



Orthogonal chemical reaction optimization algorithm for global numerical optimization problems



ZhiYong Li^{a,*}, Zheng Li^a, Tien Trong Nguyen^{a,b}, ShaoMiao Chen^a

^a College of Computer Science and Electronic Engineering, Hunan University, Changsha 410082, China

^b Faculty of Information Technology, Industrial University of Ho Chi Minh City, Ho Chi Minh, Viet Nam

ARTICLE INFO

Article history:

Available online 29 November 2014

Keywords:

Chemical reaction optimization
Orthogonal experimental design
Quantization orthogonal crossover
Global numerical optimization

ABSTRACT

Chemical reaction optimization (CRO) is a newly proposed, easy to implement metaheuristic inspired by the phenomena between molecules in chemical reactions. However, CRO behaves like a random search to traverse the whole solution space, which could confine the algorithm's search ability. The orthogonal experimental design (OED) method is a robust-design method that can obtain the best combination levels for different factors with a small number of experiment samples based on orthogonal array, thus possesses systematic reasoning ability. In this paper, OCRO, a new method based on CRO and OED, is proposed. This hybrid technique creates new molecules not only by two local search operations in CRO but also incorporates quantization orthogonal crossover (QOX) to serve as a global search operator. OCRO is tested on a set of 23 benchmark functions and compared with variants of CRO, ABC and OXDE, which is also based on the orthogonal method. The computational results show that our framework cannot only find optimal or close-to-optimal solutions but can also obtain more robust results with faster convergence speed in most parts of the experiment, especially for high-dimensional functions.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

There exist many global optimization problems in engineering design, information science, and related fields. Evolutionary algorithms (EAs) have shown considerable success in solving global optimization problems; thus, it has attracted much attention in the past few years. Recently, a large number of EAs, such as genetic algorithm (GA) (Goldberg, 1989), particle swarm optimization (PSO) (Kennedy, 1995), differential evolution (DE) (Storn & Price, 1997), artificial bee colony (ABC) (Karaboga, 2005), and chemical reaction optimization (CRO) (Lam & Li, 2010a), have been proposed.

Solving high-dimensional problems is a big challenge, and the presence of numerous local optima makes it more difficult (Leung & Wang, 2001). In the present paper, we considered global numerical optimization problems with constraints, which can be stated as:

$$\min f(x) \quad \text{subject to } l \leq x \leq u \quad (1)$$

where $f(x)$ is the objective function, $x = \{x_1, x_2, \dots, x_n\}$ is a vector of variables, n corresponds to the problem dimensions, and $l = \{l_1, l_2, \dots, l_n\}$ and $u = \{u_1, u_2, \dots, u_n\}$ define the lower and upper limits of the corresponding variables, respectively. The above equation means solution x' is the wanted optimum if $f(x') \leq f(x)$ for all x when they are in the feasible solution space.

Chemical reaction optimization (CRO) is a new population-based metaheuristic recently proposed by Lam and Li (2010a). It mimics the molecules' interactions in chemical reactions to reach a low energy stable state. CRO has received considerable attention, and it has been successfully applied in various real-world problems e.g., quadratic assignment problem, resource-constrained project scheduling problem, channel assignment problem in wireless mesh networks (Lam & Li, 2010a), population transition problem in peer-to-peer streaming (Lam, Xu, & Li, 2010), cognitive radio spectrum allocation problem (Lam & Li, 2010b), grid scheduling problem (Xu, Lam, & Li, 2010, 2011), artificial neural network training (Yu, Lam, & Li, 2011), and network coding optimization (Pan, Lam, & Li, 2011). CRO has not only shown good performance in the discrete domain but has also been proposed as a real-coded version, which was named as RCCRO, to solve continuous problems (Lam, Li, & Yu, 2012). A hybridization of PSO and CRO, which can outperform the original RCCRO, was proposed in the paper (Nguyen, Li, Zhang, & Truong, 2014). CRO explores the solution

* Corresponding author. Tel.: +86 13607436411.

E-mail addresses: zhiyong.li@hnu.edu.cn (Z. Li), zhengha1989@163.com (Z. Li), nguyenusb2005@gmail.com (T.T. Nguyen), chensm1987@hnu.edu.cn (S. Chen).

space and converges to the global optima through a random sequence of operations, which includes on-wall ineffective collision, decomposition, intermolecular ineffective collision, and synthesis. These operations have their own characteristics. On-wall ineffective collision and intermolecular ineffective collision, which are ineffective operators, give the effect of local search (Lam & Li, 2010a), in which the molecules are modified to their neighbor. Conversely, synthesis and decomposition tend to explore other regions of the PES (solution space) for better solutions after a

number of local searches by producing new molecules that may be very different from the original ones, however, they have low efficiency (Lam et al., 2012) for almost 23 benchmark functions listed in Fig. 1. The authors of CRO also mentioned in the paper (Lam, Li, & Xu, 2013) that, CRO behaved like a random search to traverse the whole PES. Its search ability and convergence speed are limited. Thus, how to focus on particular promising regions where the global optima are more likely to reside is an important issue we must pay attention to.

Category	Test Function	Name	<i>n</i>	<i>S</i>	<i>f_{min}</i>
I	$f_1(x) = \sum_{i=1}^n x_i^2$	Sphere model	30	$[-100, 100]^n$	0
	$f_2(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	Schwefel's problem 2.22	30	$[-10, 10]^n$	0
	$f_3(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$	Schwefel's problem 1.2	30	$[-100, 100]^n$	0
	$f_4(x) = \max_i \{ x_i , 1 \leq i \leq n\}$	Schwefel's problem 2.21	30	$[-100, 100]^n$	0
	$f_5(x) = \sum_{i=1}^{n-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$	Generalized Rosenbrock's function	30	$[-30, 30]^n$	0
	$f_6(x) = \sum_{i=1}^n (x_i + 0.5)^2$	Step function	30	$[-100, 100]^n$	0
	$f_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0, 1)$	Quartic function with noise	30	$[-1.28, 1.28]^n$	0
II	$f_8(x) = -\sum_{i=1}^n (x_i \sin(\sqrt{ x_i }))$	Generalized Schwefel's problem 2.26	30	$[-500, 500]^n$	-12569.5
	$f_9(x) = \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i) + 10)$	Generalized Rastrigin's function	30	$[-5.12, 5.12]^n$	0
	$f_{10}(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}\right) - \exp\left(\frac{1}{n} \sum_{i=1}^n \cos 2\pi x_i\right) + 20 + e$	Ackley's function	30	$[-32, 32]^n$	0
	$f_{11}(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	Generalized Griewank function	30	$[-600, 600]^n$	0
	$f_{12}(x) = \frac{\pi}{n} \left\{ 10 \sin^2(\pi y_1) + \sum_{i=1}^{29} (y_i - 1)^2 [1 + 10 \sin^2(\pi y_{i+1}) + (y_n - 1)^2] + \sum_{i=1}^{30} u(x_i, 10, 100, 4) \right\}$ $y_i = 1 + \frac{1}{4}(x_i + 1)$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m, & x_i > a \\ 0, & -a \leq x_i \leq a \\ k(-x_i - a)^m, & x_i < -a \end{cases}$	Generalized penalized functions	30	$[-50, 50]^n$	0
	$f_{13}(x) = 0.1 \left\{ \sin^2(\pi 3x_1) + \sum_{i=1}^{29} (x_i - 1)^2 [1 + \sin^2(3\pi x_{i+1})] + (x_n - 1)^2 [1 + \sin^2(2\pi x_{30})] \right\} + \sum_{i=1}^{30} u(x_i, 5, 100, 4)$		30	$[-50, 50]^n$	0
III	$f_{14}(x) = \left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (x_i - a_{ij})^6} \right]^{-1}$	Shekel's Foxholes function	2	$[-65.536, 65.536]^n$	1
	$f_{15}(x) = \sum_{i=1}^{11} \left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	Kowalik's function	4	$[-5, 5]^n$	0.0003075
	$f_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	Six-hump camel-back function	2	$[-5, 5]^n$	-1.0316285
	$f_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos x_1 + 10$	Branin function	2	$[-5, 10] \times [0, 15]$	0.398
	$f_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	Goldstein-Price function	2	$[-2, 2]^n$	3
	$f_{19}(x) = -\sum_{i=1}^4 c_i \exp\left[-\sum_{j=1}^4 a_{ij}(x_j - p_{ij})^2\right]$	Hartman's family	3	$[0, 1]^n$	-3.86
	$f_{20}(x) = -\sum_{i=1}^4 c_i \exp\left[-\sum_{j=1}^6 a_{ij}(x_j - p_{ij})^2\right]$		6	$[0, 1]^n$	-3.32
$f_{21}(x) = -\sum_{i=1}^5 [(x - a_i)(x - a_i)^T + c_i]^{-1}$	Shekel's family	4	$[0, 10]^n$	-10	
$f_{22}(x) = -\sum_{i=1}^7 [(x - a_i)(x - a_i)^T + c_i]^{-1}$		4	$[0, 10]^n$	-10	
$f_{23}(x) = -\sum_{i=1}^{10} [(x - a_i)(x - a_i)^T + c_i]^{-1}$		4	$[0, 10]^n$	-10	

Fig. 1. 23 benchmarks functions.

متن کامل مقاله

دریافت فوری ←

ISIArticles

مرجع مقالات تخصصی ایران

- ✓ امکان دانلود نسخه تمام متن مقالات انگلیسی
- ✓ امکان دانلود نسخه ترجمه شده مقالات
- ✓ پذیرش سفارش ترجمه تخصصی
- ✓ امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
- ✓ امکان دانلود رایگان ۲ صفحه اول هر مقاله
- ✓ امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
- ✓ دانلود فوری مقاله پس از پرداخت آنلاین
- ✓ پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات