A novel cascade optimization method based on butterfly optimization algorithm

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Abstract. The parameter optimization of a multi-component isotope separation cascade is a multi-dimensional problem, involving many variables such as cut for stages, feed stage and separation factors. In this paper, a novel metaheuristic algorithm called butterfly optimization algorithm (BOA) is applied for the first time in cascade optimization field. Different objective functions are introduced like $D$ function and a combination of $D$ function and total flow rates. BOA method solves the problem of a 20-stage square cascade optimization to separate Xenon isotopes with the aim of getting the greatest $D$ value or the least flow rates. The optimization results show that the optimal cut is close to the sum of the concentrations of the lightest $N_C$ isotopes. A 21-stage step cascade is optimized as well to obtain the best working conditions to separate $^{72}$Ge and the cut $\theta$ is consistent with the experiment results. The calculation results indicate that BOA shows good performance in terms of calculation stability, speed and convergence to global optimum compared with traditional optimization methods and other metaheuristic algorithm like TLBO.

1. Introduction
There is a great demand for stable isotopes in the world. The problem of isotope separation cascade optimization is extremely important for the production of isotope separation. Even one percent fluctuation of the flow can influence the profits to some extent.

Different from the traditional optimization methods, metaheuristic methods are inspired by nature and have comprehensive searching space. It is less likely for a metaheuristic method to fall into local optimal value. Several nature-inspired metaheuristic algorithms have been proposed in the past decades, such as Genetic Algorithm (GA) which is a simulation of the crossover and mutation of chromosome genes in biological evolution (Goldberg and Holland 1988) [1], Differential Evolution (DE) which is an adjustment of GA (Storn and Price 1997) [2], Particle Swarm Optimization (PSO) which is inspired by the swarm behavior like fish or birds in nature (Eberhart and Shi 2001) [3], Artificial Bee Colony (ABC) which is based on the intelligent foraging behavior of honey bee swarm (Karaboga and Basturk 2007) [4], Firefly Algorithm (FA) which is inspired by the flashing behavior of fireflies (Yang 2010) [5], Teaching-Learning Based Optimization (TLBO) which simulates the interactive teaching and learning process of groups (Rao et al. 2011) [6], Monarch Butterfly Optimization (MBO) which is inspired by the migration behavior of monarch butterflies (Wang et al. 2015) [7], Whale Optimization Algorithm (WOA) which is inspired from the social interaction of humpback whales (Mirjalili and Lewis, 2016) [8], Grey Wolf Optimization (GWO) which is inspired by the leadership behavior and unique mechanism of hunting of grey wolves (Kohli and Arora 2017).
and so on. These algorithms have been used in global optimization problems and have better performance in solving complex and multi-dimensional problems under complicated constraints over a short period of time.

In the field of cascade optimization, many researchers have utilized these swarm intelligence algorithms to solve different problems in recent years. In 2011, Norouzi et al. optimized a counter-current cascade successfully and obtained optimal parameters, $\alpha$, $\theta$ and $f$ based on a real coded GA. In 2017, Safdari et al. [10] developed a real coded PSO algorithm (RCPSO) to design an optimum cascade, with the ratio of maximum separation work to the number of centrifuges and other additional limits as an objective function. In 2018, Mansourzadeh et al. [11] developed an efficient code using an enhance TLBO algorithm to optimize a multicomponent isotope separation cascade for the separation of Xenon isotopes, WF$_6$ and SF$_6$. When the objective function is $D$ function, the optimal square cascade is more efficient than the optimal tapered cascade. When the objective function is a combination of $D$ function and total interstage flow rates, the results show that a tapered cascade is more efficient accordingly. In 2019, Harmony Search algorithm was utilized by Mansourzadeh et al. [12] to optimize the R-cascade with minimum total flow rates, compared with the results obtained by virtual component variation. In 2020, ABC was used by Ezazi et al. [13] to design an optimum matched-X cascade, outperforming PSO. A net cascade optimization problem was solved by Ant Colony optimization algorithm (the code ACORNET) as well [14].

2. Cascade theory and governing equations

2.1. Structure of the counter-current cascade

A symmetric counter-current cascade is the foundation of the study and the scheme is shown in Fig.1. The number of stages of the cascade is $N$ and the machines are sequenced from left to right, numbered from 1 to $N$. In the middle, there is a feed stage numbered as $N_F$.

![Figure 1. Scheme of a symmetric counter-current cascade.](image)

$F$, $P$, $W$ are the feed, product and waste stream of the cascade. Heavy components come out of the cascade from the $W$ side, while the lighter components are enriched in $P$. For each stage and centrifuge, $L_n$ and $C_{i,n}$ are the flow and concentration value of the $i$th component of the feed stream. In addition, $L_{n}^{'}$, $C_{i,n}^{'}$ and $L_{n}^{''}$, $C_{i,n}^{''}$ are parameters for the head stream and the tail stream respectively.

2.2. Cascade equations

There are a set of mass conservation equations and the light components conservation equations. The conservation relationships are suitable not only inside the centrifuge with streams flowing in and out of but also at the merging points of streams. The equations are given as follows according to [17].

The cut of the first stage $\theta_1$ is define in the equation (1).

$$\theta_1 = 0.5(1 - W / G_f)$$ (1)
The flow rates of feed streams are given by the equation (2).

\[
L_n = \begin{cases} 
G_n - L_{n-1} - W, & 1 < n \leq N_F \\
G_n - L_{n+1} + P, & N_F < n \leq N 
\end{cases}
\]  

(2)

The separation factor for two components is \( \gamma_{ij} \).

\[
\gamma_{ij} = \frac{C'_i / C'_j}{C'_j / C'_i} = \gamma_0^{M_j - M_i}
\]  

(3)

\( \gamma_0 \) is the basic separation factor for unit mass difference. There are also other restricted conditions. For instance, the sum of the concentration values of a specific component is one.

3. Proposed butterfly optimization algorithm

Butterfly optimization algorithm (BOA) is a novel optimization approach proposed by Arora [15-16] that mimics the food foraging behavior of butterflies.

3.1. Definition of fragrance

In nature, there are thousands of species of butterflies all over the world and their swarm intelligence is reliable and worthy for people. Butterflies search for food and mate partners with the help of their sense of smell, taste, touch and sight. Among all of their senses, smell is the most important sense which helps butterflies to find nectar or other sources of food even though there is a long distance. Actually, there are chemoreceptors distributed over the surface of the butterfly’s body in different organs, such as antennae and legs. These receptors are essential and indispensable for the survival, courtship and reproduction of the butterfly population. A male butterfly is capable of locating another female butterfly by identifying its scent or pheromone emitted.

In BOA algorithm, butterflies are leading roles to perform the optimization task. Based on biological knowledge and observations, it is assumed that each butterfly can generate its unique fragrance with some intensity which will spread and be perceived by other butterflies in the area. It is necessary to calculate the fragrance of each butterfly based on the understanding of how a modality like smell is processed by a stimulus.

The concept of sensing and processing the modality such as smell or fragrance is described by three fundamental terms namely sensory modality (c), stimulus intensity (I) and power exponent (\( \alpha \)). In BOA, I stands for the magnitude of the real stimulus which is correlated to the fitness of the butterfly or the solution. The definition of fragrance (\( f \)) is a function of the physical intensity of stimulus as follows:

\[
f = c I^\alpha
\]  

(4)

3.2. Movements of butterflies

In BOA, the movements of the butterfly will change its fitness. A butterfly will get closer to another butterfly which has greater fitness or emits higher fragrance. This process is similar to global search. Under another circumstance, when a butterfly can’t sense a higher fragrance than itself, it will move randomly. This phenomenon is similar to random search approach and local search. That’s to say, there are two significant steps, viz. global search phase and local search phase. Apart from the initialization phase and the final phase, the search movements of butterflies are the core of the iteration phase of the algorithm.

In global search phase, the butterfly/solution will move to the best solution with the greatest fitness as shown in the equation (5):

\[
x_{i}^{t+1} = x_{i}^{t} + (r^3 \times g^{*} - x_{i}^{t}) \times f_{i}
\]  

(5)

\( g^{*} \) represents the best solution now available. \( x_{i}^{t} \) is the solution vector in the \( t \) th iteration for the \( i \) th butterfly. \( f_{i} \) means the fragrance of the \( i \) th butterfly and \( r \) is a random number from 0 to 1.

In local search phase:
\[ x_{i}^{t+1} = x_{i}^{t} + (r^2 \times x_{j}^{t} - x_{k}^{t}) \times f_{i} \]  \hspace{1cm} (6)

\[ x_{j}^{t} \text{ and } x_{k}^{t} \text{ are the solution vector for the } j \text{ th and the } k \text{ th butterfly selected from the solution space randomly. } r \text{ is a random number generated by the equation (7):} \]

\[ r = rand(0,1) \]  \hspace{1cm} (7)

In the foraging behaviour of the butterfly, global search and local search will both take place. A switch probability \( p \) is proposed to determine it, serving as a threshold value. After the random number \( r \) is generated, \( r \) will be compared with \( p \) to perform global search or local search.

3.3. The complete algorithm

The flow chart of BOA is presented in Fig.2. The structure of this algorithm is divided into three parts: initialization phase, iteration phase and eventual phase.

\[ x_{i} = [\theta_{1}, \theta_{2}, \ldots, \theta_{N_{F}}] \]  \hspace{1cm} (8)

In the equation (8), \( \theta_{i} \) is the cut of the \( i \) th stage and the integer \( N_{F} \) is the feed stage.

In the initialization phase, \( c, \alpha, p \) are assigned to 0.01, 0.1 and 0.8. The number of search agents is 30 and the maximum iteration number is set to 500 at first.
The calculation procedure of the objective function for each solution to evaluate fitness can be described into mainly three steps. First of all, flow rates of each stage should be calculated from the given mass conservation equations with the parameters of $x_i$. Secondly, concentration distribution of each stage of the cascade can be obtained with the help of iteration proposed by Zeng in 2000 [17]. At last, the fitness of the solution can be evaluated by the objective function.

4. Optimization results

In this paper, BOA algorithm and its relevant code are constructed in order to calculate and optimize the parameters of specific cascades. The optimization is first performed on a 20-stage square cascade to separate Xenon isotopes in order to test the efficiency of BOA method. Cascade parameters are set the same as the square cascade optimized by Mansourzadeh et al. [11], such as feed flow rates 80g/h, separation factor 1.40 and the optimization results will be compared with TLBO method.

The objective function is the essence of the aim of optimization which determines the trend of final results. In this study, more than two types of objective functions are introduced which lead to the best results for separation completeness (with the greatest value of $D$ function) and economic benefits (with a relatively small flow). Furthermore, BOA method is applied in a step cascade to separate $^{72}\text{Ge}$ isotope which is also an intermediate component.

4.1. Optimization with the objective function 1/$D$

The problem of multi-component isotope separation is complicated to some extent, especially for the intermediate component. Several isotopes are divided into two groups: the light part and the heavy part of the mixture. The components can be sequenced by mass and the isotope numbered as $N_C$ is the last isotope of the former group of isotopes. The more thoroughly the two groups are separated, the better. $D$ function is the criterion for the separation completeness of two groups of isotopes mentioned in [18] by Zeng.

$D$ function is defined as follows in the equation (9).

$$D = \frac{D}{\sum_{i=1}^{N_C} C_i + \sum_{i=N_C+1}^{N} C_i}$$

The value of $D$ should be less than 1 or equal to 1. When $D$ is exactly equal to one, it means that the two groups of isotopes are separated completely. Apparently, it is an ideal condition which is hard to achieve in reality. There are two forms of objective functions. In BOA, the algorithm optimizes the minimum value. So in order to get the greatest $D$, Objective Function 1 is the reciprocal of $D$ function. Objective Function 2 is a combination of $D$ and $G$(flow).

Objective Function 1 = $f(D) = \frac{1}{D}$

Objective Function 2 = $f(D, \sum_{i=1}^{N_C} G_i / F) = \frac{1}{D + m \sum_{i=1}^{N} G_i / F}$

4.1.1. Optimization of a square cascade for the separation of $^{129}\text{Xe}$. Some parameters of the 20-stage square cascade are set at the beginning. The separation factor $\gamma_0$ is 1.4. $N_C = 4$ and the feed flow rates are 80g/h. The ratio of the flow rates of each stage to the feed $G/F$ is variable from 1.5 to 20. The cuts of 20 stages are variable within the interval [0,1]. In fact, when the total cut of the cascade $\theta$ is determined, the interstage cuts can be calculated later with the equation (1) and the equation (2). The range of total cut $\theta$ is [0,1].

The range of the feed stage is 2-18. There is a small problem that the value of the integer $N_F$ is discontinuous and it is different to initialize $N_F$ from other parameters.
There are nine natural isotopes of Xenon. It is a typical multicomponent mixture separation problem of the separation of Xenon isotopes. The natural concentrations of Xenon isotopes are given in Table 1. In order to separate the first four Xenon isotopes including \(^{129}\text{Xe}\), \(N_\text{C} = 4\).

| Relative molecular mass | 124 | 126 | 128 | 129 | 130 | 131 | 132 | 134 | 136 |
|------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Natural abundance(%)   | 0.093 | 0.09 | 1.917 | 26.44 | 4.08 | 21.18 | 26.89 | 10.44 | 8.87 |

In this case, \(G/F = 10\). After optimization, the concentration distribution of Xenon isotopes is presented in Fig.3. It is obvious that the lightest four isotopes are mainly distributed in the \(W\) side, while most of the heaviest five isotopes are located in the left region of the curves. The curves of the two groups of isotopes rise up in the opposite directions. In the \(P\) stream at the end of the cascade, the concentration of \(^{129}\text{Xe}\) is 91.09\% which is enriched to a really high level.

The results of the optimum 20-stage square cascades obtained by BOA are listed in Table 2.

| Algorithm | Cut of each stage | \(N_F\) | \(D\)          |
|-----------|------------------|---------|----------------|
| BOA       | \(\theta_1\)     | \(\theta_2\) | \(\theta_3\) | \(\theta_4\) | \(\theta_5\) | \(\theta_6\) | \(\theta_7\) | \(\theta_8\) | \(\theta_9\) | \(\theta_{10}\) |              |          |
|           | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 0.4643 | 11 | 0.99058 |
|           | \(\theta_{11}\) | \(\theta_{12}\) | \(\theta_{13}\) | \(\theta_{14}\) | \(\theta_{15}\) | \(\theta_{16}\) | \(\theta_{17}\) | \(\theta_{18}\) | \(\theta_{19}\) | \(\theta_{20}\) |               |         |
|           | 0.4643 | 0.5643 | 0.4643 | 0.5643 | 0.4643 | 0.5643 | 0.4643 | 0.5643 | 0.4643 | 0.5643 | 0.4643 | 0.5643 |         |         |

When the total cut of the cascade is 0.2864, \(D\) reaches the greatest value 0.99058 by BOA. The convergence curve of BOA with 500 iterations is shown in Fig.4.
The iteration curve converges in several iterations, almost in the first ten iterations and the curve \( \text{declines very slightly to a flat one}. \) Based on the property of fast convergence of BOA, the maximum iteration can be set to 30 to save time in the calculations behind. It takes a long time for 500 iterations because of the embedded complicated concentration calculation processes. The overall algorithm is a systemic loop with several local loops. The convergence curves of 5 tests with 30 iterations are shown in Fig. 5. The five tests show good computational stability of BOA.

In order to compare the results of BOA with TLBO, \( G/F \) is set to 18.5 which is the same as the condition in the paper [11]. The optimal results of 20-stage square cascades with the first four Xenon isotopes separated obtained by using BOA and TLBO are listed in Table 3.

**Table 3.** Comparison of the optimum 20-stage square cascades with the first four Xenon isotopes separated using BOA and TLBO algorithms (\( N_C = 4, G/F=18.5 \)).

| Algorithms | Cut of each stage | \( N_F \) | \( D \) |
|------------|------------------|-------|-------|
| BOA        | \( \theta_1 \)   | 0.4807| 11    | 0.99187|
|            | \( \theta_2 \)   | 0.4807|       |       |
|            | \( \theta_3 \)   | 0.4807|       |       |
|            | \( \theta_4 \)   | 0.4807|       |       |
|            | \( \theta_5 \)   | 0.4807|       |       |
|            | \( \theta_6 \)   | 0.4807|       |       |
|            | \( \theta_7 \)   | 0.4807|       |       |
|            | \( \theta_8 \)   | 0.4807|       |       |
|            | \( \theta_9 \)   | 0.4807|       |       |
|            | \( \theta_{10} \)| 0.4807|       |       |
|            | \( \theta_{11} \)| 0.5348|       |       |
|            | \( \theta_{12} \)| 0.4807|       |       |
|            | \( \theta_{13} \)| 0.5348|       |       |
|            | \( \theta_{14} \)| 0.4807|       |       |
|            | \( \theta_{15} \)| 0.5348|       |       |
|            | \( \theta_{16} \)| 0.4807|       |       |
|            | \( \theta_{17} \)| 0.5348|       |       |
|            | \( \theta_{18} \)| 0.4807|       |       |
|            | \( \theta_{19} \)| 0.5348|       |       |
|            | \( \theta_{20} \)| 0.4807|       |       |
When the total cut of the cascade is 0.2863, $D$ reaches the greatest value 0.99187 by BOA. In contrast with the case that $G/F$ is 10, the optimal $D$ value increases a little with the increasing of the total flow rates. The sum of the concentrations of the lightest four isotopes of Xenon is 28.54%, namely 0.2854, which is close to the cut value. The optimization results of BOA are comparable to the results of TLBO and almost the same. The best feed stage is the intermediate stage, which is also in good agreement of Mansourzadeh’s result [11].

4.1.2. Optimization of a step cascade for the separation of $^{72}$Ge. A 21-stage step cascade to separate $^{72}$Ge is studied in this part. The separation factor $\gamma_0$ is 1.10. $N'_C = 2$ and the feed flow rates are 80g/h. The ratio of the flow rates of each stage to the feed $G/F$ is variable. In the stage of 10,11,12, $G/F$ is 14. In the stage of 7,8,9,13,14,15, $G/F$ is 12. In the rest stages, $G/F$ is set to 10.

The natural concentrations of Germanium isotopes are given in Table 4.

### Table 4. Natural abundances of Germanium isotopes.

| Relative molecular mass | 70 | 72 | 73 | 74 | 76 |
|------------------------|----|----|----|----|----|
| Natural abundance(%)   | 20.57 | 27.45 | 7.75 | 36.50 | 7.73 |

The optimal cut of the cascade by BOA method is 0.47526 which is close to the sum of the natural concentrations of $^{70}$Ge and $^{72}$Ge (0.4802). Under the optimal parameters, the value of $D$ function is 0.8447. Further experiment results of the separation of GeF$_4$ also indicate this distinguishing feature. With $D$ function as objective function, the optimum performance of a step cascade is not as good as a square cascade. The concentration distribution of different components and interstage cuts are shown in Fig.6 and Table 5.

![Figure 6](image-url)  
**Figure 6.** The concentration distribution of Germanium isotopes in the optimal 21-stage step cascade with a combined objective function ($N'_C = 2$).

### Table 5. Results of the optimum 21-stage step cascades with the first two Germanium isotopes separated using BOA algorithm ($N'_C = 2$).

| Algorithm | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ | $\theta_5$ | $\theta_6$ | $\theta_7$ | $\theta_8$ | $\theta_9$ | $\theta_{10}$ | $\theta_{11}$ | $\theta_{12}$ | $\theta_{13}$ | $\theta_{14}$ | $\theta_{15}$ | $\theta_{16}$ | $\theta_{17}$ | $\theta_{18}$ | $\theta_{19}$ | $\theta_{20}$ | $\theta_{21}$ | $N_F$ | $D$ |
|-----------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|--------|------|
| BOA       | 0.4738     | 0.4738     | 0.4738     | 0.4738     | 0.4738     | 0.4738     | 0.6738     | 0.6738     | 0.6738     | 0.6738     | 0.6738     | 0.5347     | 0.4807     | 0.5347     | 0.4807     | 0.5347     | 0.4807     | 0.5347     | 0.4807     | 0.5347     | 0.4807     | 0.99193 | 0.8447 |
4.2. Optimization with the objective function combined with I/D and total flow rates

In the equation (12), Objective Function 2 is a combination of $D$ and $G$. The ratio of the flow rates of each stage to the feed $G/F$ is variable from 1.5 to 20. In this case, $m$ is set to 1.28 and $F$ is 80g/h still.

The optimization results in Table 6. show that the optimal value of $G/F$ is 4.9906 so that the value of total flow rates is 7985g/h. The optimal cut of the square cascade is 0.2871.

**Table 6.** Comparison of the optimum 20-stage square cascades using BOA and TLBO algorithms with combined objective function ($N_C' = 4$).

| Algorithms | Cut of each stage | $N_F$ | $D$ | $\sum G$ (g/h) |
|------------|-------------------|------|-----|----------------|
| BOA        | $\theta_1\theta_2\theta_3\theta_4\theta_5\theta_6\theta_7\theta_8\theta_9\theta_{10}$ | 11   | 0.9860 | 7985          |
|            | 0.4286 0.4286 0.4286 0.4286 0.4286 0.4286 0.4286 0.4286 0.4286 0.4286 |      |      |               |
| TLBO       | $\theta_1\theta_2\theta_3\theta_4\theta_5\theta_6\theta_7\theta_8\theta_9\theta_{10}$ | 11   | 0.9854 | 7704          |
|            | 0.4258 0.4258 0.4258 0.4258 0.4258 0.4258 0.4258 0.4258 0.4258 0.4258 |      |      |               |

In this case, the value of $D$ function is 0.9860. The value of the objective function 2 is 1.0012 and 1.0013 for BOA and TLBO. In Table 3., the value of $D$ is 0.99187 in comparison. With a combined objective function, the value of $D$ decreases a little but the flow rates go down and it brings economic value.

5. Conclusion

In this paper, butterfly optimization algorithm (BOA) is used in cascade optimization successfully. Different objective functions are introduced to optimize a 20-stage square cascade for the separation of $^{129}$Xe and a 21-stage step cascade for the separation of $^{72}$Ge. The optimal cut of the cascade by BOA method is close to the sum of the natural concentrations of the lightest $N_C'$ isotopes. The optimization results are comparable to another metaheuristic algorithm TLBO. In conclusion, BOA shows good performance as respect to calculation stability, speed and convergence to global optimum and it is a promising powerful tool in cascade optimization.

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