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Cleaner production for continuous digester processes based on hybrid Pareto genetic algorithm

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Abstract: Pulping production process produces a large amount of wastewater and pollutant emitted, which has become one of the main pollution sources in pulp and paper industry. To solve this problem, it is necessary to implement cleaner production by using modeling and optimization technology. This paper studies the modeling and multi-objective genetic algorithms for continuous digester process. First, model is established, in which environmental pollution and saving energy factors are considered. Then hybrid genetic algorithm based on Pareto stratum-niche count is designed for finding near-Pareto or Pareto optimal solutions in the problem and a new genetic evaluation and selection mechanism is proposed. Finally using the real data from a pulp mill shows the results of computer simulation. Through comparing with the practical curve of digester, this method can reduce the pollutant effectively and increase the profit while keeping the pulp quality unchanged.

Keywords: cleaner production; multi-objective optimization; genetic algorithm; Pareto stratum; concentration of residual alkali; Kamyr continuous digester

Introduction

With obsolete technology, equipment, and management, China' s pulp and paper industry is recognized as being one of the most highly polluting sectors. Its plants discharged over 3 million t/a of COD in 1995, accounting for 41.8% of the overall industry pollution load of China(Ren, 1998). In the pulp industry, Kraft pulping is the most widely method of chemical product pulps, and its waste liquor brings the main pollution from digester process. It is the key part of cleaner production by using optimal technology to decrease wastewater discharge or wastewater content of NaOH and Na_2S in the digester process. In the research of modeling for the digester process, Sidrak(Sidrak, 1995), Williams(Williams, 1992) *et al*. analyzed the fundamental model of kaft pulping process; Chen and McAvoy(Chen, 1996) proposed to setup multivariete statistical models by using historical data. In the way of optimization and control, the mainly optimal approach is alone the quality object of pulp for batch digester(Chari, 1973; Lee, 1994). Wang and Xiao(Wang, 2000) used weighting method to transform multi-objectives to an objective optimal problem. Weighting factors, however, are often abstract and do not have physical meaning when dealing with disparate performance criteria. It is usually very difficult to fix on the weighting coefficient well and truly. In this paper, a model of multi-objective is set up, in which pulp's quality pollution and cost factor is considered; a hybrid genetic algorithm based on Pareto stratum-niche count is designed for finding near-Pareto or Pareto optimal solutions for the problem.

1 Multi-objective models of continuous digester process

1.1 Models for continuous digester

The most important variable in determining the pulp quality is the Kappa number, which is a measure of the residual lignin content in the pulp. It not only is related to ratio of gain pulp and rigidity, but also directly influences the dosage of chloride in bleach process (relate to pollution of wastewater in bleach process). The Kappa number is fixed on by H-factor and the concentration of effective alkali in the phase of a mass of removes lignin(Richard, 1983).

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$$k = \frac{\alpha D^{\beta}}{H^{\mu} E_n^{\delta}}. \tag{1}$$

Where, H is the H-factor; it is expressed as Eq.(2)

$$H = \int_0^{t_d} e^{43.18 - \frac{16113}{T+491.69}} dt = t_d e^{43.18 + \frac{-16113}{T+491.69}}. \tag{2}$$

Then, Kappa number is Eq.(3)

$$k = \frac{\alpha D^{\beta}}{t_d^{\mu} E_n^{\delta}} e^{-\mu(43.18 - \frac{16113}{T+491.69})}. \tag{3}$$

Where, α, β, μ, δ are estimated by using real data. For parameter estimation, the logarithmic form of Eq.(3) is used since the results in a linear parameter estimation problem(Parthasarath, 2000).

The relationship among Kappa numbers, concentrations of residual and initial alkali can be presented by equation as follow(Mortimer, 1984):

$$E_n = \frac{1}{a}(k - bE_0 - c). \tag{4}$$

In the Eq.(1), k is the Kappa number, D is the mass radio of white liquor chip, E_n is the concentration of residual alkali (g/L), E_0 is the concentration of initial alkali, T is the average temperature of digester area (℃), t_d is the time that pulp stuff pass digester area(minutes), a, b, c are constants by experiment. They depend on category of tree, sulfidity, chips size, and so on.

The black liquor is primary pollutant in the continuous digester process and its primary component is alkali (NaOH and Na_2S). If the concentration of residual alkali is controlled to minimal value of craft set, the concentration of alkali in black liquor will be reduced so that the working load of recovery alkali section will be lightened. The concentration of alkali in black liquor also can be regarded as the final concentration of residual alkali. Therefore, the concentration of residual alkali E_n is the primary control parameter to decrease pollution.

1.2 Objective functions

First, the quality of pulp is considered. It is fixed on Kappa number, which is shown in Eq.(1), where let Kappa number to close the minimal set value of craft k_p.

Objective function 1:

$$f_1 = (k - k_p) = \frac{\alpha D^{\beta}}{t_d^{\mu} E_n^{\delta}} e^{-\mu(43.18 - \frac{16113}{T+491.09})} - k_p. \tag{5}$$

Second, the concentration of residual alkali is minimized. The concentration of residual alkali E_n in digester process is presented by Eq.(3).

Objective function 2:

$$f_2 = E_n = \frac{1}{a}(k - bE_0 - c). \tag{6}$$

Third, the cost of pulp in pulping process is also minimized. The cost of pulp is consisted of gain rate of pulping, alkaline consumption and steam consumption.

According to real data, the regression equation of gain rate of pulping ρ and temperature T_d is represented as follows:

$$\rho = -0.5385 T_d - 13.61. \tag{7}$$

Alkali consumption is sum that cost in the digester and alkali recovery process.

$$\Delta m = E_0 m_1 - \eta E_n m_1 = E_0 m_1 - \eta m_1 (k - bE_0 - c). \tag{8}$$

The thermal consumption of steam in the digester process is

$$Q = \lambda(T_d - T_0)(m_1 + m_2). \tag{9}$$

Use p_1, p_2, p_3 to denote the price coefficient of chip, alkali and steam respectively, the production cost of pulping can be described as:

$$p = p_1 m_1 (1 - \rho) + p_2 \Delta m + p_3 Q. \tag{10}$$

Objective function of production cost is

$$f_3 = \min(p_1 m_1 (1 - \rho) + p_2 \Delta m + p_3 Q). \tag{11}$$

The model of multi-objective can be denoted the problem of vector mathematical programming (VMP; Hu, 1990):

$$V - \min f(x) = [f_1, f_2, f_3]^T$$

$$\text{Subject to: } 0 \leqslant t \leqslant 250,\ 100 \leqslant T \leqslant 190. \tag{12}$$

In Equation (1)—(11), m_1, m_2 are denoted the mass of chip and white liquor, T_0 is the initial temperature of digester, λ is the specific heat of steam, $\alpha = 26900, \beta = 0.153, \delta = 2.13, \mu = 0.927, a = 2.153, b = -119.8, c = 159.47, T_0 = 100(℃), E_0 = 130.5(g/L), k_p = 20$, $m_1 = 12000(kg)$, $m_2 = 48000$ (kg), $\lambda = 1.34$ kJ/kg(℃), alkali recovery-rate is $\eta = 86\%, p_1 = 400, p_2 = 1700, p_3 = 220$.

2 Hybrid Pareto GA

Genetic algorithm (GA) is a search technique based on the biological process of natural selection and genetic inheritance. Since first introduced by Holland (Holland, 1975), several algorithms for multi-objective optimization have been explored (Ritzel, 1994; Goldberg, 1989).

The proposed hybrid multi-objective genetic algorithm in this paper combines the Pareto GA (Schaffer, 1985) with the niche Pareto GA (Horn, 1993). The two methods are combined to make up the weakness of each other, so that it can be attempted to simultaneously meet the two issues of the quality and diversity of solutions. The fitness function is determined by the non-dominated sorting procedure as described earlier; the selection strategy uses niche Pareto GA, which mainly maintains the diversity of solutions.

2.1 Niche counts

The proposed selection method associates each individual with a rank that is determined by the density of individuals and Pareto. We use the concepts of niche counts and Pareto strata.

Niche counts are calculated for each individual of a generation first. D_{ij} is the distance of an individual and other individual. In the domain $D \leqslant R$ (R is a constant), the number of all individuals is niche counts.

$$D_{ij} = \sqrt{\sum_{k=1}^{M} (x_{ik} - x_{jk})^2}, (i = 1, \cdots, M - 1, j = i + 1, \cdots, M). \tag{13}$$

Where M is the size of population. A solution located in a less niche count is allowed to have a higher probability to survive in the next generation if these individuals are included in the same Pareto stratum, which is described below.

2.2 Pareto strata

The means of Pareto stratum is basically the same as the non-dominated frontier suggested by Goldberg

(Horn, 1993). A higher probability will be assigned to a solution contained in a stratum found earlier.

Using these two indirect measures, i.e. non-dominated frontier and density, we carry out the fitness evaluation. The overall selection procedures are presented below. $P(t) = \{p_1, \cdots, p_M\}$ is the current population and $p_{(r)}$ is the individual whose rank is r.

Step 0: Let $r = 0$, $n = 1$ and $P_n = P(t)$.

Step 1: For each individual in $P(t)$, its niche count is calculated.

Step 2: Find the nth Pareto stratum, select k non-dominated solutions from P_n, denote $PS_n = \{(p_i, b_i)\}$, $i = 1, \cdots, k$, b_i is the niche count associated with p_i.

Step 3: The individuals of PS_n are sorted by the niche count in increasing order of the niche count of b_i, $|PS_n|$ denote maximum rank in the PS_n, and assign the $(r + s)$ to the sth individual, for $s = 1, \cdots, |PS_n|$.

Step 4: Let $r = r + PS_n$, $n = n + 1$ and $P_n = P_{n-1} - PS_{n-1}$. If $P_n \neq 0$, go to step 2; otherwise, go to step 5.

Step 5: For each individual, determine the probability of survival using a rank-based selection scheme wherein the Eq.(14) is used

$$\text{Prob}\ [p_{(r)}] = q(1-q)^r, r = 1, \cdots, N. \tag{14}$$

Where q is the selection parameter $(0 < q < 1)$.

In this selection, the primary factor of selecting individuals is the Pareto stratum. Solution density is considered secondarily for individuals in a same Pareto stratum. It contributes to maintaining a distribution of diverse solutions in a population.

3 Hybrid Pareto GA for the continuous digester process

In this section, the genetic representation, initial population, fitness function, genetic operators and various genetic parameters are described in the hybrid Pareto GA.

3.1 Float point representation (Jomikow, 1991)

Due to multi-objective optimization for continuous digester process is continuous non-line functions optimal problem, which demands higher precision. The characteristic of float point representation is that can denote more large scaled number, adapt to high precision genetic calculation, easy research for large space and dispose complex constraint conditions.

3.2 Initial population

An initial population is necessary to run the algorithm. In this research, individuals in the initial population are all generated randomly.

3.3 Fitness functions

Fitness is a criterion of the selection process. Since the continuous digester process deals with multiple objective problems, each individual has multiple fitness values. In the domain, its fitness for each objective is evaluated by using the objective functions described in the Eqs. (5), (6) and (11). The selection mechanism for multiple objective problems is discussed in Section 2.

3.4 Arithmetic crossover

In this research, arithmetic crossover operator is jointly used to adapt float point representation (Michalewicz, 1992). Assuming arithmetic cross-over is carried out between two individuals X_A^t and X_B^t, two new individuals are generated after arithmetic crossover according to follow equations:

$$\begin{cases} X_A^{t+1} = \theta X_B^t + (1-\theta)X_A^t \\ X_B^{t+1} = \theta X_A^t + (1-\theta)X_B^t \end{cases}. \tag{15}$$

Where θ is a constant, $0 \leqslant \theta \leqslant 1$.

3.5 Uniform mutation(Michalewicz, 1993)

Assuming an individual $X = x_1 \cdots x_k \cdots x_l$, if x_k is the point of mutation, and its scope is $[U_{min}^k, U_{max}^k]$, after uniform mutation operation go through to this individual in the point, a new gene value of mutation point is:

$$x'_k = U_{min}^k + \xi(U_{max}^k - U_{min}^k). \tag{16}$$

Where ξ is a random number in scope $[0,1]$, in which submits the distribution of uniform probability.

All parameters in above genetic algorithm are: the size of population $M = 240$; the step of genetic operator terminating $T = 500$; crossover rate p_c is 0.8; mutation rate p_m is 0.1; the distance of an individual and other individual $D_{ij} \leqslant 0.5$; $\theta = 0.93$; $\xi = 0.43$.

The process of Pareto stratum-niche GA is summarized as follows:

Step 1: Set $t = 0$, generate and evaluate initial population $P(t)$.

Step 2: For 3 objective functions, an initial population is divided into 3 subpopulations, each of which has the same number of individuals. Each subpopulation is associated with one objective function. The solution in a subpopulation is evaluated by only using the associated objective. Select k ($k < M$) individuals from each subpopulation. The selection is performed independently on each subpopulation according to 2.2 Section, but cross-over is carried out across subpopulation boundaries, and each subpopulation produce k offsprings.

Step 3: Copy the offsprings into $P(t+1)$.

Step 4: Select M-k distinct individuals from $P(t)$ into $P(t+1)$.

Step 5: Evaluate individuals in $P(t+1)$, $t = t+1$.

Step 6: Estimate $t <= T$? If $t > T$, stop, else go to step 2.

4 Optimal results

Applying the hybrid Pareto GA algorithm, 6 Pareto solutions are gotten, and they are shown in Table 1. In Table 1, the value of cost is disposed by using standardization. In Table.2, optimal result is shown which practical measure data from pulp plant and optimal data in the same operation condition.

Table 1 Pareto solutions

No	Temperature, K	Length, min	Object 1	Object 2	Object 3 (cost)
1	172	167	28	17.7	31
2	160	180	33	16.3	36
3	158	207	35	15.7	48
4	181	126	22	18.6	26
5	147	241	38	14.4	85
6	160	151	24	18.1	27

Table 2 Compared optimal results with actual data

No.	Actual Kappa number, r	Actual residual alkali, g/L	Residual alkali reduce, %	Cost degrade, %
1	27	17.1	0.6	1.9
2	33	17.1	4.6	1.3
3	34	23.9	8.2	-0.6
4	23	16.9	-8.8	2.8
5	39	16.7	15.8	-1.8
6	23	17.4	-3.5	3.3

Choosing No.2 solution in Table 1 as control parameters of digester terminal, $T = 160$(℃), $t = 180$ (min), the concentration of residual alkali is 16.3 (g/L); the Kappa number is 33 as set value to control quality of pulp, a PID control is used to control the temperature of the digester process. The response curve of practical Kappa number and optimal curve are shown in Fig.1. Which the optimal curve is gotten by using optimal parameters and Eq.(5), and the practical Kappa curve is close to the optimal curve, it shows that control effect is satisfactory, the optimal result of digester process is also practical. The optimal digester curve and practical curve is shown in Fig.2. By optimization the concentration of residual alkali reduces from 17.1(g/L) to 16.3(g/L) in the final of digester process.

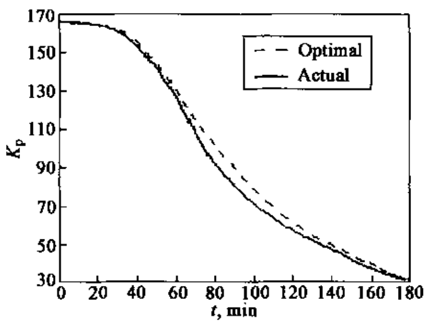

Fig.1 Practical and optimal curve of Kappa number

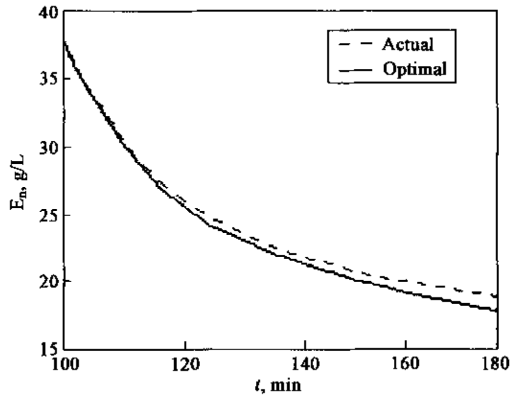

Fig.2 Practical and optimal curve of the concentration of effective alkali

5 Conclusions

In this research, a hybrid genetic algorithm is developed to obtain diverse near-Pareto optimal solutions to multiple objective optimizations in the continuous digester process. Mathematical models for the three objectives are setup. The simulation result according to real data from a plant shows that the concentration of residual alkali can be reduced by 4.6%, cost is decreased 1.3% in the precondition of guaranteeing pulp's quality. Simultaneously, the alkali recovery-rate can be improved; the load of follow alkali recovery section is lightened. The results illustrated that the model of multi-objective is good, the hybrid multi-objective genetic algorithm is an effective optimal approach and the effect of environmental protection to the pulping process is obvious.

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