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Multiobjective optimization of an industrial grinding operation under uncertainty

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ABSTRACT

Multiobjective optimization of an industrial grinding operation under various parameter uncertainties is carried out in this work. Two sources of uncertainties considered here are related to the (i) parameters that are used inside a model representing the process under consideration and subjected to experimental and regression errors and (ii) parameters that express operators' choice for assigning bounds in the constraints and operators prefer them to be expressed around some value rather than certain crisp value. Uncertainty propagation of these parameters through nonlinear model equations is reflected in terms of system constraints and objectives that are treated here using chance constrained fuzzy simulation based approach. Such problems are treated in literature using the standard two stage stochastic programming methodology that has a drawback of leading to combinatorial explosion with an increase in the number of uncertain parameters. This problem is overcome here using a combination of fuzzy and chance constrained programming approach that tackles the problem by representing and treating the uncertain parameters in a different manner. Simultaneous maximization of grinding circuit throughput and percent passing mid size fraction are studied here with upper bound constraints for various performance metrics for the grinding circuit, e.g. percent passing of fine and coarse size classes, percent solids in the grinding circuit final outlet stream and circulation load of the grinding circuit. Uncertain parameters considered are grindability indices of rod mill and ball mill, sharpness indices of primary and secondary cyclones and the respective upper bounds for the constraints mentioned above. The deterministic multiobjective grinding optimization model of Mitra and Gopinath [2004. Multiobjective optimization of an industrial grinding operation using elitist nondominated sorting genetic algorithm. Chem. Eng. Sci. 59, 385–396.] forms the basis of this work on which various effects of uncertain parameters are shown and analyzed in a Pareto fashion. Nondominated sorting genetic algorithm, NSGA II, a popular elitist evolutionary multiobjective optimization approach, is used for this purpose.

1. Introduction

Grinding is one of the very important comminution operations for many chemical, mining, metallurgical and mineral processing industries. Considering the mineral processing sector as an example, wet grinding is strategically important because it is one of the most energy and cost intensive operations in the whole ore beneficiation process, whereas for operational reasons, it is also equally important since the particle size distribution generated as a result of grinding operation is going to play a very crucial role in the following mineral separation operations, e.g. flotation circuits. Similarly, grinding plays a key role in cement manufacturing operation where it is used twice, before and after the kiln operation, once for preparing the right mixture for clinker production in lime kiln and the other for controlling the blain in the final product, respectively. Thus, modeling, optimization and control of industrial grinding circuits have been among the key focus areas for continuous improvement of comminution process performance by respective process experts as well as researchers in various engineering sectors (Wei and Craig, 2009).

There has been a considerable progress in modeling, optimization and control of industrial grinding circuits (Powell and Morrison, 2007; Wei and Craig, 2009). Grinding circuit under consideration consists of different kinds of milling operation (e.g. rod mill, ball mill, etc.), classification units (e.g. hydrocyclones) and sumps, where modeling the grinding operation is the key. Power based models presented by Bond (1952, 1961) are among the first few efforts towards the direction of modeling grinding operation, where a well documented laboratory test to the standard rod and ball mills is correlated. The strength of these techniques is that if the design operation is in the same regime as the database, then the predictions are generally good, otherwise not. These techniques are not very friendly to be extrapolated to new operating conditions or ore types

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(Powell and Morrison, 2007). A step change to the concept of modeling was introduced with the introduction of population balance methods (Austin et al., 1984; Herbst and Fuerstenau, 1980; Whiten, 1972; Morrell et al., 1993; Napier-Munn et al., 1996), where primarily three relationships, selection function, breakage function and discharge function, are used to capture the result of grinding inside the grinding unit. With improvements in computational power, various computationally expensive techniques e.g. computational fluid dynamics (Chakraborti et al., 2008a, 2008b), discrete element method (Mishra, 1991; Mishra and Rajamani, 1994; Datta and Rajamani, 2002), etc. are also evolved for modeling particle–particle interaction in grinding operation. For many such techniques (computational fluid dynamics and finite element method), the user specifies a grid of points, appropriate boundary conditions and set of starting values. A similar calculation is carried out for all grid points sequentially, values are updated and the process of simulation is terminated based on some termination criteria got satisfied. An interesting variation of this is discrete element method where a particle as a point on movable grid is set to motion as per its interaction with surrounding particles as proposed by Cundall and Strack (1979). Similarly, modeling the effect of hydrocyclones is also found in the literature (Lynch and Rao, 1975). In an integrated grinding circuit, where many of these unit operations are carried out simultaneously, a population balance modeling approach can be adopted for simulating the circuit performance (Herbst and Fuerstenau, 1973; Lynch and Rao, 1975; Herbst et al., 1983; Kinneberg and Herbst, 1984; Rajamani and Herbst, 1991a, 1991b; Mitra and Gopinath, 2004). These kinds of models can not only be used as softsensors to predict various circuit performance indicators as well as stream attributes which are otherwise not measurable, but also be integrated with control and optimization modules for carrying out optimization in real time mode. Based on the progress of studying the control of grinding circuit, several researchers and practitioners have proposed different sets of manipulated variables (MVs), control variables (CVs) and objectives in the last two decades. Variables such as flowrate of water to the sump, flow rate of water to the mill, flowrate of solids to the mill and flowrate of slurry from sump are among the few that dominate the list of MVs practiced globally (Wei and Craig, 2009). Similarly, variables such as product particle size, slurry level in the sump, sump discharge slurry density, feed ratio, cyclone feed pressure, cyclone overflow product density, mill load are the most frequently used CVs (Wei and Craig, 2009). Different control philosophies adopted globally for grinding control study are PID control, multi variable control, expert system based control, fuzzy logic control, where PID control is in the lead as opposed to model predictive control (MPC) that dominates other alternatives in the process industries (Wei and Craig, 2009).

Most of the existing control and optimization work cited above are based on the assumption that all model parameters of the system under consideration are crisply known. However, real world situations are quite different and involve uncertainty at the core of the problems due to many factors such as lack of accurate representation of the process models and variation in the process and environmental data. Optimization under uncertainty, therefore, emerged aiming at developing approaches and methodologies to create reliable solutions that remain feasible in the presence of parameter uncertainty (Sahinidis, 2004; Floudas, 2005; Floudas and Lin, 2004, 2005). Beginning with pioneering work of Beale (1955), Bellman (1957), Bellman and Zadeh (1970), Charnes and Cooper (1959), Dantzig (1955) and Tintner (1955), there have been different philosophies on which several methods for optimization under uncertainties can be categorized: stochastic programming, chance constrained programming and fuzzy mathematical programming (Sahinidis, 2004).

Stochastic programming formulations assume that the probability distributions governing the uncertain parameters are either known or can be estimated from the exiting data. Two-stage approach is the most commonly cited stochastic approach, where the decision variables are partitioned into two sets: the first stage variables ("here and now" decisions) are to be decided before the realization of uncertain parameters whereas the second stage variables ("wait and see" decisions) are chosen as a corrective measure against any infeasibility arising due to a particular realization of uncertainty (Diwekar, 2003). The goal is to choose the first stage variables, in such a way that the sum of the first stage costs and the expected value of the second stage costs are minimized. This approach has been profusely experimented in process system engineering literature (Liu and Sahinidis, 1996; Ahmed and Sahinidis, 1998; Petkov and Maranas, 1998; Ierapetritou et al., 1994; Ierapetritou and Pistikopoulos, 1994a, 1994b; Pistikopoulos, 1995; Pistikopoulos and Ierapetritou, 1995; Clay and Grossmann, 1994; Subrahmanyam et al., 1994; Shah and Pantelides, 1992; Kim and Diwekar, 2002; Gupta and Maranas, 2000, 2003). One of the drawbacks of this approach is an exponential increase in problem size with the increase in the number of uncertain parameters. Unlike stochastic programming where decisions have to be feasible for all the outcomes of uncertain parameters, chance constrained programming (Prekopa, 1995; Birge and Louveaux, 1997; Gill et al., 1981; Kall and Wallace, 1994; Loeve, 1963; Charnes and Cooper, 1959) requires feasibility of solutions with at least some probability specified on constraints having uncertain parameters. This is expressed in terms of reliability of the solution. To make the problem more tractable, this probabilistic formulation of chance constrained programming leads to an equivalent deterministic formulation that can be solved. The main advantage of chance constrained programming technique is the emergence of the relatively small deterministic equivalent problem even in presence of a large number of uncertain parameters that can be solved quite easily. Applications of CCP in process system engineering literature are limited to few applications (Maranas, 1997; Gupta et al., 2000; Gupta and Maranas, 2003; Li et al., 2008; Mitra et al., 2008).

In fuzzy mathematical programming, proliferated by Zimmermann (1978, 1991), a mathematical programming model is formulated that takes into account the decision maker's expectations of a target range of the objective values and soft constraints based on decision making in a fuzzy environment. In this approach, the degree of satisfaction of a constraint is defined in terms of a membership function of the constraint and a small extent of constraint violation is allowed. Another approach from the similar class could be handling uncertainty using rough set approaches (Dubois and Prade, 2000; Dey et al., 2009). Indiscernibility and fuzziness are distinct facets of imperfect knowledge that can be handled by rough and fuzzy set theories, respectively. Indiscernibility is related to the granularity of knowledge affecting the definition of universes of discourse, whereas fuzziness refers ordering of relations that express intensity of membership. The advantage of fuzzy approach over the other two approaches mentioned in the earlier paragraph is that fuzzy approach neither assumes that the uncertain parameters have to follow any statistical distribution nor allows the final deterministic equivalent formulation of the uncertain model to blow up in size with increase in number of uncertain parameters. Application of FMP is widely spread across different applications such as capacity planning (Liu and Sahinidis, 1997), supply chain planning (Mitra et al., 2009b), production scheduling (Balasubramanian and Grossmann, 2003), bio-energy production (Ayoub et al., 2007), etc. to name a few.

In this paper, we consider the more realistic scenarios of handling uncertainty in model parameters that are otherwise assumed constant such as grindability indices and sharpness indices in a nonlinear industrial grinding case study and explore the merits of fuzzy chance constrained programming towards analyzing their impact on the overall optimization of the grinding system. We further