Economic optimisation of an ore processing plant with a constrained multi-objective evolutionary algorithm

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Abstract. Existing ore processing plant designs are often conservative and so the opportunity to achieve full value is lost. Even for well-designed plants, the usage and profitability of mineral processing circuits can change over time, due to a variety of factors from geological variation through processing characteristics to changing market forces.
Consequently, existing plant designs often require optimisation in relation to numerous objectives. To facilitate this task, a multi-objective evolutionary algorithm has been developed to optimise existing plants, as evaluated by simulation, against multiple competing process drivers. A case study involving primary through to quaternary crushing is presented, in which the evolutionary algorithm explores a selection of flowsheet configurations, in addition to local machine setting optimisations. Results suggest that significant improvements can be achieved over the existing design, promising substantial financial benefits.

1 Introduction

Design in any sphere means the specification of a system that satisfies a given set of requirements whilst optimising performance parameters. In most industries, the principal parameter is profit, usually by some combination of minimising capital investment and operating costs, and maximising return on investment, throughput, and efficiency.

Usually, good designs cannot be derived analytically, and the design process will involve at least some aspect of trial-and-error or expert judgement. This has led many people to suggest that the process should be automated. Automation has often taken the form of a search, and in recent years this search has often utilised various artificial intelligence techniques.

The major contribution of this paper is the description of a case study that applies multi-objective evolutionary algorithms (EAs) to optimise the design of a comminution plant. The flexibility of the multi-objective evolutionary approach is illustrated by the ease with we are able to deal with two real-world complications: risk management, and complex feasibility conditions. The initial results from this study are promising.

2 Previous applications of EAs to plant design

Ventner *et al.*[8] proposed an approach for plant design using learning classifier systems. Intelligent objects bid against each other for a position in the circuit. The simple flowsheets examined in the study demonstrated the concept, but most of the intelligence was in the form of subjective heuristics or empirical data. The strength of the work was that it showed that circuits could be assembled with the evolutionary approach, however full process optimisation of the assembled circuit remained elusive.

While *et al.*[9] used an evolution strategy to optimise the performance of a simple comminution circuit with a single cone crusher and a recirculating load. They allowed the algorithm to vary the shape of the crusher's liners and various operating parameters, trying to simultaneously maximise the quality of the product and the capacity of the circuit. Relative to an existing design, they reported an improvement of up to 12% in P80 (a product quality measure), or up to 224% in capacity, or simultaneous improvements of 7% in P80 and 192% in capacity. In [5], a multi-objective algorithm was used to optimise product quality and circuit cost, examining options for make, size, and number of processing units at various points in the circuit, as well as their operational settings.

Subsequently, other researchers have begun to report similar work in the minerals engineering literature: [3], [4], [7].

3 Case study problem

The processing circuit used in this study is a comminution circuit, the default version of which is shown in Fig. 1.

The term *comminution* is used to describe a collection of physical processes that can be applied to a stream of ore to reduce the sizes of the particles in the stream. The purpose of comminution is to transform raw ore into a more usable or more saleable product or to prepare it for further processing. A comminution circuit consists of a collection of processing units connected together (typically by conveyor belts), and may contain loops, typically re-cycling large particles through crushers until they reach the desired size. One or more streams of ore form the feed stream, entering the circuit typically from some preprocessing stage. One or more streams of transformed material exit the circuit as the product stream of the comminution process. More detailed information about comminution is available from [6].

In the circuit under study here, run of mine material is fed into a primary crusher, and the output is screened. Screen undersize goes directly into the fine ore bins, and the oversize is stacked in a coarse ore stockpile.

Reclaimed coarse ore is fed into a crushing plant consisting of an open circuit secondary crusher and a tertiary crusher in closed circuit with two single-deck screens. The screens are fed with the combined output of the secondary and tertiary crushers. Screen oversize is (re-)processed by the tertiary crusher and the undersize forms the crushing plant product and is taken to the fine ore bins.

The fine ore bins feed two parallel milling circuits and their combined product is treated in a leaching process. Each milling line has a selected target P80 value (the 80th percentile of particle size) which determines the capacity of that line. The milling lines have a pre-defined order in which they are utilised: material is fed into the preferred line until that line reaches capacity, then excess material is fed into the subsequent line(s).

The fundamental design goal of the circuit is to maximise the profit of the operating company. Circuit performance depends on the prevailing operating conditions, which are typically unknown or uncertain in advance. As such, a circuit that can perform well in response to changing circumstances is desirable; i.e., some risk management is required. This makes the problem well-suited to a multi-objective approach, which can return a population of designs offering a range of trade-offs between multiple objectives. In this study we use one objective that represents the profit of a circuit given the expected feed, and another objective that represents the profit given a harder feed that is more difficult to process. This enables us to evolve more robust circuits.

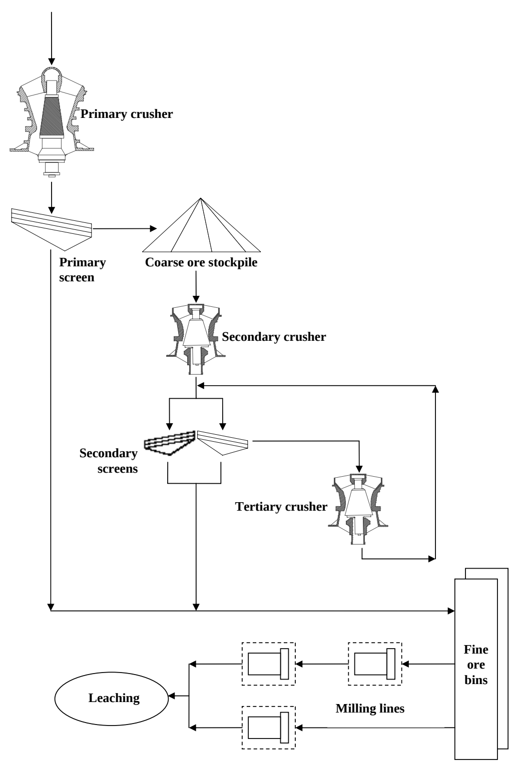

Fig. 1. The basic comminution circuit used in this study.

4 Design of the EA

In this study, we derived our initial population randomly and ran the algorithm for a fixed number of generations. This section examines the remaining algorithm design issues, with particular reference to the problem under discussion.

4.1 Representation of a design

We vary the following design parameters:

- The percentage of product mineral in the feed.
- Independently, the closed-side settings of the secondary and tertiary crushers, i.e. the gap between the liners at their closest approach.
- Whether the design re-circulates the product of the tertiary crusher, or whether this crusher processes the material only once.
- The apertures of the decks in the primary screen, the type of this screen (either conventional inclined, or multi-slope), and its custom load factor.
- The aperture of each unit in the secondary screen-pair, and the type of these screens (either conventional inclined, or multi-slope).
- Independently, the charge level of each mill, i.e. the proportion of the interior volume that is occupied by balls or rods as appropriate.
- Independently, the target P80 of each milling line.
- The placement and types of the mills: either two milling lines with one ball mill each; or three lines with one ball mill each; or one line with one ball mill and another line with one rod mill followed by a ball mill (as in Figure 1).
- The feed order of the milling lines.

4.2 Evaluation of a design

Designs are evaluated independently according to four objectives.

- **Maximise plant value when applied to "hard" material** This value takes into account set-up costs for the design, interest on the set-up costs, and summed daily net income over the design's lifetime.
- **Maximise plant value when applied to "soft" material** This objective considers the performance of the design when applied to soft material, characterised by both a lower P80 and lowered ore hardness values.
- **Minimise overflow in crusher feeds** A poor design might require a crushing machine to process material at a greater rate than its capacity. Excess material then overflows the mouth of the crusher and is lost. Obviously we want to minimise the amount of overflowing material: in fact we consider a design to be successful only if there is no overflowing material.
- **Minimise oversize material in crusher feeds** A poor design might present material to a crusher that is larger than it can accept. The amount of this material is to be minimised, and we consider a design to be successful only if there is no oversize material.

4.3 Treatment of infeasible designs

Some designs perform so poorly that they must be considered "infeasible". But such designs might have some useful features, so we do not discard them immediately. Instead, we quantify their "degree of infeasibility" and then select against them for future generations. For this we use the third and fourth objectives listed in Section 4.2, in a selection process (similar to the "constraint-domination" principle introduced in [1]) that is discussed in Section 4.4.

4.4 Selection of designs

To select which designs become the parents of the next generation, we rank them according to their fitness values. We sort the population according to the fourth objective; then break ties according to the third objective; then break remaining ties by a Pareto ranking on the first and second objectives.

4.5 Mutation and crossover

We used a uniform crossover variant with probability 0.8. Each design parameter was mutated with probability 0.5. Mutation varies depending on the nature of the parameter:

- Crusher identifiers: switch to one of the "neighbouring " crusher variants (a crusher variant which is different in only one attribute).
- real-valued machine settings: NSGA-II's polynomial mutation variant[2] with distribution index 50, constrained to the machine's operating range.
- integer unit counts: NSGA-II's polynomial mutation variant with distribution index 10, constrained to the range 1–20.

5 Experiments, results and discussion

We ran the algorithm with a population of 100 for 500 generations. We performed five runs, each taking 12-18 hours on a modern PC.

Fig. 2 shows attainment surfaces that plot the increase through time of the performance of the population from each run. A 50% attainment surface shows the level of performance attained by half of the runs after a specified number of generations. The 0% attainment surface shows the level of performance attained by the best designs derived at the end of the runs. The plant value objectives are normalised relative to the existing design, therefore the performance of the existing design is (1, 1) by definition. We plot only feasible designs, so the two error objectives are 0 for all designs and need not be plotted.

Table 1 shows selected designs produced by the five runs, along with performance figures. The algorithm returns a *set* of designs, so we have chosen four interesting ones to compare with the existing design. We list the designs with the highest soft value, and the highest hard value. Both of these sacrifice one

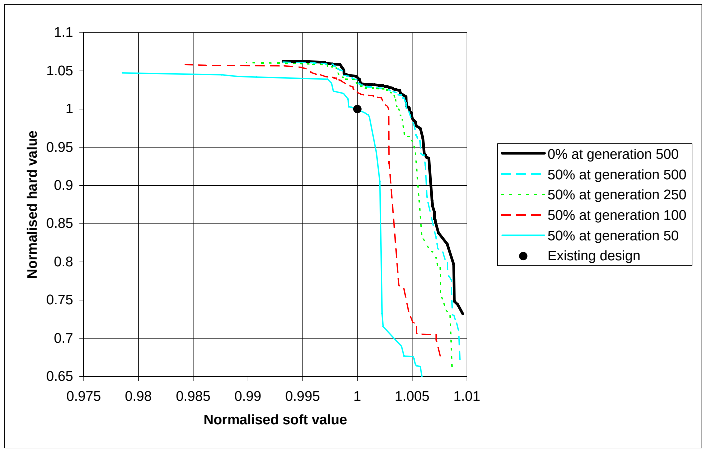

Fig. 2. Increase in normalised performance through time from five runs of the EA.

objective to maximise the other, so we also list two interesting designs that dominate the existing design: the design with the highest soft value that also beats the existing design in hard, and the design with the highest hard value that also beats the existing design in soft.

The algorithm has identified a number of realistic operational changes that could add significantly to the total earnings over the life of the project without any additional investment. Perhaps more importantly, examination of the optimised solutions shows great potential as a process diagnostic:

– All solutions fully utilise available crushing plant hours. This clearly identifies a bottle-neck that could be removed by simply improving the current low levels of availability without a costly capital investment;
– The gains in overall project value achieved are relatively modest. This suggests that the existing process may not contain any significant “hidden” values, and that capital upgrades must now be considered to provide the required improvements in operational performance.

6 Conclusions and future work

We have described the application of an EA to the problem of optimising the performance of a comminution plant, by fine-tuning the settings of individual machines, by tuning machines in the circuit to work well in tandem, and by making (minor) structural changes to the circuit. The performance of the plant is optimised independently for two different types of feed, and the algorithm returns a range of designs offering different trade-offs between them.

The results indicate that the algorithm is able to find designs that offer useful improvements in performance, particularly when applied to hard material, and

Table 1. Details of the best designs from five runs of the evolutionary algorithm, and their normalised performance values.

	Existing	**Best soft value**	**Matched hard value**	**Matched soft value**	**Best hard value**
Normalised soft value	1.0000	1.0096	1.0047	1.0002	0.9932
Normalised hard value	1.0000	0.7319	1.0021	1.0387	1.0624
Normalised % mineral in feed	100.00%	99.83%	99.91%	100.44%	101.01%
Screen-Prim-Config	CI	CI	CI	CI	CI
Screen-Prim-AppTop (mm)	65.0	50.7	66.0	67.7	47.7
Screen-Prim-AppBottom (mm)	17.0	28.5	26.8	29.0	20.7
Screen-Prim-CustomLoadFactor	160%	220%	201%	169%	164%
Crusher-Second-CSS (mm)	24.0	20.4	19.7	32.9	20.0
Screen-Second-App (mm)	19.0	14.7	18.1	18.4	22.0
Screen-Second-Config	CI	CI	CI	CI	CI
Closed Circuit	True	True	True	True	True
Crusher-Tert-CSS (mm)	12.0	12.0	12.0	12.0	12.0
RodMill	Retained	Retained	Retained	Discarded	Converted
FeedOrder	1,2	1,2	2,1	1,2	2,1,3
RodMill-Charge	40%	30%	32%		
BallMill-1-Charge	45%	27%	29%	38%	36%
BallMill-2-Charge	36%	30%	35%	38%	35%
BallMill-3-Charge					44%
Line-1-TargetP80 (μm)	298	351	315	370	324
Line-2-TargetP80 (μm)	306	267	284	327	332
Line-3-TargetP80 (μm)					480

that it is able to find designs that beat the existing design in both objectives. A full investigation promises significant financial benefits. We will allow the algorithm more scope to vary aspects of the design in the search for improvements, in particular we will allow a wider range of structural changes. We also plan to modify the definitions of our value objectives to more-closely mirror the usual metric of NPV, or Net Present Value.

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