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A hybrid evolutionary performance improvement procedure for optimisation of continuous variable discharge concentrators

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ABSTRACT

An iterative hybrid performance improvement approach integrating artificial neural network modelling and Pareto genetic algorithm optimisation was developed and tested. The optimisation procedure, code named *NNREGA*, was tested for tuning pilot scale Continuous Variable Discharge Concentrator (CVD) in order to simultaneously maximise recovery and upgrade ratio of gold bearing sulphides from a polymetallic massive sulphide ore. For the tests the CVD was retrofitted during normal operation on the flotation tailings stream. On the basis of mineralogical data showing strong pyrite-gold association in the flotation tailings, iron assays were used as an indicator of CVD performance on recovery of gold bearing sulphides. Initially, 17 pilot scale statistically designed tests were conducted to assess metallurgical performance. The Matlab 2010a software was used to train and simulate back propagation ANNs on experimental results. Regression models developed from simulation data were used to formulate the objective functions used to optimise the CVD using the NSGA-II genetic algorithm. Results show that the *NNREGA* procedure provides an efficient way of exploring the design space to learn the relationship between interacting variables and outputs and is capable of generating the operating line, which is a non-dominated recovery/grade line. The paper forms a basis for future work aiming to model and scale up processing equipment.

1. Introduction

The mineral processing industry has not yet managed to leverage the processing edge presented by the high mass yield Continuous Discharge Centrifugal (CDC) concentrators, introduced in the early 1990s, due to lack of knowledge and experience in operating and optimising these multi variable concentrators. The dominant CDC concentrators include the Knelson Continuous Variable Discharge Concentrator (CVD), Falcon C, Kelsey Jig and Multi Gravity Separator. These machines are distinct from conventional batch centrifugal concentrators in that whilst batch concentrators have to be stopped to discharge concentrates the continuous machines continuously discharge concentrates whilst concentrating is progressing. Continuous concentrate discharge introduces additional machine variables, which require manipulation to achieve optimum performance. To date, no optimisation strategy exists for operators to move from current plant settings to optimum performance. Previous mineral processing optimisation employed the classical preference based approach, which imposes weighting on objectives and yields a single optimum point instead of generating an optimum operating line, thereby failing to exploit the competing grade/recovery relationship.

The Knelson CVD concentrator has four interacting machine variables [1–3], making it difficult to tune them to achieve optimum metallurgical performance. For the CVD, the objective is to maximise both grade and recovery as a function of machine variables; pinch valve open duration (PVO), pinch valve closed duration (PVC), bowl speed (BS) and fluidisation flow rate, and ore specific variables subject to some process constraints. McLeavy [2] showed that for the CVD 6 the optimum fluidisation flowrate was around 30.3 l/min, such that if kept within this range it can be eliminated as a variable. Each CVD unit is also unique owing to variation in length and material type used for the pneumatic lines [2], and for every new installation the set points have to be determined prior to optimisation. In addition, the mechanism of concentration of the CVD is poorly understood making it difficult to formulate both mechanistic and phenomenological models to fully describe the relationship between response and variables. Thus most of the models developed to date have been

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phenomenological, which are site and machine specific [4,5]. As a result, operators do not know how to efficiently and systematically tune the operational variables to improve metallurgical performance. The approach that varies one variable at a time, currently used by operators, is potentially misleading when there are multiple interacting operating variables [6] and such an approach might lead to operating the CVD at sub-optimum variable settings.

This study explores application of Pareto's non-dominated approach to multi-objective optimisation in order to simultaneously maximise both grade and recovery for the CVD without a priori weighting objectives. Since mineral processing involves gangue rejection in order to produce a high-grade concentrate, maximizing concentrate grade can only be achieved at the expense of a reduction in recovery. An iterative hybrid performance improvement approach that incorporates artificial neural network modelling and genetic algorithm was developed and tested at operating conditions of a mill which processes polymetallic massive sulphide ore. The objective was to generate the operating line, which is a non-dominated recovery/grade line independent of economic factors.

2. General concept

Fig. 1 is an illustration of Pareto's non-dominated approach to solving multi objective optimisation problems. For a candidate to be included in the optimum solution; it should either be no worse than the other for all objectives or should be strictly better than the other in at least one of the objectives. In Mineral processing we aim to maximise both concentrate grade and recovery. Using dominance for ordering the 5 solutions: comparing solutions 1–5, solution 2 is better than 3 in both objectives and therefore dominates solution 3. Solution 5 is better in both objectives to solution 4 and therefore dominates solution 4. Comparing solutions 1 and 2, it cannot be said which one is better than the other since solution 1 is better than 2 in grade, but worse in recovery. So solutions 1 and 2 are considered non-dominated. Comparing solutions 2 and 5, it cannot be said which of the solutions is better than the other, since solution 5 is better than solution 2 in recovery, but worse in grade. So, solutions 2 and 5 are considered non-dominated with respect to each other.

Due to the transitive nature of dominance, since solution 2 is non-dominated by solutions 1 and 5 is non-dominated by solution 2 therefore solution 5 is non-dominated by solution 1. A Pareto front is a set of such non-dominated solutions for an optimisation problem and defines the operating line in this study. Optimisation of CVD performance involves simultaneous maximisation of both upgrade ratio/grade and recovery subject to three CVD machine variables (BS, PVO, PVC) keeping the fluidisation water velocity constant.

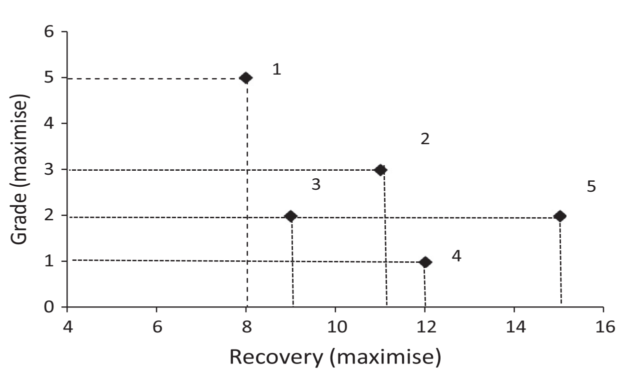

Fig. 1. Illustration of non-dominance using a population of five candidate solutions.

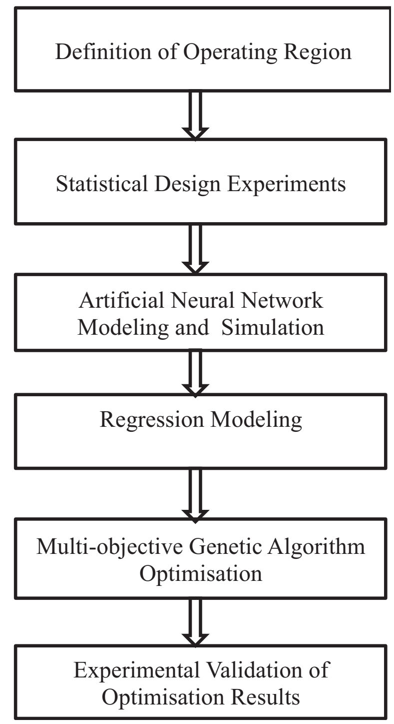

Fig. 2. Flow of the *NNREGA* optimisation technique.

Fig. 2 shows a schematic of the hybrid optimisation approach code named *NNREGA*. It involves defining the region contained by the maximum and minimum control variables level by conducting scoping tests based on mass yield. This is followed by exploration of the design region using statistically designed experiments so as to determine how each variable, and the combination of variables affects recovery and upgrade ratio. The experimental results are used to train artificial neural network models to learn the relationship between predictors (bowl speed and pinch valve duration and response variables.

The trained artificial neural networks are used to further explore the design space in order to understand the nature of the response surface, significantly reducing the number of necessary experimental tests to be conducted and consequently the cost and time for the test program. Because ANN models do not provide much information about the relationship between variables and response, in order to define the fitness (objective) function for genetic algorithm optimisation and better understand the effect of variables on response, regression models of recovery and upgrade ratio are developed from ANN simulation data. Instead of a single optimum point, the resultant solution is a set of non-dominated solutions of upgrade ratio and recovery, which gives the optimum recovery/upgrade ratio curve. Experimental validation of these results is conducted and the necessary adjustments done based on the validated results.

3. Materials and methods

A pilot scale Knelson CVD 6 was tested on flotation tailings at the Myra Falls processing plant at Vancouver Island, Canada. Fig. 3 shows a schematic of the flowsheet and the flotation tailings stream where the CVD was installed for the tests.

3.1. Sample and preliminary tests

The ore comes from a polymetallic massive sulphide deposit with varying proportions of pyrite. The principal gold carrier is