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Research Article

APPLICATION OF SIMULATED ANNEALING ALGORITHM FOR THE MAGNETIC FILTRATION PROCESS

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ABSTRACT

The optimization of the magnetic filtration processes parameters on the separation performance of corrosion particles from waste-water suspensions by magnetic filter have been discussed. By using the magnetic filter performance formulas presented in the literature, a base model for magnetic filter performance is selected and the magnetic filter cleaning coefficient is optimized by changing several selected filter process parameters. The magnetic field intensity, diameter of the matrix elements (balls), filter length and filtration velocity are chosen as the inputs parameters and cleaning coefficient as output parameter. The Simulated Annealing (SA) Algorithm was applied to the model. Four variables were successfully optimized.
Keywords: Magnetic filtration, simulated annealing, optimization.

1. INTRODUCTION

In all industrial areas, the cleaning of corroded substances from liquids and gases continues to be one of the most actual problems today, by means of contribution to the solution of environmental problems [1-9]. Since corrosion particles generally exhibit magnetic properties therefore magnetic filters are recommended as effective method for the removal of these particles [1-5]. Cleaning of liquids and gases with magnetic filters is a physical method and does not involves chemical reagents. Due to the magnetic force applied to the particles held in the pores of the matrices of these kind of filters, the performance of the magnetic filters is higher than the conventional filters operating under the same conditions. Such filters allow effective removal of corrosion particles in micron scale [2-5]. The most important part of the magnetic filter, which consists of a non-magnetic body and the inlet-outlet tubes, is a packed bed matrix which is magnetized by the external magnetic field. The matrix of the magnetic filter is made up of ferromagnetic ball, chips, steel wools, cylinders, rods, shaped plate, and so on. Ferromagnetic balls should be preferred as filter matrix elements for building mathematical models of the cleaning of liquids and gases from the corrosion particles, the geometry of the filter matrix and the filtering kinetics [2, 3]. In spite of the fact that, the theory and practice of high gradient magnetic filter in general are mainly formed in the 1970s, both the theory and practical applications of magnetic filters with matrices from ferromagnetic balls have been and are still

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being made by the Russian scientist Prof. A.V. Sandulyak and his students since 1980 [2-5] and developed by other researches [6,7]. According to these studies; the cleaning coefficient (ψ) in the magnetic filters varies exponentially [2-4],

$$\frac{\psi}{\lambda} = 1 - \exp(-\alpha L) = 1 - \exp(-\xi) \quad (1)$$

Here in Eq.1 λ the magnetic mixture contained in the filtered liquid, α is the retention coefficient of the particle, L is the length of the filter and $\xi = \alpha L$is the logarithmic cleaning coefficient of the filter [2, 3]. In magnetic filters, logarithmic cleaning coefficient depends on almost all parameters of the filtering process such as magnetical, geometrical, hydrodynamical, and rheological, etc.

$$\xi = f\left(H, d, L, V_f, \mu, \rho, \eta, \delta, k\right) \quad (2)$$

Here in Eq.2 definitions of parameters are as follows; H, the magnetic field intensity; d, diameter of matrix elements (balls);L, filter length; V_f filtration velocity of the suspension; μ, magnetic permeability of matrix elements (balls);ρsuspension density;η, dynamic viscosity of the suspension;δ, size of the captured particles; k, magnetic susceptibility of captured particles. Some of these parameters such as the magnetic field intensity, filtration velocity of the suspension, dynamic viscosity of the suspension, suspension density and filter length can be adjusted during the filtration process. Other parameters like magnetic permeability of matrix elements, size of the captured particles, the concentration of particles that accumulate in the retention zone and others are the parameters that cannot be directly controlled in the filtration process. In general, parameters affecting filtration processes are defined as active and passive parameters in the literature [2-4]. It has been determined that one of the most important parameters affecting the magnetic filtration process in many laboratory and industrial experiments is the filtration velocity of the suspension [2-4]. Accordingly, it is of great importance to examine the effect of the basic parameters of the magnetic filtration processes on the filter cleaning coefficient. Therefore, the examination of the fundamental parameters H, d, L and V_f which affect the filter cleaning coefficient still remains as a significant problem. Comprehensive and detailed theoretical and experimental examinations of magnetic filters, which are generally composed of ferromagnetic granules, have been carried out and presented in the literature [2,3]. But the modeling and simulation of the factors affecting the magnetic filter performance by different algorithms and the resolution of many problems in terms of using these results in the automation of the magnetic filtering process still remains as an actual technical problem. In this paper, the problem of determining the optimum values of certain operating parameters of magnetic filters which are formed by ferromagnetic spherical matrix elements by means of SA algorithm is discussed. For this purpose, general relation between filtering coefficient and optimized parameters is established by using the filter performance formula selected from literature. In this relation, magnetic field intensity, size of matrix elements, filtering velocity and filter length were selected as variable parameters. Iterations are run to optimize the filter cleaning coefficient values according to the changes of the selected variable parameters while keeping the other performance parameters that affect the filter performance constant. The input parameters of magnetic filters and the relations between these parameters are presented in the literature and has been proven by many experiments[2-4]. The parameters used here has been selected based on the working parameters of the real magnetic filters in use which has been proven by numerous experiments [2-5,7]. The results obtained from the optimization process are compared with these values by means of similarity. Considering these results, it is determined that SA algorithm model can be used for optimization of magnetic filter performance. In the optimization model with the SA algorithm, the input parameters of the electromagnetic filtration process are selected as follows:

- Magnetic susceptibility (k) : 0,4
- Suspension density(ρ) : 1000 kg/m^3
- Size of the captured particles(δ) : 2×10^{-6}m
- Magnetic mixture contained in the filtered liquid (λ): 1

The theoretic models are rep orted in the literature to calculate performances of magnetic filter and magnetic separator [1-9]. Theoretic models used for performance of the magnetic filter that have magnetic granules is gives in following equations [2-4,6].

$$\frac{\psi}{\lambda} = \left(1 - exp\left\{-a_1 \frac{kH^{0.75}\delta^2 L}{v_f d^2 \eta}\right\}\right) \quad (3)$$

$$\frac{\psi}{\lambda} = \left(1 - exp\left\{-a_2 \left[\frac{\kappa\mu^{1.38} H^2 (1-\phi)\delta}{\rho d V_f^2}\right]^{0.6} \frac{L}{d}\right\}\right) \quad (4)$$

where a_1 and a_2 is coefficients. After analysis of similar models reported in the literature [2-6] the filtering coefficient of the magnetic filter is selected as follows according to the optimization parameters,

$$\psi = \left(1 - exp\left\{-A \left[\frac{H^{0,455} L}{d^{1,6} V_f^{1,2}}\right]\right\}\right) \quad (5)$$

The parameters in equations 5 are dimensionless to be easy for optimum model calculations.

2. SIMULATED ANNEALING (SA)

Annealing simulation has been applied as a optimization technique to many optimization problems in various fields such as computer design, image processing and modeling and scheduling. In recent years, many researchers have used SA in combinatorial optimization problems. Annealing simulation is preferred in many studies because it is a simpler method than other intuitive such as genetic algorithm. It is easy to use computer program and needs few control parameters. SA was originally motivated by the process of physical annealing in metal work and successfully used in optimization [10]. SA is a decision-making technique derived from statistical mechanics to find solutions to large-scale optimization problems simulating the annealing process in which the enthalpies are slowly cooled from a specific starting temperature to a global minimum. The purpose or energy function corresponds to the function that will be minimized by the annealing simulation algorithm. The control parameter is temperature and evaluates the probability of achieving a better solution for minimization problems. In the annealing process, the states of the float represent possible solutions of the optimization problem, and the energy values of these cases correspond to the calculated objective function values for the solutions. The minimum energy state represents the optimal solution to the problem. SA is an iterative algorithm that tries to continuously develop a solution expressed in the form of numbers in the solution space. According to this analogy, the temperature value is used to determine the probability of accepting worse solutions than the best solution obtained. It is started with a high temperature value and a certain number of solutions are produced before the temperature value is lowered in each step. New solutions are either accepted or rejected according to criteria specified. Every falling temperature affects the likelihood of leaving a solution at hand and passing a new solution. The algorithm terminates when the temperature reaches a minimum value or when the algorithm runs for the desired iteration [11-15].

2.1. Simulated Annealing Algorithm

The algorithm is an iterative and iterative algorithm that does independent random research on the problem. SA has the ability to find global optimum by getting rid of local minimums with various strategies applied. Physical annealing was modeled by Metropolis et al. Based on Monte Carlo technique. E system energy and k is the Boltzmann constant, the probability of an energetic increase in energy E is expressed by the following equation:

$$p(\delta E) = \exp(-\delta E/kT) \quad (6)$$

Metropolis and colleagues developed the Monte-Carlo method to simulate a crystal thermal equilibrium access for a constant T temperature value. This simulation generates a deterioration in the current situation and the resulting energy change due to this change is calculated. If energy is reduced, the system is shifting towards this new situation. If the energy is increased, the new situation is assessed according to the probability given above. In short, the method produces a series of crystal states. A slight deterioration of the crystal state is achieved by displacing a randomly selected molecule after the current state of the crystal (S, characterized by the positions of the molecules) is set.

If the difference between the current state (S) and the newly produced state (S) energy levels (E) is negative, the new state is at the lower energy level and S is considered as new state. S is accepted then processing is continued from this state. $\delta E \geq 0$ is generated from a uniform distribution random number (0,1). If this number is smaller than the probability value defined by Equation ($\theta \leq e^{-\delta E/T}$) then S is considered as new.

Otherwise the current state (S) is maintained as a new solution. This acceptance is called the metropolis (or simulation) criterion. According to Equation 11, p (δE) converges to 1 for all energy states at high temperatures. Even at low temperatures it is likely that the system has a high energy level. For this reason, the statistical distribution of the energies allows the system to go from a minimum of local energy.

In the course of the application of a SA probing, an appropriate initial value for the temperature parameter T must be determined, the cooling rate and the temperature change must be defined, the number of iterations to be performed at each temperature should be decided and the stop criterion for termination of the call be determined (fig.1) [14-15].

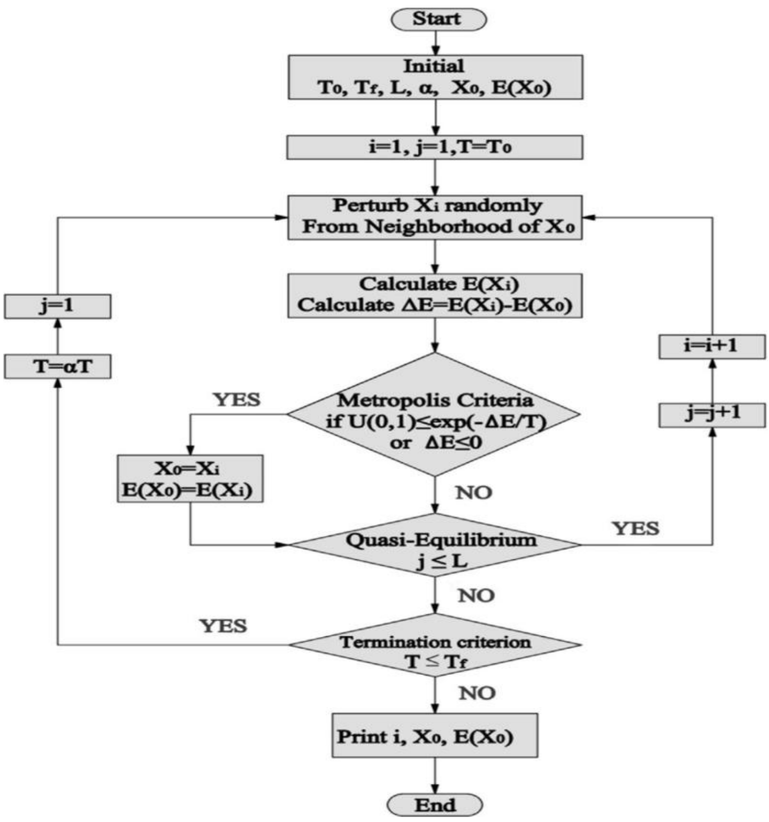

Figure 1. Flowchart of the simulated annealing algorithm.

2.2. Optimization of Cleaning efficiency by Simulated Annealing

In the optimization of the worker's annealing simulation, the values of the starting temperature, annealing type, temperature function, stop condition are given in the literature and they are given in Table 1. The choice of this plan is important for the effectiveness of the algorithm. The initial temperature was set at 100 and the temperature was reduced exponentially to $0.75.10^{-3}$ at the end of 3000 iterations. The computation was performed in MATLAB 7.0 environment [16].

Table 1. SA option values

Option SA optimumset	Annealing function	Initial temperature	Maximum iteration	Temperature function
Value	Boltz type annealing	100	3000	Exponential (temperature exp)

It is obvious that the cleaning performance of the magnetic filter will depend on the operating levels of the relevant variables. In this work, we aimed at the optimization of the magnetic strength, the diameters of the balls, the filter length and filtration velocity for the cleaning efficiency of the magnetic particles from the artificial corrosions suspensions. For this purpose we employed a SA to achieve a maximum level of cleaning performance based on the model given by Eq.5.

3. RESULTS AND DISCUSSION

The results of annealing simulations used to maximize the cleaning performance are shown in Table 1. The optimum experimental conditions levels such as the diameter of the balls, the filter length, the magnetic strength, and the filtration velocity were found to be the most influential factors affecting the cleaning performance. The maximum cleaning performance was found as 0,838 while the optimum levels of the variables that produced this output is given in Table 2.

Table 2. SA optimum values

Diameter of the ball (m)	The filter length (m)	The magnetic strength (kA/m)	The filtration velocity (m/s)	Cleaning performance
$4{,}80\text{x}10^{-3}$	0,10	120	$5\text{x}10^{-2}$	0,838

As a result of the optimization method, it was seen that the electromagnetic filtration cleaning performance reached the lower limit of the selected values for the diameter of ball and the filtration velocity ranges, the magnetic strength and the filter length approached the upper limit of the selected values. SA was successfully employed for the optimization of magnetic filtration variables to obtain the high cleaning efficiency. Optimum variables levels are $4{,}8\text{x}10^{-3}$ m of the diameters of the balls, 0,10 m of the filter length, 120 kA/m in the magnetic strength and 0,05 m/s in the filtration velocity for maximum cleaning efficiency (ψ). It is make confirm experiment on the optimum variables and obtained similar result for cleaning efficiency. The mathematical model found by the SA (R^2=0.90) is quite satisfactory. In conclusion, the SA has proved suitable in finding a global optimum for an exponential model. On the other hand, MATLAB Simulated Annealing tool has been found very convenient to carry out such an optimization task. A confirmation experiment is the final step of the optimization. It is made experiment that the optimum conditions suggested in the table 3. The confirmation experiment results (cleaning performance=0,825) is performed to find suitable.

4. CONCLUSIONS

SA was successfully employed for the optimization of EMF variables to obtain the highest cleaning performance. Optimum variables levels are $4{,}75\times10^{-3}$ m of the diameters of the balls, 0,10 m of the filter length, 98,00 kA/m in the magnetic strength and 0,05 m/s in the filtration velocity for maximum cleaning efficiency coefficient (ψ). It is make confirm experiment on the optimum variables and obtained similar result for cleaning efficiency. The mathematical model found by the SA (R^2=0.90) is quite satisfactory. In conclusion, the SA has proved suitable in finding a global optimum for an exponential model. On the other hand, MATLAB Simulated Annealing tool has been found very convenient to carry out such an optimization task.

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