

Optimization of Hazardous POL Transportation Problem Based on Simulated Annealing Genetic Algorithm

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Hazardous POL is Inflammable and explosive dangerous chemical product, so a vehicle loaded with hazardous POL is under strictly transportation speed limit for security reasons, which cause that transportation cost per distance of a vehicle loaded with hazardous POL is more than that of an empty vehicle. Optimization of hazardous POL transportation problem (HPOLTP) is a common problem in the chemical industry, the decision maker has to find the optimal route that satisfies the following criteria: the least cost. The genetic algorithm (GA) has often been used to solve this NP-hard problem. However, the GA has to run repeatedly with its random search process before finding a relatively good solution. Besides, the algorithm is easy to fall into the local optimum trap. To overcome the defects, this paper puts forward a hybrid method called SAGA. The purpose is to find the global optimal solution without premature convergence. Several classic functions with lots of local minimum points were chosen to verify the performance of the SAGA. The test shows that the algorithm boasts stronger global searching ability than the GA. Then, the SAGA was applied to solve a typical HPOLTP. The results demonstrate that the SAGA can provide more reliable solution than the GA.

1. Introduction

Hazardous POL transportation problem (HPOLTP) is one typical problem of logistics distribution route problem (LDRP), LDRP is a common problem in the logistics industry (Ren et al., 2010). To minimize the total transport cost, the decision maker is asked to arrange the number and route of vehicles in a rational manner. Being a typical case of combinatorial optimization, the HPOLTP is essentially an NP-hard (non-deterministic polynomial-time hard) problem that can be solved by exact or heuristic methods (Díaz-Parra et al., 2014). Featuring heavy computation load and massive storage, the exact method is only applicable to small-scale LDRPs. By contrast, the heuristic method consumes less time and yields better results for the same problem, and works better in large-scale LDRPs (Sivakumar, 2008).

A number of studies have been conducted to solve LDRP and many traditional heuristic algorithms have been applied to the LDRP, including neural network algorithm (Arquez and Nieto, 2013; Yu and Meng, 2008), genetic algorithm (GA) (Moin et al., 2011; Razali et al., 2015; Anbuudayasankar et al., 2012), ant colony algorithm (ACA) (Zhang et al., 2016; Veen et al., 2013), particle swarm optimization algorithm (PSOA) (Belmecheri et al., 2013; Yao et al., 2016) and simulated annealing algorithm (SAA) (Shaabani and Kamalabadi, 2016; Mu et al., 2016). However, the application of one single heuristic algorithm often faces such problems as slow search speed, local optimum trap, and poor accuracy. The combination of the existing algorithms has become a major direction of future research. Researchers have made a lot of work to explore the combination of genetic algorithm and simulated annealing algorithm (Lan and Lin, 2016), and apply these combinations on solving practical problems, such as product returns optimization (Ghezavati and Nia, 2015), cell information problem (Zeb et al., 2016), and bus network design (Liu et al., 2010). This paper combines the GA and the SAA into a hybrid optimization algorithm called SAGA, aiming to integrate the strong local search ability of the GA with the strong global search ability of the SAA, and eliminate the threat of local optimum trap to the GA. Then, some classic functions were introduced to verify the robustness and reliability of the SAGA, and a case study was carried out to prove the applicability of the SAGA in HPOLTP optimization.

The rest of this paper is organized as follows: Section 2 introduces the basic concepts of the HPOLTP and the SAGA; Section 3 selects several classic functions to test the robustness and reliability of the SAGA in the

search for global optimum; Section 4 conducts a simulation test of HPOLTP optimization; Section 5 wraps up this research with some meaningful conclusions.

2. Basic concepts

2.1 HPOLTP description

The HPOLTP usually has a central distribution depot, from where hazardous POL are delivered to several demand points on vehicles with the same capacity. At one time point, the demand information from all demand points are received at the central depot, the decision maker must put up a schedule on the routes to the corresponding demand points, aiming to minimize the total transport cost. The transportation cost of a loaded vehicle is much higher than an unloaded vehicle for that speed of a vehicle loaded with hazardous POL is always limited considering safety, and the total vehicle capacity at the central depot is always greater than the total demand from all demand points.

2.2 HPOLTP model

The modelling of the HPOLTP uses the following symbols.

Data

- n: the number of demand points;
- 0, n + 1: the central depot and demand points;
- V: the set of demand points ($V = \{0, 1, \dots, n, n + 1\}$);
- d_i : the amount of goods to be delivered to demand point i ;
- K: the set of vehicles ($K = \{0, 1, \dots, m - 1, m\}$);
- Q_k : the capacity of vehicle k ;
- d_{ij} : the distance from node i to node j ;
- z_l^k : the cost of vehicle k per distance when loaded;
- z_{nl}^k : the cost of vehicle k per distance when non-loaded.

Variables

$x_{ij}^k \in \{0, 1\}$: $x_{ij}^k = 1$ if and only if vehicle k travels from node i to node j .

Hence, the object function of the HPOLTP model is written as:

$$\min \left(\sum_{i=0}^n \sum_{j=0}^n \sum_{k=1}^m d_{ij} x_{ij}^k z_l^k + \sum_{i=1}^n \sum_{k=1}^m d_{i,n+1} x_{i,n+1}^k z_{nl}^k \right) \quad (1)$$

Subject to:

$$\sum_{k=1}^m \sum_{i=0}^n x_{ij}^k = 1, \forall j = 1, 2, \dots, n \quad (2)$$

$$\sum_{k=1}^m \sum_{j=1}^{n+1} x_{ij}^k = 1, \forall j = 1, 2, \dots, n \quad (3)$$

$$\sum_{j=1}^n x_{0,j}^k = 1, \forall k \in K \quad (4)$$

$$\sum_{j=1}^n x_{j,n+1}^k = 1, \forall k \in K \quad (5)$$

$$\sum_{i=0}^n x_{i,p}^k = \sum_{j=1}^{n+1} x_{p,j}^k, \forall k \in K, \forall p = 1, 2, \dots, n - 1, n \quad (6)$$

$$\sum_{i=0}^n \sum_{j=1}^{n+1} x_{ij}^k d_j \leq Q_k, \forall k \in K \quad (7)$$

Formula (1) indicates that the total cost should be as small as reasonably possible; Formulas (3) and (4) reveal that each demand point should be visited by only one vehicle; Formulas (4) and (5) stipulate that each vehicle leaving the central depot must return to the depot; Formula (6) specifies that the vehicle that has arrived at a demand point must eventually depart from the demand point; Formula (7) means the load of each vehicle should not surpass its capacity.

2.3 SAGA

The GA, known for its broad range of application, is implemented in the following steps. First, a population of individuals is randomly generated, with each individual representing a solution; then, the fittest individuals are selected through crossover and mutation operations; the previous steps are repeated again and again until the termination condition is satisfied. Despite its popularity in the optimization of logistic distribution routes, the GA fails to achieve stable results though its random search processes. The search result, fluctuating from search to search, is a far cry from the global optimal solution. To make up for the defect, the decision maker has to perform the optimization operation repeatedly, which is a great waste of time. The SAA was introduced to the GA to get the latter out of the local optimum trap, and continue to look for the global optimum in the case of evolutionary stagnation.

3. Classic function test

3.1 Classic functions

Three classic multi-peak functions were chosen to test the performance of the SAGA. The classic functions are as follows: Schaffer function

$$\min f(x_1, x_2) = 0.5 + \frac{(\sin \sqrt{x_1^2 + x_2^2})^2 - 0.5}{(1 + 0.001(x_1^2 + x_2^2))^2} \quad (8)$$

$$-10.0 \leq x_1, x_2 \leq 10.0$$

The function is a 2D complex function with countless local minimum points, and the global minimum (0) appears at (0, 0). Due to the strong shock, it is difficult to find the global optimum with this function. Shubert function

$$\min f(x, y) = \left\{ \sum_{i=1}^5 i \cos[(i+1)x + i] \right\} \times \left\{ \sum_{i=1}^5 i \cos[(i+1)y + i] \right\} \quad (9)$$

$$-10.0 \leq x, y \leq 10.0$$

The function is a 2D complex function with over 760 local minimum points, and the global minimum (-186.7309) appears at (-1.42513, 0.80032). Rosenbrock function

$$\min f(x, y) = (1 - x)^2 + 100(y - x^2)^2 \quad (10)$$

$$-10.0 \leq x, y \leq 10.0$$

The function is a 2D complex function with countless local minimum points, and the global minimum (0) appears at (1, 1). Due to the strong shock, it is difficult to find the global optimum with this function.

3.2 Results analysis

The above classic functions were solved by GA and SAGA-based programs written on MATLAB. Each algorithm is run till reaching a stop criterion which is chosen to be 2000 generation. 50 individuals were used for the simulation. Figure 1 shows how the objective function evolved through generations when the three functions were solved here using the classic GA and SAGA under the same conditions.

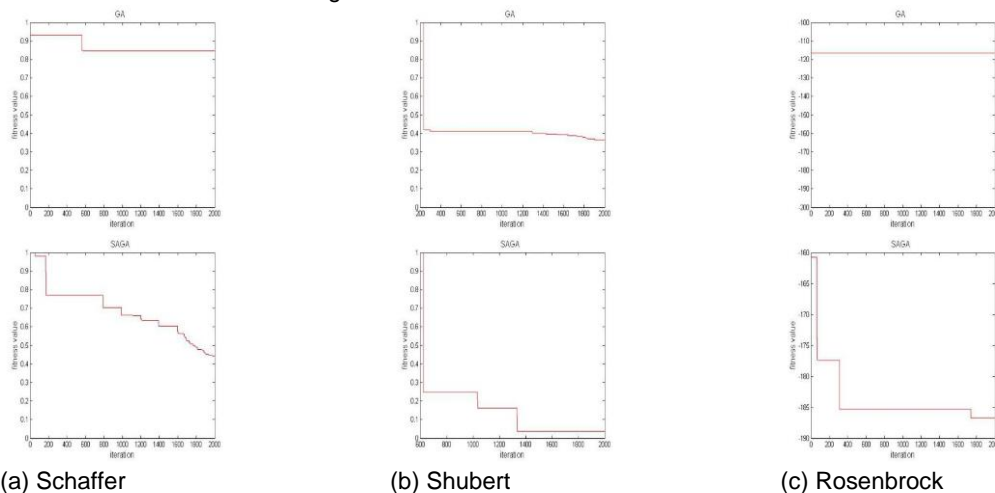


Figure 1: The objective function evolution for the 3 test functions.

It can be seen that the GA converged faster than the SAGA, but it was easily trapped in the local optimum, leading to premature convergence. On the contrary, the SAGA, with a slower convergence speed, effectively avoided the premature and local optimum and continued to search for the global optimum.

Table 1: Numerical results obtained by GA and the proposed SAGA

Function	Algorithm	Best	Worst	Mean	variance(Std.Dev)
Schaffer	GA	0.97E-02	0.11	0.99E-02	0.483
	SAGA	0.63E-04	0.18E-03	0.74E-03	0.002
Shubert	GA	-135.26	-103.34	-128.2937	0.33
	SAGA	-186.71	-186.70	-186.7119	2.06E-03
Rosenbrock	GA	0.0159	0.3289	0.18E-02	0.02
	SAGA	0.12E-03	0.9E-05	0.11E-03	8.45E-04

Tables 1 lists the numerical results obtained by the GA and the SAGA for each of the classic functions. All algorithms were repeated for 20 independent runs. The best results are bolded. According to Table 2, the SAGA achieved better best value and average value than the GA. This means the SAGA boasts stronger search ability for global optimum. Moreover, the SAGA had a smaller variance than the GA, an evidence for better reliability and robustness.

4. Case study

4.1 Case description

A logistics company is supposed to deliver hazardous POL from a central depot to several demand points. The company has enough vehicles to complete the logistics task. The capacity of each vehicle is limited to 25 ton. The transport cost of each vehicle is 2 per distance when unloaded, and 3 per distance when loaded. Table 2 presents the location information and the amount of hazardous POL to be delivered to each demand point.

Table 2: Location information and demand

Point	Hazardous POL amount	Coordinate(km)		Point	Hazardous POL amount	Coordinate(km)	
		x	y			x	y
1	-	15	10	10	5.8	6	18
2	8.2	1	5	11	7.8	15	12
3	5.5	4	7	12	6.2	22	5
4	4.5	3	11	13	2.4	27	9
5	2.3	9	6	14	7.6	15	19
6	1.4	10	2	15	10	20	17
7	4.1	17	3	16	6.0	24	20
8	5.8	12	9	17	4.2	28	18
9	4.6	7	14				

4.2 Result analysis

The maximum number of generations was taken as the termination condition, which is set to 100. The results are shown in Figure 2.

As can be seen from the figure 2, four routes were generated separately by the SAGA and the GA. The visiting sequence, length and cost of each route are listed in Tables 5 and 6. The total length and total cost were calculated as well.

Comparing the results of the GA and the SAGA, it is observed that the SAGA has obviously outperformed the GA, as it can avoid the local optimum and find a solution close to the global optimum.

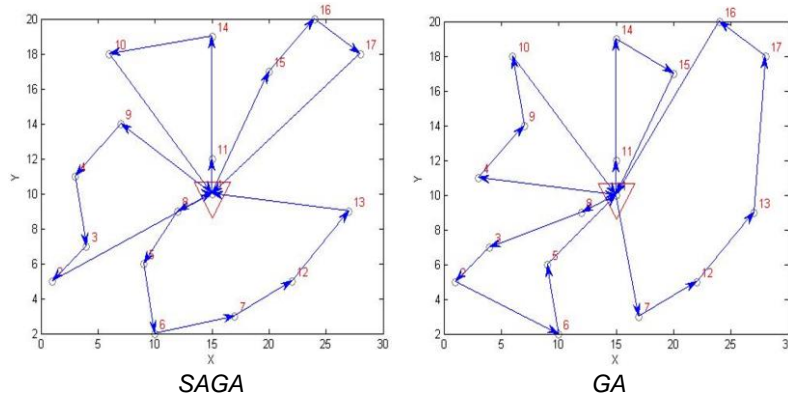


Figure 2: The schematic diagram of SAGA and GA.

Table 3: Results of SAGA and GA

SAGA				GA			
Path	Visit order	Length	Cost	Path	Visit order	Length	Cost
1	1-11-14-10-1	30.096	78.247	1	1-11-14-10-1	30.096	78.247
2	1-9-4-3-2-1	36.437	94.751	2	1-9-4-3-2-1	36.437	94.751
3	1-8-5-6-7-12-13-1	42.428	115.242	3	1-8-5-6-7-12-13-1	42.428	115.242
4	1-15-16-17-1	33.338	84.75	4	1-15-16-17-1	33.338	84.75
Total		142.299	372.99	Total		142.299	372.99

5. Conclusion

Focusing on the HPOLTP, this paper combines two commonly used algorithms the GA and the SAA into the SAGA. With the GA as the core, the SAGA improves the efficiency of the GA by adopting the strategy of the SAA to accept certain disturbed solutions with worse performance. In this way, the proposed algorithm avoids the local optimum and continues to look for the global optimum. Through the classic function test, it is learned that the SAGA has effectively circumvent the local optimum trap, and greatly outshines the GA. The results of our case study show that it is feasible to solve the HPOLTP based on the SAGA; the SAGA can obtain a solution more closer to the optimal solution than the GA. The reliability of the SAGA is bound to boost the confidence of the decision maker in handling the HPOLTP.

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