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Particle Swarm Optimization Approach for Maximizing the Yield of a Coal Preparation Plant

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Abstract

This paper presents the use of particle swarm optimization to maximize the clean coal yield of a coal preparation plant that typically has multiple cleaning circuits that produce the same product quality so that the blend of clean coal meets the targeted product quality constraints. Particle swarm is used for the yield optimization while satisfying multiple product quality constraints. The results show a 2.73% increase in the yield can be achieved leading to additional revenue of $5,460,000 per annum for a plant producing 10 million tons of clean coal per year without significantly adding to the implementation/operation cost.

Keywords: Coal, optimization, particle swarming, coal plant optimization.

1. Introduction

A modern coal preparation plant flowsheet integrates three or four cleaning circuits that cleans the coarser (+ 6 mm), intermediate (6 x 0.6 mm) and finer (- 0.6 mm) size fractions. Figure 1 shows a block diagram of a coal processing plant that runs with a four unit operations which are categorized as heavy medium vessel (HMV), heavy medium cyclone (HMC), spiral and froth-flotation. The feed is screened and classified into different size fractions to be treated in respective circuits. The heavy medium vessel cleans the coarsest (152 x 16 mm) size fraction while heavy medium cyclone treats the intermediate (16 x 1 mm) size particles.

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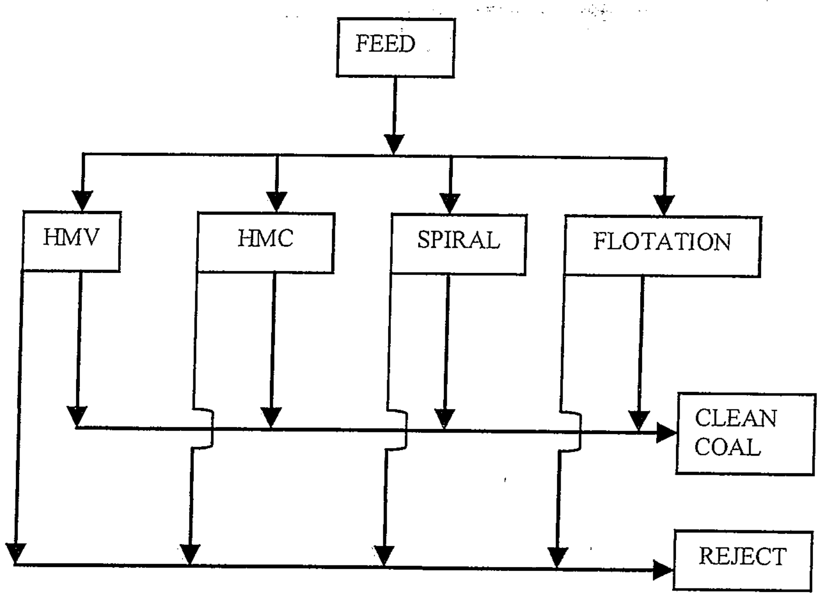

Figure 1. A simplified block diagram of a four circuit coal processing plant.

The fine (1 x 0.15 mm) and ultra-fine (0.15 x 0.045 mm) size fractions are cleaned in spiral and flotation processes, respectively. The size fraction below 0.045 mm is discarded as slimes due to its high ash content. Each circuit is operated at specified operating conditions to produce the same product quality as the targeted plant product quality. The key operating conditions may be listed as medium density for HMV and HMC splitter position for coal spirals, and residence time for flotation process. Although, the targeted overall plant product quality is satisfied by this approach, the plant yield is not maximized. The output of normal plant operation is considered as baseline for further comparison with the different optimization models used in the study.

Numerous studies have been conducted in the past to optimize the clean coal yield (defined as percentage of plant feed reporting to the plant product stream) of a coal preparation plant. A graphical approach was suggested by Sarkar *et al.* (1960) for maximization of yield of composite clean coal at desired ash content. It was suggested that cleaning of coarser coal at higher ash content and finer coal at relatively lower ash content gives the maximum yield while satisfying the product ash constraint. Additional graphical approaches were suggested by other investigators (Salama, 1991, Lyman, 1993 and Salama, 1998) to optimize the yield of a coal preparation plant on the basis of product ash. The yield-ash curves were plotted for each circuit. The points of equal slope were located on these curves and the one that met the product ash constraint was considered as the optimum yield of the plant. Salama (1986) suggested a numerical approach to maximize plant yield. A Lagrangian approach was used for a constrained nonlinear optimization process. The product ash was considered as the only constraint for the yield optimization process. The necessary condition was determined to maximize the yield by equalizing the incremental product ash for each circuit. Honaker *et al.* (1997) and Luttrell *et al.* (2004) also arrived at the same conclusion that the equal incremental ash approach gives the maximum yield at target ash content. Gupta *et al.* (2004 and 2005) developed a model using genetic algorithms and concluded that genetic algorithm serves as better alternative for coal preparation plant yield optimization in comparison to the equalization of incremental product ash approach when it is required to satisfy multiple product quality constraints.

The present study describes the application of an evolving evolutionary algorithm, known as particle swarm optimization (PSO) for solving the coal plant yield maximization problem while satisfying multiple product quality constraints. The PSO is a stochastic optimization technique that can be compared to the behavior of a flock of birds or the sociological behavior of a group of people (Bergh and Engelbrecht, 2004). This technique has been used to solve a range of optimization problems, including neural network training and function minimization. Kennedy and Eberhart (1995) used particle swarming for a neural net application and concluded that it could train neural network weights as effectively as the usual error back propagation method. The particle swarm optimization has also been used to train a neural network to classify the Fisher Iris Data Set (Fisher, 1936). Over a series of ten training sessions, the trained weights found by particle swarms sometimes generalize from a training set to a test set better than solutions found by gradient descent. Pomeroy (2003) discusses the application of particle swarm optimization in optimizing a function whose value depends on four dimensional position vectors.

This paper considers the yield optimization of the coal preparation plant based on two product quality constraints, i.e., product ash assay and sulfur assay. Two approaches, i.e., traditional incremental ash based approach and PSO, were investigated to maximize plant yield while satisfying the target product ash and sulfur assays. The optimal yields obtained from both approaches have been compared.

2. Data Analysis

The coal preparation plant, studied in this investigation, receives coal from two different sections of a mine blended at a ratio of 75% from Section-1 and 25% from Section-2. The operating conditions for each unit operations (HMV, HMC, Spiral and Flotation Cell) were varied in succession to conduct a series of experiments and generate characteristic partition curves for each process. The medium specific gravities were varied over a range of 1.32 to 1.48 for the HMV and HMC as indicated in Table 1.

Table 1. Operating conditions maintained during plant-testing carried out during this investigation

Test	Spiral Splitter Position		HMV Medium Density	HMC Medium Density
	A (inch)	B (inch)		
1	6.5	0.25	1.32	1.32
2	6.5	0.5	1.36	1.36
3	6.5	0.75	1.40	1.40
4	6.5	1	1.44	1.44
5	6.5	1.25	1.48	1.48

For Spiral, the product splitter (B) position was varied over 5 individual locations. The partition data for each unit operation were generated by plotting percentage of feed corresponding to a specific density class that reported to the product stream. Model equations were developed to best fit the normalized (reduced partition) partition data generated for each density based process. The kinetic rate equation was developed for the flotation process in the lab (using the same coal) since the flotation tests conducted in the plant failed to produce meaningful results. Model equation for each process was simulated to generate a huge amount of data for the process yield and corresponding product ash and sulfur assays for small incremental change in operating condition, i.e., for each 0.01 unit change in the separation density (D_{50}) for density based process and each 10 second increase in the residence time for the froth flotation process. These data were stored in a database to be used for the optimization model.

3. Particle Swarming Optimization Model

The particle swarm algorithm works by searching iteratively in a region that is defined by each particle's best previous success, the best previous success of any of its neighbors, the particle current position, and its previous velocity (Mendes *et al.*, 2004). A particle searches through its neighbors in order to identify the one with the best result so far and uses information from that one source to bias its search in a promising direction.

A simplified block diagram of a modern four circuit coal preparation plant investigated during this study is shown in Figure 1. The analogy of finding an optimal yield of the plant is similar to a flock of birds searching for the roost area. The flock of birds has a common behavior in which they fly in a group in search for a roost area. All other birds follow their neighbor. The neighbor follows their neighbors and so on. So, if any single bird finds the roost area, all the birds eventually group around that area. In the coal plant optimization problem, the yield value from each circuit at different operating conditions can be thought of single dimension and so on. An initial population of particles was created as a function of yield value of each circuit which can be given as:

$$\text{Particle population} = [x\ y\ z\ w] \tag{1}$$

where,
x = yield values of heavy medium vessel process at different specific gravity
y = yield values of heavy medium cyclone process at different specific gravity
z = yield values of spiral process at different specific gravity
w = yield values of flotation process at different residence time

The yield values of respective circuit as represented by x, y, z and w were generated randomly but within realistic limits as determined from the experimental results. The position of a particle is defined in terms of four dimensional x, y, z and w vector in a solution space. A set of random numbers were generated to create neighbors for each particle. For an initial population of forty particles, five neighbors were defined for each particle. These five neighbors were chosen among the population of particles excluding the particle itself.

$$\text{Neighbor particle} = [n_1\ n_2\ n_3\ n_4\ n_5] \tag{2}$$

where, n_1, n_2, n_3, n_4 and n_5 = neighbors

Also, an initial velocity vector was generated randomly for each particle. This was done so that the particles have a finite initial velocity in the solution space. This particle velocity vector is given below:

$$\text{Particle velocity} = [v_x\ v_y\ v_z\ v_w] \tag{3}$$

The velocity vector is a four dimensional vector, for the movement in each dimension represented for each circuit. For example, v_x is a velocity with which a particle changes its position in the x- dimension and so on, i.e., change in yield value for the heavy medium vessel process.

An objective function is defined to evaluate the fitness value of each particle. The objective function can be given as:

$$\text{Objective function} = f(Y, \Delta A, \Delta S) \tag{4a}$$
$$= w_y Y + w_a \Delta A + w_s \Delta S \tag{4b}$$

where,

Y = Overall yield value of the plant, i.e., weighted mean of the yield value of each circuit
= g(x, y, z, w)
ΔA = Difference in actual ash content and targeted ash content
= targeted ash content – actual ash content
ΔS = Difference in actual sulfur content and targeted sulfur content
= targeted sulfur content – actual sulfur content

w_y, w_a, w_s = weights for each cost component

The multiple product quality constraints are incorporated in the fitness function. The weights w_y, w_a and w_s are very sensitive to the specific type of constraints and need to be optimized with the change in product quality constraints.

The particle fitness is evaluated with the above objective function. The particle remembers its best position in the successive generation known as *pbest*. Also, the particle remembers the best fitness value of its neighbors it has achieved so far known as *gbest*. The fitness value of the particle (*pbest*) thus determined is compared with the best fitness value of the particles in its neighborhood (*gbest*). The best particle is chosen as the particle with the maximum fitness value. If the best particle is some particle in the neighborhood then the particle will orient itself toward the best particles by changing its position using the velocity vector. The particle updates its velocity and also changes its position as follows:

$$v[v'_x\ v'_y\ v'_z\ v'_w] = v[v_x\ v_y\ v_z\ v_w] + c1 * \text{rand}(0,1) * (\text{pbest}[x_p\ y_p\ z_p\ w_p] - \text{present}[x'\ y'\ z'\ w']) + c2 * \text{rand}(0,1) * (\text{gbest}[x_g\ y_g\ z_g\ w_g] - \text{present}[x'\ y'\ z'\ w']) \tag{5}$$

$$\text{present}\,[x''\,y''\,z''\,w''] = \text{present}\,[x'\,y'\,z'\,w'] + \text{velocity}\,[v'_x\,v'_y\,v'_z\,v'_w] \tag{6}$$

where,

present $[x'\,y'\,z'\,w']$ = Particle with current position
present $[x''\,y''\,z''\,w'']$ = Particle with updated position
velocity $[v_x\,v_y\,v_z\,v_w]$ = Particle current velocity vector
velocity $[v'_x\,v'_y\,v'_z\,v'_w]$ = Particle updated velocity vector
rand(0,1) = random number between 0 and 1
pbest$[x_p\,y_p\,z_p\,w_p]$ = Particle best position in successive generations
gbest$[x_g\,y_g\,z_g\,w_g]$ = Best neighbor particle
c1 and c2 = Stochastic weight factor

This process is repeated over the generations. The process stops when there is no change in the fitness value of the particles in consecutive generations.

4. Results and Discussion

The optimal yield of the plant determined from equal incremental product ash approach and particle swarm optimization over the baseline is presented in Table 2. It was revealed that plant produces 52% yield for the targeted plant constraints of 6.75% product ash and 1.3% product sulfur.

The same set of data was used for equal incremental ash analysis and particle swarming based models. The two models were simulated to determine the maximum yield for satisfying the plant product quality constraints of 6.75% ash and 1.3% sulfur. It can be observed from the simulation data presented in Table 1 that 2.73% higher yield can be generated from both equal incremental ash quality approach and particle swarm optimization. The results presented in Table 2 also recommend the necessary operating condition for each unit operation to achieve the optimal plant yield. Whereas the results listed for HMV and HMC are self explanatory, the set of operating condition and result listed for spiral appear to have some anomaly. Moving the product splitter (B) more inward helped increase the yield from 57.13% (for existing plant) to 67.16% (for PSO Approach) and 67.09% (for Incremental Ash Approach). However, the product ash content obtained from spiral decreased to 4.73% and 4.72%, respectively, instead of increasing from 5.22% obtained for the existing plant with this change in operating condition. It may be noted that the input data used for generating the simulated results from PSO and Incremental Ash optimization approaches were based on the size-by-size washability analysis conducted on a composite spiral feed sample collected over the entire period of spiral test program (almost 8 hours). On the other hand, the spiral product ash content listed for the existing plant was obtained from the product sample collected over only ½ hour period that Test 2 (listed in Table 1) was conducted. The authors believe that variation in plant feed characteristics may have caused the resulting anomaly.

The increase in the plant yield may have significant impact on the overall profitability of the plant. In terms of monetary value, even a 0.5% incremental in the yield of the plant by merely changing the operating settings of each circuit may contribute significantly to the profitability of the plant. For example, assuming the plant capacity of 10 million tons of clean coal per annum, and $20 per ton the selling price of the coal, an increment of 2.73% high yield may generate an additional revenue of $5,460,000 per annum.

Table 2. Comparative plant optimization results obtained from this investigation

Comparative Optimal Results					
	HMV	HMC	Spiral	Flotation	Overall
Feed Characteristics					
Ash (%)	37.13	50.23	33.37	49.66	42.61
Sulfur (%)	0.94	1.12	2.06	0.74	1.17
Product Characteristics					
Operating Conditions	D50 1.50	D50 1.44	Splitter Position A = 6.5", B = 0.5"	Residence Time (168 s)	
Yield (%)	63.49	39.60	57.13	55.01	52.00
Ash (%)	6.81	6.67	5.22	10.86	6.75
Sulfur (%)	1.11	1.27	1.11	0.90	1.18
PSO Approach					
Product Characteristics					
Operating Conditions	D50 1.69	D50 1.61	Splitter Position A = 6.5", B = 1.40"	Residence Time (93.89 s)	
Yield (%)	63.87	42.78	67.16	47.36	54.73
Ash (%)	7.03	7.15	4.73	9.95	6.75
Sulfur (%)	1.07	1.33	1.04	0.90	1.15
Incremental Ash Approach					
Product Characteristics					
Operating Conditions	D50 1.69	D50 1.61	Splitter Position A = 6.5", B = 1.46"	Residence Time (95.33 s)	
Yield (%)	63.89	42.76	67.09	47.52	54.73
Ash (%)	7.04	7.15	4.72	10.01	6.75
Sulfur (%)	1.07	1.33	1.04	0.90	1.15

CONCLUSION

Particle swarm optimization is a new generation of evolutionary algorithms and is used for the first time for optimizing the clean coal yield obtained from a coal preparation plant while simultaneously satisfying multiple product quality constraints. It is a non-linear way of optimizing the yield of a coal preparation plant and is suitable for any set of discrete data. Both, equal incremental ash quality approach and particle swarm optimization generates an additional yield of 2.73% over the normal operation of the plant contributing $5,460,000 per annum towards the profitability of a plant producing 10 million tons of clean coal per year. The particle swarming based optimization can be generalized for any number of product quality constraints. The product quality constraints just need to be incorporated in the objective function and the weights need to be optimized for increasing number of product quality constraints.

Particle swarming appears to be a promising approach to optimize the yield of a complex coal plant. The future prospect of the study lies in modifying the objective function to one unique function that can incorporate any quality constraints with no reward / penalty on the cost components.

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