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A Rapid Mixed Batch Blending Method Based on Chaos Genetic Algorithm

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Abstract: Aiming at the shortcomings of low accuracy and low efficiency of the conventional genetic algorithm, an improved chaos genetic algorithm is proposed to solve the problem of mixed batch blending. Firstly, turbulence of chaos is adopted to produce initial population. Secondly, a real number coding space is taken as genotype of the problem in which the crossover and mutation operations are carried out. Thirdly, after the crossover, mutation and selection operations are performed, turbulence of chaos is once again applied to those individuals with relatively low fitness so as to accelerate the speed of convergence. In the experiment, both our improved chaos genetic algorithm and the conventional genetic algorithm are utilized to solve the problem of mixed batch blending of Chinese herbal medicine. As the experimental results show, our improved chaos genetic algorithm is proved to be superior to the conventional genetic algorithm with respect to accuracy and efficiency.

Key words: Mixed batch blending, chaos, genetic algorithm, turbulence

INTRODUCTION

Mixed batch blending is a common process in the production of foods, medicines, drinks and wines. To produce the products with good quality is to ensure the stability of the contents of each component of the products, so it is an important problem in the quality control of production in enterprises. Solving of this problem can bring a good fame and plenty of economic benefits for the related enterprises. Therefore, there are great meanings to solve this problem well.

Conventional manual calculation of blending scheme is not only time-costly but also inaccurate. And now it is gradually replaced by some computerized blending methods. Nonlinear least square method was adopted to solve the problem of mixed batch blending of Chinese medicine extractive and the codes were realized in Matlab (Liu and Cao, 2006). Similarity degree of finger print of Chinese medicine and RDC of index components were took as indexes of quality evaluation, optimal model was built and gradual quadratic programming method was adopted to realize the mixed batch blending of Chinese medicine (Qu *et al*., 2006). The similarity degree of finger print and root-mean-square error of contents of index components were selected as common optimal goal, genetic algorithm was utilized to calculate coefficient of blending and mixed batch blending of each batch of extractive was made (Yang *et al*., 2009). A kind of new method was suggested which utilized HPLC finger print to measure multiple contents of index components and utilized linear and nonlinear optimal theories to blend Chinese medicine in order to ensure the stability of multiple contents of index components of Chinese medicine mixture (Yang *et al*., 2007;Yang and Wang, 2010).

Genetic algorithm is an optimal method which is widely applied to the fields of function optimization, combination optimization, production and scheduling, automation control, pattern recognition, multi-object optimization, etc. The nature of the problem of mixed batch blending is the problem of optimization. Therefore, genetic algorithm is suitable for solving this problem. Genetic algorithm has been proposed by J. Holland since 1975. In the past 4 decades, genetic algorithm has been greatly developed and various transmutations of genetic algorithm come into being. A michigan-based variable-length coding genetic algorithm was proposed which adopted various heuristic strategies to select genes for crossover operation (Wang and Gong, 2011). An attempt to intermix the search properties of GA and reinforcement learning were made in order to develop a hybrid algorithm which had a better searching ability and power to reach a near optimal solution of TSP problem (Liu *et al*., 2011). In order to reduce the sensitivity of the support vector machines(SVM) to noise and outliers, a new fuzzy least squares-support vector machines classifier based on chaos genetic algorithm was proposed (Wang *et al*., 2011). To improve the accuracy of remote sensing image classification, a kind of remote sensing image classification method based on chaos genetic algorithm was proposed (Huang and Wu, 2011). A multi-constraint evolutionary algorithm based scheduler for fuzzy grid job scheduling was presented (Liu *et al*., 2006). A novel genetic algorithm, named Double Population Genetic Algorithm (DPGA) to improve the performance of the conventional genetic algorithm was proposed (Zhao and Xiu, 2011). Human reproduction mode was used for reference and an improved genetic algorithm named adaptive genetic algorithm simulating human was proposed (Yan, 2009).

MATHEMATICAL MODEL OF MIXED BATCH BLENDING

The nature of mixed batch blending is to solve the problem of multi-object optimization. That's to say, we need to ensure each component in solution vector lies within a certain range. The mathematical model of mixed batch blending can be denoted as Eq. 1:

$$\begin{bmatrix}1\\ b_1-c_1\\ \vdots\\ b_m-c_m\end{bmatrix} \le \begin{bmatrix}1 & 1 & \cdots 1\\ a_{10} & a_{11} & \cdots a_{1,n-1}\\ a_{20} & a_{21} & \cdots a_{2,n-1}\\ \cdots & & \\ a_{m0} & a_{m1} & \cdots a_{m,n-1}\end{bmatrix} \begin{bmatrix}x_0\\ x_1\\ \vdots\\ x_{n-1}\end{bmatrix} \le \begin{bmatrix}1\\ b_1+c_1\\ \vdots\\ b_m+c_m\end{bmatrix} \tag{1}$$

where, n is the batch number of Chinese herbal medicine, m is the component number of Chinese herbal medicine, $[a_{i0}, a_{i1}, \cdots, a_{i,n-1}]$ is the contents of No. i component of n batches, $[x_0, x_1, \cdots, x_{n-1}]^T$ is the solution vector, b_i is the ideal content of No. i component, c_i is the permitted maximal deviation of No. i component and $c_i>0$.

CHAOS GENETIC ALGORITHM

Creation of initial population: Firstly, in the chaos genetic algorithm, the initial population of genotype is created. A real number type of genotype is used to denote each individual in the coding space which can accelerate the speed of following operations of crossover and mutation. Each initial individual is denoted as vector $[x_{m1}, x_{m2}, \cdots, x_{mn}]$, where $x_{mi} \in [0,1], m = 1, 2, \cdots, M$ and this vector must meet the constraint:

$$\sum_{i=1}^{n} x_{mi} = 1$$

Generally speaking, chaos is the movement state with randomness obtained from specific equation and the variable presenting chaos state is named as chaos variable. In this study, chaos turbulence is applied to those individuals with relatively low fitness in order to increase the global searching ability and accelerate the speed of solution convergence. Here logistic mapping is adopted to represent the mathematical model which can be denoted as equation 2:

$$u_i^{k+1} = \mu u_i^k (1 - u_i^k) \tag{2}$$

where, k is the iteration number, μ is the control parameter and $u_i^0 \in [0, 1]$. So we can get an specific sequence of. With different values of $u_i^0, u_i^1, \cdots, u_i^k$ μ, the solutions of the system present different characters.

The initial value of chaos value can be produced by equation 3:

$$u_{mi}^0 = \frac{x_{mi} - a_{mi}}{b_{mi} - a_{mi}} \tag{3}$$

where, m = 1, 2..., M and i = 1, 2, ..,n. So the chaos sequence can be obtained by equation 2 and 3. The optimization algorithm of chaos is to map the chaos space to original solution space. The mapping function can be denoted as equation 4:

$$x_{mi} = a_{mi} + (b_{mi} - a_{mi}) u_{mi}^k \tag{4}$$

where, m = 1, 2, .., M and i = 1, 2, ..,n.

Crossover operator: Assume P_c is the crossover probability and select $M \bullet P_c$ pieces of individuals from population M to make crossover operations. Assume X_1, X_2,... represent the parent population and divide these individuals into pairs (X_1, X_2), (X_3, X_4) (X_5, X_6). Take pair (X_1, X_2) as an example to describe the operation of crossover. A random number e is created with range (0, 1) and the crossover operator can be denoted as equation 5 and 6:

$$X_1' = eX_1 + (1 - e)X_2 \tag{5}$$

$$X_2' = (1 - e)X_1 + eX_2 \tag{6}$$

Mutation operator: Assume (x_1, x_2,...,x_n) is a parent individual and $x_i \in [a_i, b_i]$. Then the mutation operation can be denoted as equation 7:

$$x_i' = \begin{cases} x_i + \Delta(g, b_i - x_i) & \text{random}(\bullet) > 0 \\ x_i - \Delta(g, x_i - a_i) & \text{random}(\bullet) < 0 \end{cases} \tag{7}$$

where, $(\bullet)$ is the random function with mean distribution, $\Delta(g,x) = x[1 - \eta^{(1-\frac{g}{G})^\beta}]$, η is a random number, $\eta \in [0,1]$, G is the maximal generation number of mutation, g is the current generation number of mutation, β is a parameter which determines the degree of disagreement.

Selection operators: In this study, an optimal selection operator is adopted to select the fittest individuals from the parent population, the population after crossover operation and the population after mutation operation. And to ensure the stability of the number of individuals in the new generation, a fixed number of individuals with optimal fitness are selected as the population of next generation.

Postponed chaos turbulence: After the operations of crossover, mutation and selection, chaos turbulence is carried out on those individuals with relatively low fitness. Assume the individual after the operations of crossover, mutation and selection is denoted as $(x_1^*, x_2^*, \cdots, x_n^*)$. Chaos turbulence is performed on those individuals using the equation 8:

$$x_i(k) = x_i^* + \alpha u_{ki} \tag{8}$$

where, i = 1, 2, ..., n, x_i (k) is the chaos variable in smaller feasible region of traverse, α is an adjustment parameter which is related to iteration number k and:

$$\alpha = 1 - \left(\frac{k-1}{k}\right)^n$$

COMPARISON EXPERIMENT

In the experiment, both conventional genetic algorithm and our improved chaos genetic algorithm are adopted to solve the problem of mixed batch blending of Chinese herbal medicine. The content data of Chinese herbal medicine are shown in Table 1, in which there are 6 batches of Chinese herbal medicine with 2 components.

The comparison experiment is divided into 3 groups. The first group is the 2-batch blending in which No. 4 batch and No. 6 batch are utilized to make blending. The second group is the 3-batch blending in which No. 3 batch, No. 4 batch and No. 6 batch are utilized to make blending. The third group is the 4-batch blending in which No. 1 batch, No. 2 batch, No. 4 batch and No. 6 batch are utilized to make blending. The experimental results are shown in Table 2, Table 3 and Table 4, respectively.

As we can see from Table 3, all the average deviations by our improved chaos genetic algorithm is lower than 1% and those by the conventional genetic algorithm are higher than 2%. Therefore, the accuracy of our improved chaos genetic algorithm is much higher than that of the conventional genetic algorithm. As we can see from Table 4, all the iteration number of our improved chaos genetic algorithm is 1 and those of the conventional genetic algorithm are 3 or much more

Table 1: Content data of 6-batch Chinese herbal medicine

Batch No.	Content of puerarin	Content of daidzei
Blending goal		
	3.06	0.322
	2.89	0.376
	3.18	0.272
	2.49	0.393
	2.72	0.341
	2.61	0.375
	3.28	0.308

Table 2: Optimal solutions of the 2 methods

	Conventional genetic algorithm			Improved chaos genetic algorithm		
Optimal solution	No. 1	No. 2	No. 3	No. 1	No. 2	No. 3
2-batch blending	(0.7323, 0.2677)	(0, 1)	(0.0315, 0.9685)	(0.3467, 0.6533)	(0.3675, 0.6325)	(0.3766, 0.6234)
3-batch blending	(0.3622, 0.1732, 0.4646)	(0.0630, 0.5906, 0.3465)	(0.1260, 0.6063, 0.2677)	(0.0560, 0.2629, 0.6811)	(0.0950, 0.2308, 0.6742)	(0.0805, 0.1935, 0.7260)
4-batch blending	(0.3228, 0.1181, 0.5512, 0.0079)	(0.0079, 0.1260, 0.8110, 0.0551)	(0.3937, 0.2992, 0.1890, 0.1181)	(0.3838, 0.4400, 0.0567, 0.1196)	(0.2636, 0.2626, 0.1492, 0.3246)	(0.2003, 0.1254, 0.1621, 0.5122)

Table 3: Accuracy comparison of the 2 methods

	Conventional genetic algorithm			Improved chaos genetic algorithm		
Average deviation	No. 1 (%)	No. 2 (%)	No. 3 (%)	No. 1 (%)	No. 2 (%)	No. 3 (%)
2-batch blending	4.68	5.77	5.32	0.82	0.52	0.39
3-batch blending	6.16	4.31	6.18	0.55	0.52	0.90
4-batch blending	7.10	5.44	2.41	0.48	0.21	0.70

Table 4: Efficiency comparison of the 2 methods

	Conventional genetic algorithm			Improved chaos genetic algorithm		
Iteration No.	No. 1 (%)	No. 2 (%)	No. 3 (%)	No. 1 (%)	No. 2 (%)	No. 3 (%)
2-batch blending	6	3	4	1	1	1
3-batch blending	9	7	21	1	1	1
4-batch blending	14	15	12	1	1	1

Therefore, the efficiency of our improved genetic algorithm is much higher than that of the conventional genetic algorithm.

CONCLUSION

In this study, an improved chaos genetic algorithm is proposed and applied to solving the problem of mixed batch blending of Chinese herbal medicine. An initial population is created and chaos turbulence is performed to those individuals with relatively low fitness. A real number coding space is taken as the genotype of the problem, in which the operations of crossover and mutation are carried out. After the operations of crossover, mutation and selection, a chaos turbulence is once again performed to those individuals with low fitness in order to increase the ability of searching optimal solutions. In the comparison experiment, both the accuracy and efficiency of our improved genetic algorithm are much higher than those of the conventional genetic algorithm.

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