplace ← initplace(Mine, t);  // start place for truck
        for j=2 to (J + 1) do
            s^k_tj ← curplace;
            // assign random valid destination
            curplace ← nextRandPlace(t, curplace, Mine);
    P ← P ∪ S̃^k
return P
```

to a mutation scheme where matrix elements are replaced by randomly drawn from an alphabet composed of feasible states for the corresponding truck, again with a certain probability.

A method based on the Pareto Iterated Local Search (PILS) [4] was also implemented in this work. The specificities of this method, as well as its perturbation steps, are provided in [2]. Besides the usual structure of the PILS, we employ a reduced VNS (RVNS) [5] as a local search mechanism, as detailed in Algorithm 2.

Algorithm 2: Reduced Variable Neighbourhood Search

```
Input: Current solution (S̃'); neighborhood size (N)
Output: Resulting solution (S̃')
iter ← 1
while iter ≤ N do
    S̃'' ← MakeNeighborhood(S̃')
    evaluate(S̃'')
    if S̃'' ≺ S̃' then
        S̃' ← S̃''
        iter ← 0
    iter ← iter + 1
return S̃'
```

4 EXPERIMENTAL RESULTS

For the experiments we employ four instances based on those proposed by Souza *et al.* [6]. The performance of the algorithms was quantified using [3]: (i) the *Spread* metric, which quantifies diversity; (ii) *Inverted Generational Distance* (IGD), which measures both convergence and diversity; and (iii) *Runtime* (in seconds). For all indicators, smaller values indicate better performance. The algorithm setup, experimental design, and instances used are available in [2].

Figure 1 shows the mean performance and confidence intervals of the results obtained in the experiment. MILS was outperformed by both MOEA approaches in terms of *IGD*, but the small magnitude of the differences shown in Fig. 1 possibly means little practical significance in terms of this indicator. Regarding *Runtime*, SPEA2 presented a much larger computational overhead, which can be attributed to its heavy clustering approach. MILS was also slightly better than NSGA-II in this aspect, with an expected Runtime for the family of instances about 3 seconds faster. Finally, SPEA2's clustering approach yielded relatively good gains for this method

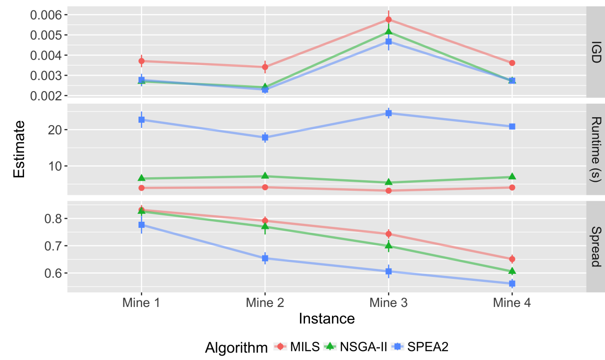

Figure 1: Results for the three methods on each test instance, for each quality metric considered. Vertical bars indicate 95% **confidence intervals. Smaller is better for all indicators.**

over MILS in terms of the *Spread* indicator, but not enough to significantly outperform the NSGA-II. In all cases, indicated differences were statistically significant at the $\alpha = 0.01$ significance level.

5 CONCLUSIONS

We presented an extension of the optimization model for the Multiobjective Open-Pit Mining Operational Planning Problem originally discussed in [1], as well as three algorithms adapted for the solution of this specific problem. These approaches were tested on 4 test instances. The results indicate small differences in convergence, as measured by the IGD indicator; a clear superiority of SPEA2 and NSGA-II over the PILS variant in terms of diversity; and much faster processing times for PILS and NSGA-II when compared to SPEA. Overall, these results appear to suggest the use of the NSGA-II as a preferred method for the solution of this class of problems.

Future possibilities include the development of tools for handling uncertainties in the mine parameters; further investigations on specialist operators; and the inclusion of preferences into the multiobjective formulation.

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