DOI: 10.3901/CJME.2012.01.***, available online at www.cjmenet.com; www.cjmenet.com.cn

# New Optimization Method, the Algorithms of Changes, for Heat Exchanger Design

TAM Houkuan[1, *], TAM Lapmou[1], TAM Sikchung[2], CHIO Chouhei[2], GHAJAR Afshin J[3]

1 *Department of Electromechanical Engineering, Faculty of Science and Technology, University of Macau, Macao, China*
2 *Department of Mathematics, Faculty of Science and Technology, University of Macau, Macao, China*
3 *School of Mechanical and Aerospace Engineering, Oklahoma State University, Stillwater, Oklahoma, USA*

Received June 4, 2010; revised July 6, 2011; accepted August 16, 2011; published electronically August 25, 2011

**Abstract:** Heat exchangers are widely used in the process engineering such as the chemical industries, the petroleum industries, and the HVAC applications etc. An optimally designed heat exchanger cannot only help the optimization of the equipment size but also the reduction of the power consumption. In this paper, a new optimization approach called algorithms of changes (AOC) is proposed for design and optimization of the shell-tube heat exchanger. This new optimization technique is developed based on the concept of the book of changes (I Ching) which is one of the oldest Chinese classic texts. In AOC, the hexagram operations in I Ching are generalized to binary string case and an iterative process, which imitates the I Ching inference, is defined. Before applying the AOC to the heat exchanger design problem, the new optimization method is examined by the benchmark optimization problems such as the global optimization test functions and the travelling salesman problem (TSP). Based on the TSP results, the AOC is shown to be superior to the genetic algorithms (GA). The AOC is then used in the optimal design of heat exchanger. The shell inside diameter, tube outside diameter, and baffles spacing are treated as the design (or optimized) variables. The cost of the heat exchanger is arranged as the objective function. For the heat exchanger design problem, the results show that the AOC is comparable to the GA method. Both methods can find the optimal solution in a short period of time.

**Key words:** optimization, genetic algorithms (GA), travelling salesman problem (TSP), heat exchanger design, algorithms of changes (AOC).

## 1 Introduction

Heat exchangers are widely used in heating, ventilation, and air conditioning (HVAC) facilities, oil refineries, and other large chemical processes. Especially, shell-tube is the most widely used type of exchanger in the process industries. Therefore, design of shell-tube heat exchanger is one of the important topics in process industries and in thermal engineering. The traditional design method for shell-and-tube heat exchangers[1–3] requires the iterative process which involves the design conditions, the equipment geometries, and the heat transfer and friction factor correlations. Using the traditional iterative method, many trials are needed to satisfy the compromise between the heat exchange performance and the cost consideration. The optimized heat exchanger design can reduce not only the capital and running cost, but also can achieve the purpose of energy savings. However, the traditional method is time-consuming, and does not guarantee an optimal solution. Therefore, many researchers such as GOSSELIN, et al[4], applied the genetic algorithms (GA)[5] for designing the heat exchanger. The results outperformed the traditional method. Although GA is a powerful tool for the optimization (or design) problem, it is of interest whether there is any alternative approach that can provide a quick and accurate solution for such problem.

The book of changes (I Ching), which is one of the oldest Chinese classic texts, is a collection of statements about divination with 64 hexagrams. There are generally three processes of divining with I Ching: (1) obtain a hexagram, (2) read or understand the obtained hexagram, there are several methods (operators) of obtaining more information from a hexagram (e.g. to see the intricate, synthesis or mutual ancient divination symbol of the original one), and (3) obtain the corresponding inscriptions of the hexagrams through the book, I Ching. In China, people used the inscriptions as an aid of making decision or predicting future. In this paper, it is proposed that the 64 hexagrams can be generalized to the set of binary string with length $L$ such that the points in the domain of the

* Corresponding author. E-mail: hktam@umac.mo
This project is supported by Science and Technology Development Fund of Macao SAR (Grant No. 033/2008/A2), and Research Grant of University of Macau (Grant No. RG081/09-10S/TSC/FST), China

optimizing function can be encoded to the generalized hexagrams, thus the corresponding operators (methods of obtaining more information from a hexagram) is also generalized. As computation is needed, random search is used in obtaining hexagram in the first process. The inscriptions of hexagrams is changed to the optimizing function values such that comparison can be made in each iteration. Through the generalized I Ching process, the optimal solution can be found.

In this paper, the objective is to propose algorithms of changes (AOC) for optimal design of shell-tube heat exchanger. In comparison with the traditional method and GA, the I Ching will be evaluated whether it is an effective method for the heat exchanger design problem. Before solving the practical case, there is also a comprehensive examination for the new algorithms through treating the benchmark optimization problems such as the global optimization test functions and the travelling salesman problem.

## 2 Traditional Method and GA for Shell-Tube Heat Exchanger Design

Design of the heat exchanger is a complicated iterative process. Many variables are necessary to be taken into account. For designing the shell-tube heat exchanger, referring to Ref. [6], the equations with the design variables used in the traditional iterative process can be written as follows.

For a shell-tube heat exchanger, based on the specified heat rate ($Q$) and the log-mean temperature difference ($T_{LM}$), the tube surface area ($S$) can be obtained from

$$S = \frac{Q}{U \Delta T_{LM} F}, \tag{1}$$

where $F$ is the temperature difference correction factor.

The universal heat transfer coefficient ($U$) is computed through

$$U = \frac{1}{\frac{1}{h_s} + R_{foul,s} + \frac{d_o}{d_i} \cdot (R_{foul,t} + \frac{1}{h_t})}, \tag{2}$$

where $R_{foul}$ denotes the fouling inside the tube or the shell, $d_i$ and $d_o$ are the tube inside and outside diameters. CAPUTO, et al[6], defined the tube inside diameter as 0.8 of the tube outside diameter. The tube heat transfer coefficients ($h_t$) are calculated by the heat transfer correlations. According to the different flow regimes, the suitable heat transfer correlation[7, 8] is selected. For the shell-side heat transfer coefficients ($h_s$), they can be determined by the methods proposed by Refs. [9–11]. In Ref. [6], the Kern's method[9] was selected to calculate the shell-side heat transfer coefficient.

The Reynolds number in the tube and the shell sides must be calculated prior to the calculation of the heat transfer or friction factor coefficients. To evaluate the Reynolds numbers, the flow velocities in tube or shell sides are computed as follows[9]:

$$v_t = \frac{m_t}{\frac{\pi d_i^2}{4} \cdot \rho_s} \cdot \frac{n}{N_t}, \tag{3}$$

$$v_s = \frac{m_s}{a_s \cdot \rho_s}, \tag{4}$$

$$a_s = \frac{D_s \cdot B \cdot (P_t - d_o)}{P_t}, \tag{5}$$

where $m_t$ and $m_s$ are the tube-side and shell-side mass flow rates and $\rho_t$ and $\rho_s$ are the densities of the fluid inside tube and shell sides. The variables, $n$, $D_s$, $B$, and $P_t$ denote the number of tube passages, the shell-side inside diameter, the baffle spacing, and the tube pitch.

With the heat exchange surface area ($S$), the tube length ($L$) can be determined:

$$L = \frac{S}{\pi \cdot d_o \cdot N_t}, \tag{6}$$

where $N_t$ is the number of tubes, which can be calculated by

$$N_t = K_1 \cdot \left(\frac{D_s}{d_o}\right)^{n_1}, \tag{7}$$

where $K_1$ and $n_1$ are determined according to the number of passes and tubes arrangement as described in Ref. [3].

After getting the design specifications (mass flow rate, fluid properties, the in/outlet temperatures, and the heat exchanger configurations), the size of the heat exchanger ($S$, $L$) can be obtained through Eqs. (1)–(7). The procedures are repeated until the objective function (usually, the cost) is minimized. By the traditional method, the variables, $D_s$, $d_o$, and $B$, are necessary to be pre-determined in each iteration. Therefore, CAPUTO, et al[6], defined them as the optimization (or input) variables of GA and used the GA method to determine those values for minimizing the objective function:

$$C_{tot} = C_i + C_{oD}, \tag{8}$$

where the total annual cost ($C_{tot}$) is the sum of the capital investment ($C_i$) and the total discounted operated cost ($C_{oD}$). $C_i$ is computed as a function of the exchanger surface area:

$$C_i = a_1 + a_2 S^{a_3}, \tag{9}$$

where $a_1$ = 8 000, $a_2$ = 259.2, and $a_3$ = 0.91 are for exchangers made with stainless steel.

Then, $C_{oD}$ is computed from

$$C_{oD} = \sum_{k=1}^{ny} \frac{PC_E H}{(1+i)^k}, \tag{10}$$

$$P = \frac{1}{\eta}\left(\frac{m_t}{\rho_t}\cdot \Delta P_t + \frac{m_s}{\rho_s}\cdot \Delta P_s\right), \tag{11}$$

where the energy cost ($C_E$), the annual operating time ($H$), annual discount rate ($i$), equipment life ($k$), and the overall pumping efficiency are pre-defined. For the tube-side pressure drop ($\Delta P_t$), it is computed as the summation of the pressure drop in tube length ($\Delta P_{t,len}$) and elbows ($\Delta P_{t,elb}$):

$$\Delta P_t = \Delta P_{t,len} + \Delta P_{t,elb} = \frac{\rho_t \cdot v_t^2}{2}\cdot\left(\frac{L}{d_i} f_t + p\right)\cdot n, \tag{12}$$

where $p$ is a constant, and it can be obtained from Ref. [6] or Ref. [9]. According to various flow regimes and boundary conditions, the corresponding tube-side friction factor correlation ($f_t$) can be found from Ref. [7].

Regarding to the shell-side pressure drop, $\Delta P_s$ can be written in the form:

$$\Delta P_s = \frac{\rho_s \cdot v_s^2}{2}\cdot f_s \cdot \frac{L}{B}\cdot\frac{D_s}{D_e}, \tag{13}$$

where the hydraulic diameter ($D_e$) can be calculated based on the pitch arrangement[3] and, similar to the heat transfer coefficients in shell side, the friction factor ($f_s$) can also be computed by the methods proposed by [9-11].

For simplification, CAPUTO, et al[6], used the equation [12]

$$f_s = 2b_o \mathrm{Re}_s^{-0.15}, \tag{14}$$

as the shell-side friction factor.

SINNOTT[3] defined a methanol-brackish water shell-tube heat exchanger with the design specifications shown in Table 1. The original design assumed the heat exchanger with two tube-side passages and one shell-side passage. Based on the traditional method, the results from SINNOTT[3] are shown in Table 2. CAPUTO, et al[6], applied the GA method for optimal design of that heat exchanger. The upper and lower bounds of the optimization variables were employed: 0.1 m ≤ $D_s$ ≤ 1.5 m; 0.015 m ≤ $d_o$ ≤ 0.051 m; 0.05 m ≤ $B$ ≤ 0.5 m. Moreover, all values of discounted operating costs were computed with 10 yr, annual discount rate $i$ = 10%, energy cost $C_E$ = 0.12 \$/kW · h and an annual amount of work hours $H$ = 7 000 h/yr. Based on the objective/fitness function, the optimization variables were computed iteratively by the GA method in Ref. [6]. The results are shown in GA[6] of Table 2. In Eqs. (1) – (14), the values of some parameters such as $K_1$, $n_1$, and $\eta$, etc. were not totally presented in the article[6]. Therefore, the values of those parameters were re-defined in this paper and the design variables such as the length, surface area, and the cost, etc., were computed again by the simple genetic algorithms (SGA) method. The present results are represented in SGA in Table 2. As shown in Table 2, the size of the heat exchanger and the total cost calculated by the GA in Ref. [6] or SGA is lower than using the traditional method. It represents that the design of the heat exchanger given by GA is more optimized than that designed by the traditional method.

**Table 1. Design specifications of the methanol-brackish water exchanger**

| Specifications | Shellside: methanol | Tubeside: sea water |
|---|---|---|
| Fluid mass flow rate $m$/(kg · s$^{-1}$) | 27.80 | 68.90 |
| Inlet fluid temperature $T_i$/(°C) | 95.0 | 25.0 |
| Outlet fluid temperature $T_o$/(°C) | 40.0 | 40.0 |
| Fluid density $\rho$/(kg · m$^{-3}$) | 750 | 995 |
| Fluid heat capacity $C_p$/(kJ · kg$^{-1}$ · K$^{-1}$) | 2.84 | 4.20 |
| Fluid viscosity $\mu$/(Pa · s) | 0.000 34 | 0.000 80 |
| Thermal conductivity $\lambda$/(W · m$^{-1}$ · K$^{-1}$) | 0.19 | 0.59 |
| Conductive fouling resistance $R_{foul}$ /(m$^2$ · K · W$^{-1}$) | 0.000 33 | 0.000 20 |

**Table 2. Comparison of traditional method, GA from Ref. [6], and SGA in shell-tube heat exchanger design**

| Optimized variables | Traditional method | GA[6] | SGA |
|---|---|---|---|
| Shell inside diameter $D_s$/m | 0.894 | 0.830 | 0.832 |
| Tubes length $L$/m | 4.830 | 3.379 | 2.919 |
| Baffles spacing $B$/m | 0.356 | 0.500 | 0.500 |
| Tube outside diameter $d_o$/m | 0.020 | 0.016 | 0.015 |
| Tubes number $N_t$ | 918 | 1 567 | 1 761 |
| Overall heat transfer coefficient $U$/(W · m$^{-2}$ · K$^{-1}$) | 615 | 660 | 684.7 |
| Heat exchange surface area $S$/m$^2$ | 278.6 | 262.8 | 242 |
| Capitial investment $C_i$/\$ | 51 507 | 49 259 | 46 311 |
| Annual operating cost $C_o$/(\$ · yr$^{-1}$) | 2 111 | 947 | 944 |
| Total discounted operating cost $C_{oD}$/\$ | 12 973 | 5 818 | 5 803 |
| Total annual cost $C_{tot}$/\$ | 64 480 | 55 077 | 52 114 |

## 3 Algorithms of Changes and Results Discussion

In order to develop the new optimization algorithms, structural understanding of the I Ching divination system is needed. Below is a brief introduction of the divination system:

### 3.1 I Ching search space

In China, I Ching has been used as divination system since several thousand years. Basically, the divination is based on the 64 (that is $2^6$) sets of hexagrams. Each hexagram has 6 line segments, which can be divided as full line (positive) and broken line (negative). All the hexagrams form the search space shown in Fig. 1.

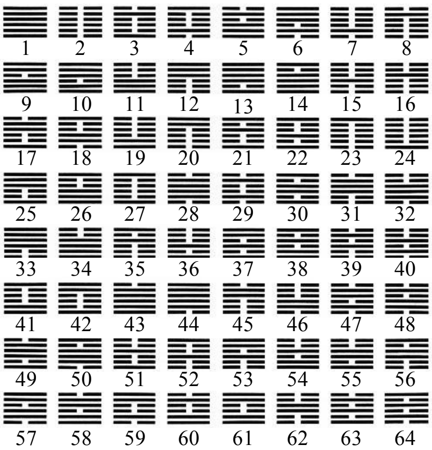



Fig. 1. I Ching search space (64 hexagrams)

### 3.2 Hexagram initialization and transformation

For initializing each line segment of the hexagram, the yarrow stalks or the coins methods are always adopted. When one of the 64 hexagrams is found, the obtained hexagram can also be transformed into different hexagrams by the intricate, synthesis, and the mutual methods (or operators), etc. The purpose of transformation is to obtain the complemented, dual and internal information of a hexagram. The transformation process is actually a way to explore the search space.

### 3.3 Objective evaluation

Each hexagram has its own meaning in text which is the interface between the divinator and the I Ching divination system. The divinator evaluates the outcoming hexagrams and determines the best hexagram for him. Certainly, the meaning is matched with the divinator's intuition. Through the divination system, the optimum hexagram can be obtained objectivity. Meanwhile, the divinator can make the corresponding decision according to the divination result. Therefore, such decision-making method is a kind of optimization method.

Based on the I Ching divination system, the algorithms of changes (AOC) is developed with originality. The new algorithm can be summarized in Fig. 2.

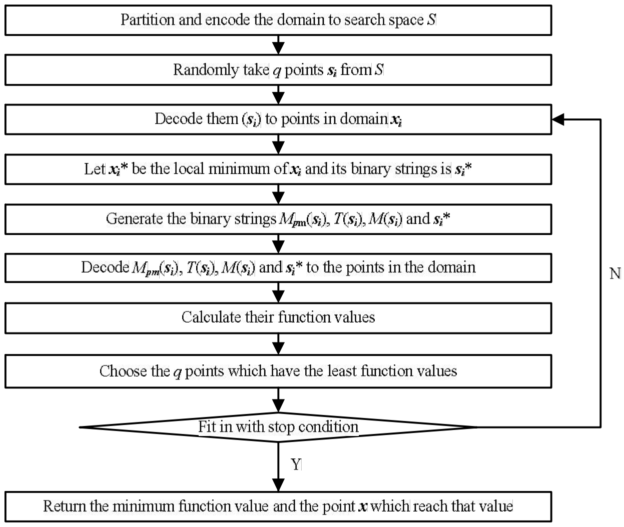



Fig. 2. New algorithms of changes

Suppose that an objective function is defined on a rectangular domain $W$ in $\mathbf{R}^n$ and let an input vector $x$ be $(x_1, x_2, ..., x_n)$. The input vector is encoded to be a binary string $[x_1]_2[x_2]_2 \cdots [x_n]_2$ with the length $L$ where $[\cdot]_2$ is the standard binary encoding on the corresponding intervals. By composition, the objective function can be considered to be a function defined on the search space $S$ of all the binary strings with the length $L$. Seeking for the minimum $x$ is now equivalently looking for the minimum string in $S$. For instance, as shown in Fig. 3, the domain $W$ in $\mathbf{R}^3$ is a $1\times1\times1$ cube. The search space is represented with the red cross point. It is the case of $L = 6$. The circled point (0, 1, 2/3) is encoded to [00 11 10]. Increasing the binary length $L$ can increase not only the number of search points in $S$ but also the accuracy.

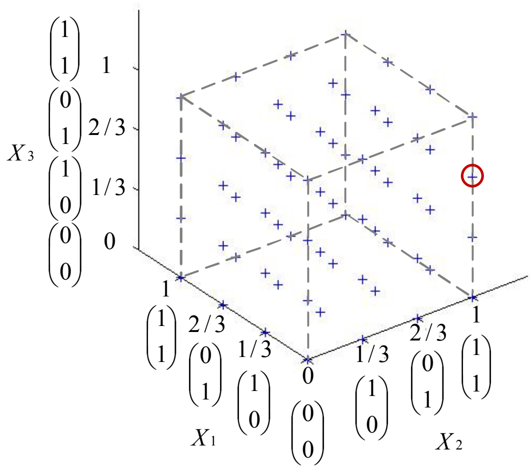



Fig. 3. Search space of AOC

Similar to GA, the AOC starts with randomly generating $q$ binary strings in search space $S$ to form an initial population. The binary strings here are considered as the extended version of hexagrams. Then the three kinds of I Ching operators are applied to those $q$ strings and form other $3q$ new strings. In order to find their functional values, all strings are decoded. The $q$ strings with the least functional values will be chosen to form the initial population for the next generation. After $N$ iterations, the best string in the last population can give out the most accurate interpretation i.e. the global minimum of the objective function.

In I Ching, there are three kinds of operators (namely intricate, synthesis and mutual) commonly used in the hexagram transformation. The generalization of those operators will be defined below. In order to define the generalized I Ching operators (intricate, synthesis, and mutual operators), let $S_L = \{0,1\}^L$ be a set of binary strings with length $L$. For instance, the 64 (that is $2^6$) hexagrams in I Ching can be represented as $S_6$.

### 3.3.1 *Mutation operator*

The mutation operator $M_{p_m}: S_L \to S_L$ imitates the intricate operator. It is the same as the mutation in GA. It maps $s \in S_L$ to $M_{p_m}(s) \in S_L$ by changing each bits of $s$ from 1 to 0 or 0 to 1 according to the probability $p_m$, see Fig. 4.

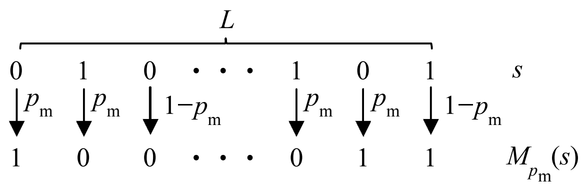



Fig. 4 Mutation operator of AOC

### 3.3.2 *Turnover operator*

The turnover operator $T: S_L \to S_L$ is a generalization of the synthesis operator. It maps $s \in S_L$ to $T(s) \in S_L$ by turnover the first $r$ bits or the least $L-r$ bits of $s$ with probability 0.5 respectively where $r$ is a random integer form 1 to $L$, refer to Fig. 5.

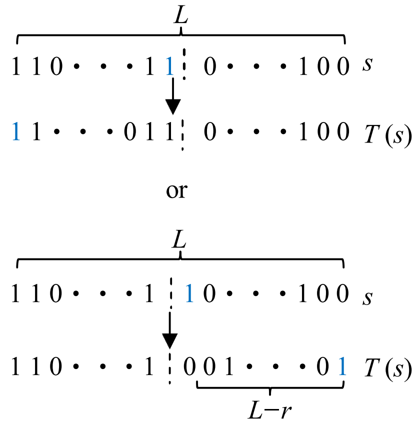



Fig. 5 Turnover operator of AOC

### 3.3.3 *Mutual operator*

The mutual operator $M: S_L \to S_L$ is a generalization of the mutual operator in I Ching. Let $s[i]$ and $M_{<k>}(s)[i]$ be the $i$-th bit of $s$ and $M_{<k>}(s)$ respectively. It maps $s \in S_L$ to $M_{<k>}(s) \in S_L$ by using operators $M_{<1>}: S_L \to S_L$ or $M_{<2>}: S_L \to S_L$ with probability 0.5 respectively. Operators $M_{<1>}$ and $M_{<2>}$ are defined as follows:

$$M_{<1>}(s)[i] = \begin{cases} s[2(i-1)+1], & 1 \leqslant i \leqslant \lceil \frac{L}{2} \rceil, \\ s[2(i-\lceil \frac{L}{2} \rceil)], & \lceil \frac{L}{2} \rceil + 1 \leqslant i \leqslant L, \end{cases} \quad (15)$$

$$M_{<2>}(s)[i] = \begin{cases} s[2i], & 1 \leqslant i \leqslant \lceil \frac{L}{2} \rceil - 1, \\ s[2(i-\lceil \frac{L}{2} \rceil)+1], & \lceil \frac{L}{2} \rceil \leqslant i \leqslant L. \end{cases} \quad (16)$$

The mutual operator is also depicted in Fig. 6.

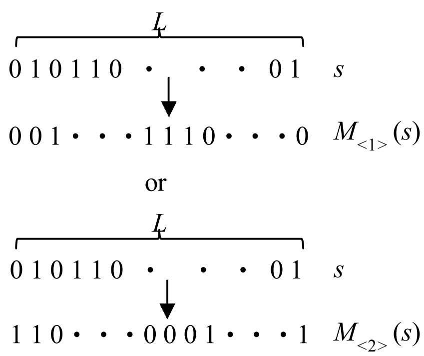



Fig. 6 Mutual operator of AOC

## 3.4 Verification of the AOC method

Based on the algorithms and those operators, the AOC method used in this paper is written in the Matlab® code and run in the personal computer with Windows® platform.

Then, the next step is to examine the AOC with the existing tested functions. In the open literature, there are numerous test functions provided for checking the performance of the global optimization methods. In this paper, two of those functions from Ref. [13] are arbitrarily selected to examine the AOC. The information of the two functions is shown below.

(1) Easom Function:

$$f(x_1,x_2) = -\cos(x_1)\cos(x_2)\exp[-(x_1-\pi)^2-(x_2-\pi)^2] .$$

Domain: $-100 \le x_i \le 100$ , $i = 1,2$ .
Global minimum: $f(\pi,\pi) = -1$ .

(2) Griewank Function:

$$f(x_1,x_2) = \frac{x_1^2+x_2^2}{4\,000} - \cos(x_1)\cos\left(\frac{x_2}{\sqrt{2}}\right) + 1 .$$

Domain: $-600 \le x_i \le 600$ , $i = 1,2$ .
Global minimum: $f(0,0) = 0$ .

For computing the optimum of the two functions, the parameters of the AOC are necessary to be pre-determined. For function (1), the population was set as 200, the encoding bits $L$ was 32, the iteration was 500, and the mutation probability was 0.1. For function (2), the population was set as 200, the encoding bits $L$ was 64, the iteration was 1 000, and the mutation probability was 0.01. After 50 trials, the best results are shown in Table 3. For the two functions, the optimal function value found by AOC is the same as the theoretical global minimum. Furthermore, the optimal input variables, $x_1$ and $x_2$ , can also be found by AOC. Therefore, it is apparent that the AOC method is an accurate method for the basic optimization problem.

**Table 3. Comparisons of the AOC results with the theoretical optimal solution**

| Optimized item | Easom function | Griewank function |
|---|---|---|
| Global minimum | −1 | 0 |
| $x_1$ reach the optimal | π | 0 |
| $x_2$ reach the optimal | π | 0 |
| The optimum value (found by AOC) | −1 | 0 |
| $x_1$ reach the optimal (found by AOC) | 3.144 | 0 |
| $x_2$ reach the optimal (found by AOC) | 3.146 | 0 |

In addition to testing the AOC by a function tested bed, the method would also be applied for a kind of complicated benchmark problems, travelling salesman problems (TSP). The TSP problems and the corresponding data can be founded from Ref. [14]. The unit of the traveling distance ($T_d$) is not provided in Ref. [14]. Table 4 shows the three problems/cases used in this paper. The increase of the number of cities means the increase of the complication of problem.

**Table 4. Three TSP problems**

| Case No. | Problem name | Number of cities |
|---|---|---|
| Case 1 | gr24 | 24 |
| Case 2 | gr48 | 48 |
| Case 3 | kroA100 | 100 |

The procedure for calculation can be referred to Fig. 2. However, there is a slight difference in encoding between optimizing the test function and finding optimal tour in TSP. The path representation is adopted for the TSP, i.e., String $v = a_1a_2a_3\cdots a_n$ implies that the salesman travel from the city $a_1$ to the city $a_2$ and so on, and finally back to the city $a_1$ . Due to the path representation, the mutation, turnover, and mutual operators are necessary to be re-defined and explained as follows.

*3.4.1 Mutation operator for TSP*

The exchange mutation[15] is used as a mutation operator of AOC for TSP. The operator randomly selects two cities in the tour then exchanges the positions of those two cities. For example, in Fig. 7, the operator exchanges city 2 and city 5 in the tour.

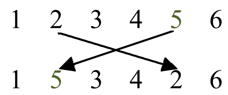



Fig. 7. Mutation operator for TSP

*3.4.2 Turnover operator for TSP*

The turnover operator for TSP is similar to the turnover operator for optimizing test functions with binary encoding. A random point is selected in the tour and the operator turns over either the left part or the right part of the tour with the probability 0.5 (as shown in Fig. 8).

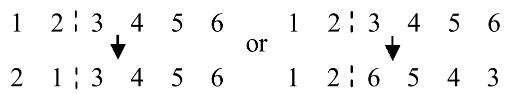



Fig. 8. Turnover operator for TSP

*3.4.3 Mutual operator for TSP*

The mutual operator for TSP is similar to the mutual operator for optimizing functions with binary encoding. The operator maps the original tour to the new tour by picking out the odd-indexed integers in the tour to the front and the even-indexed integers to the back or vice versa, each with the probability 0.5 (see Fig. 9).

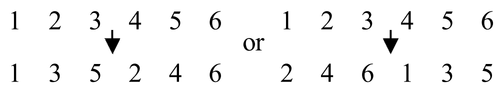
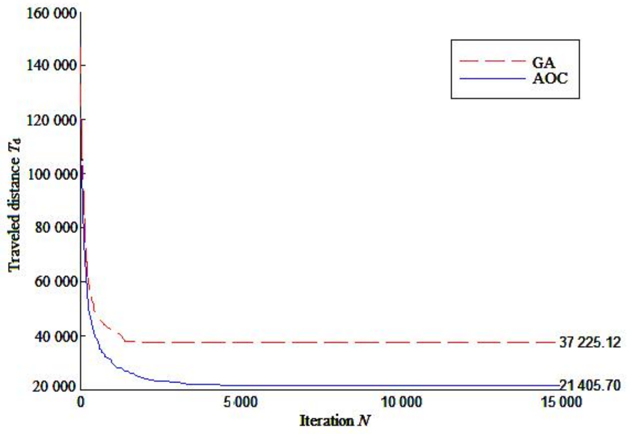



Fig. 9. Mutual operator for TSP

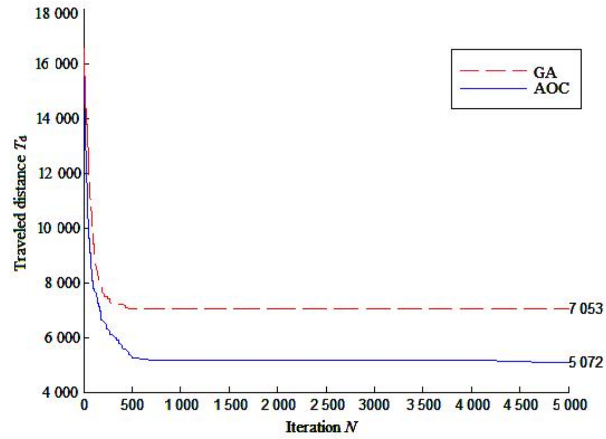
For comparison purpose, the simple genetic algorithms (SGA) with mutation and crossover operators were also applied for the TSP problems. The calculation process is shown in Fig. 10. This figure shows the performance (traveling distance) of the three TSP cases along with the iterations of calculation when using the SGA method and the AOC. Obviously, the AOC method can find the shorter distance for the salesman traveling all the cities than that done by the SGA method. After 20 trials, the best results of SGA and AOC are summarized in Table 5. In the table, the values of the path length of the three cases provided by Ref. [14] are optimal and benchmark because those values were computed by different global optimization methods and selected from the best one. As compared with those values provided by Ref. [14], the results of the three cases found by AOC are nearly the same (less than 1% deviation) whatever the number of cities is. Using the SGA method, the results deviates at most 75% from those of Ref. [14]. Therefore, for the complicated TSP problem, the AOC method is not only superior to the simple GA method, but also competing with the best global optimization method used in Ref. [14].

**Table 5. TSP results by GA and AOC**

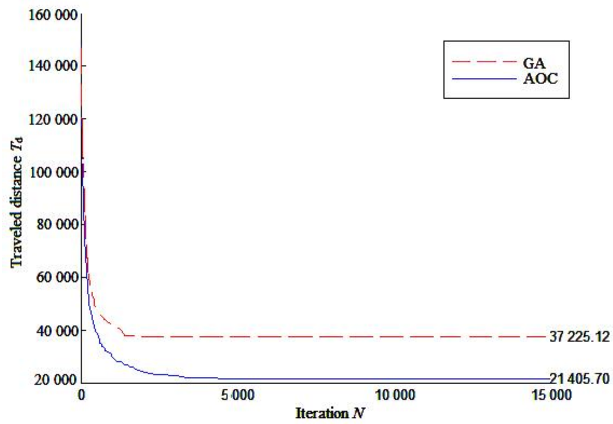
| Parameters and results | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| Population | 200 | 200 | 500 |
| Iteration | 1 000 | 5 000 | 15 000 |
| Mutation probability | 0.1 | 0.1 | 0.1 |
| Optimal path length in Ref. [14] | 1 272 | 5 046 | 21 282 |
| Optimal path length by SGA | 1 399 | 7 053 | 37 226 |
| Best path length by AOC | 1 272 | 5 072 | 21 406 |




(a) Case 1: gr24 (24 cities)




(b) Case 2: gr48 (48 cities)




(c) Case 3: kroA100 (100 cities)

Fig. 10. Traveling distances of three cities calculated by the AOC and GA methods

### 3.5 AOC method for heat exchanger design

After the investigation of the AOC for the benchmark problems, the AOC will then be used for the practical problem, i.e., design of the shell-tube heat exchanger[6]. Suppose that the objective function is defined on a domain $W$ in $\mathbf{R}^3$ and an input vector $x$ is $(D_s, B, d_o)$. The objective function is given by the total annual cost (Eqs. (8)–(13)). The AOC was applied to find the optimal $D_s$, $B$, and $d_o$. Since it is not the TSP problem, the path presentation is not required and, thereof, the basic mutation, mutual and the turnover operators are the same as Fig. 2 and Fig. 3. The population size, the length of the strings, mutation probability $p_m$, the mutual parameter $k$ and iteration parameter $N$ were set to be 8, 96, 0.1, 1 and 500, respectively. It was observed that the optimal input vectors were stable in 100 runs. The results are summarized in Table 6 and compared with the results obtained by the traditional method and SGA. The optimal variables obtained from SGA and AOC were nearly identical. As compared with the traditional method, the size of tube and surface area and the total cost can be reduced based on those optimal variables. Therefore, the performance of AOC is comparable with that of the GA methods and they obviously outperform the traditional method. Hence, the AOC can also effectively be used for optimal design of the shell-tube heat exchanger.

**Table 6. Comparison of the results obtained by traditional method, SGA, and AOC**

| Optimized variables | Traditional method | SGA | AOC |
|---|---|---|---|
| Shell inside diameter $D_s$/m | 0.894 | 0.832 | 0.832 |
| Tubes length $L$/ m | 4.830 | 2.919 | 2.920 |
| Baffles spacing $B$/ m | 0.356 | 0.500 | 0.500 |
| Tube outside diameter $d_o$/m | 0.020 | 0.015 | 0.015 |
| Tubes number $N_t$ | 918 | 1 761 | 1 761 |
| Overall heat transfer coefficient $U$/(W • m$^{-2}$ • K$^{-1}$) | 615 | 684.7 | 684.8 |
| Heat exchange surface area $S$/m$^2$ | 278.6 | 242 | 242 |
| Capital investment $C_i$/$ | 51 507 | 46 311 | 46 308 |
| Annual operating cost $C_o$/($ • yr$^{-1}$) | 2 111 | 944 | 945 |
| Total discounted operating cost $C_{oD}$/$ | 12 973 | 5 803 | 5 807 |
| Total annual cost $C_{tot}$/$ | 64 480 | 52 114 | 52 114 |

## 4 Conclusions

(1) The algorithms of changes (AOC) based on I Ching was successfully developed and examined by the benchmark functions and three complicated TSP problems. For those problems, the AOC was proved to be able to obtain the optimal solutions more accurately than GA.

(2) The AOC was successfully applied to the design of shell-tube heat exchanger. The results obtained by AOC outperform the traditional method. Comparing with GA, both algorithms can find the optimal solution, which helps in reducing the equipment size and the total cost of the heat exchanger.

(3) Absence of interchanging information between binary strings (the crossover operations), the AOC has advantage over GA on parallelism of computing. In the future, the parallel computing for the AOC method will be conducted.

(4) The AOC is expected to widely apply for the practical and complicated optimization problems such as the micro-scale heat exchanger design or the optimization analysis for micro-tubes in the future.

### References

[1] HEWITT G F, SHIRES G L, Bott T R. *Process heat transfer*[M]. US: CRC Press, 1994.
[2] HEWITT G F, HEWITT J. *Heat exchanger design handbook*[M]. New York: Begell House, 1998.
[3] SINNOTT R K. *Chemical engineering design (Coulson & Richardson's chemical engineering series)*[M]. US: Butterworth-Heinemann, 2005.
[4] GOSSELIN L, TYE-GINGRAS M, MATHIEU-POTVIN F. Review of utilization of genetic algorithms in heat transfer problems[J]. *International Journal of Heat and Mass Transfer*, 2009, 52(9, 10): 2 169–2 188.
[5] GOLDBERG D E. *Genetic algorithms in search, optimization, and machine learning*[M]. US: Addison-Wesley, 1989.
[6] CAPUTO A C, PELAGAGGE P M, SALINI P. Heat exchanger design based on the economic optimization[J]. *Applied Thermal Engineering*, 2008, 28(10): 1 151–1 159.
[7] KAKAC S, SHAH R K, Aung W. *Handbook of single-phase convective heat transfer*[M]. New York: Wiley, 1987.
[8] TAM L M, GHAJAR A J. Transitional heat transfer in plain horizontal tubes[J]. *Heat Transfer Engineering*, 2006, 27(5): 23–38.
[9] KERN D Q. *Process heat transfer*[M]. New York: McGraw-Hill, 1950.
[10] BELL K J. *Final report of the co-operative research program on shell-and-tube heat exchangers*[M]. Bulletin 5, Engineering Experimental Station, University of Delaware, Newark, 1963.
[11] WILLS M J N, JOHNSTON D. A new and accurate hand calculation method for shell side pressure drop and flow distribution[C].//*22nd Nat. Heat Transfer Conf., HTD.* New York: Am. Soc. Mech. Eng., 36: 67–79.
[12] PETERS D E, TIMMERHAUS K D. *Plant design and economics for chemical engineers*[M]. US: McGraw-Hill, 1991.
[13] Global optimization test problems: Test Functions for Unconstrained Global Optimization[DB/OL]. HEDAR A, Kyoto: Kyoto University, 2009 [2010-3-2]. http://www-optima.amp.i.kyoto-u.ac.jp/member/student/ hedar/Hedar_files/TestGO.htm.
[14] TSPLIB: Symmetric traveling salesman problem[DB/OL]. REINELT G, Germany: University of Heidelberg, 2008. [2010-2-15].http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95/
[15] LARRAÑAGA P, KUIJPERS C M H, MURGA R H, et al. Genetic Algorithms for the Travelling Salesman Problem: A Review of Representations and Operators[J]. *Artificial Intelligence Review*, 1999, 13(2), 129–170.

### Biographical notes

TAM Houkuan is currently a PhD candidate at *Department of Electromechanical Engineering, Faculty of Science and Technology, University of Macau, China.* His research interests include heat transfer and applications of artificial intelligence.
Tel: +853-83974289; E-mail: hktam@umac.mo

TAM Lapmou is currently a full professor at *Department of Electromechanical Engineering, Faculty of Science and Technology, University of Macau, China*. He received his PhD degree in mechanical engineering from *Oklahoma State University, USA*, in 1995. He is also the President of *Institute for the Development and Quality, Macau, China* and senior member of *Chinese Mechanical Engineering Society*. His research interests include heat transfer, chaos, and energy saving.
Tel: +853-83974465, +853-28371008; E-mail: fstlmt@umac.mo

TAM Sikchung is currently an associate professor at *Department of Mathematics, Faculty of Science and Technology, University of Macau, China.* He received his PhD degree in mathematics from *University of Missouri-Columbia, USA*, in 1993. His research interests include computational intelligence: neural networks, evolutional optimization, and applications of Mathematics.
Tel: +853-83974475; E-mail: fstsct@umac.mo

CHIO Chouhei is an MSc candidate at *Department of Mathematics, Faculty of Science and Technology, University of Macau, China*. His research interest is evolutional optimization.
E-mail: evanchio@gmail.com

GHAJAR Afshin J is a regents professor and director of graduate

studies in *School of Mechanical and Aerospace Engineering* at *Oklahoma State University, USA* and a honorary professor of *Xi'an Jiaotong University, Xi'an, China*. He received his BS, MS, and PhD degrees, all in mechanical engineering from *Oklahoma State University*. His expertise is in experimental and computational heat transfer and fluid mechanics. Dr. Ghajar has been a Summer Research Fellow at *Wright Patterson AFB* (Dayton, Ohio) and *Dow Chemical Company* (Freeport, Texas). He and his coworkers have published over 160 reviewed research papers. He has received several outstanding teaching/service awards. Dr. GHAJAR is a fellow of *American Society of Mechanical Engineers (ASME)*, *Heat Transfer Series Editor* for *Taylor & Francis / CRC Press* and *Editor-in-Chief* of *Heat Transfer Engineering*. He is also the co-author of the 4th Edition of CENGEL and GHAJAR, *Heat and Mass Transfer – Fundamentals and Applications*, McGraw-Hill, Feb. 2010.
Tel: 405-744-5900; E-mail: afshin.ghajar@okstate.edu