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Solving transportation problems using hybrid simulated annealing and genetic algorithm

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Abstract
This study presented a hybrid genetic-simulated annealing technique. The simulated annealing approach improves population solutions at each step if the algorithm mostly uses genetic algorithm search processes. The suggested approach solved the transportation issue and was compared to the simulated simulation algorithm and genetic algorithm.

Keywords: Transportation problem, fuzzy genetic algorithm, distribution center

1. Introduction

As an essential part of every country's economic foundation, transportation is crucial to the country's development. Whether a facility is dedicated to manufacturing or providing a service, transportation is an integral part of the economy and an essential support function. As a result, it is reasonable to assume that the facility will make every effort to minimize the transportation expenses it incurs and passes down to the final customer. The loss of the facility would be doubled if cutting costs meant sacrificing accuracy or quality of performance. Scientific planning of transportation operations is now more important than ever before in order to keep transportation costs in check while yet meeting demand as swiftly and efficiently as feasible.

GAs are a kind of self-adapting stochastic search algorithm [1]. Survival of the fittest genetic algorithms use selection, crossover, and mutation operators to create new individuals in a Darwinian "race to the top" environment. Many issues may be resolved with the help of GAs see [2, 3, 4, 6, 6]. Despite its utility in other settings, GAs are not applicable to reservoir optimum issues. Researchers such as [7, 8, 9], have all employed GAs to enhance reservoir management.

Simulated annealing (SA) is the use of stochastic generic search to mimic the annealing process in metals [10]. SA may sometimes prevent the needless reduction of locally optimum solutions (see) [11]. Using the Metropolis criteria with a probability function, the algorithm must escape from a local least energy state and achieve a global minimum in order to update the system unless the created new state has lower energy than the previous one, in which case it is accepted unconditionally [12]. Rarely does SA maximize reserve systems. Researchers such as [13]. The GA-SA hybrid algorithm is an innovative approach to finding global optimums. The GA-SA helps communities better organize themselves and set their own values. There are several applications for the hybrid method, such as system design [12], system and network optimization [14], and information retrieval [14]. In terms of reservoir optimization, the GA-SA is seldom employed. When it comes to electrical power districting, Bergey *et al*. introduced and analyzed the simulated annealing-genetic technique.

Based on the study's findings, researchers advocated for a new kind of algorithm that shares features with both the genetic algorithm and the simulated annealing method. If the genetic algorithm is utilized for the majority of the search, then the simulated annealing technique is employed at each step to enhance the population's solutions. The transportation issue was solved using the suggested method, and the results were compared to those found using the simulated simulation algorithm and the genetic algorithm by randomly creating a series of transport problems.

2. Methodology

2.1 Transportation problem

The transportation model is one of the important applications of linear programming, and the first to come up with this method is the mathematical scientist (Hitchcok) in 1941.

Transport models aim to reduce the transportation cost of a commodity that is available from a group of processing sources (Sources) to distribute it to a group of demand centers (Destinations) to meet the needs of those centers, provided that the supply by the supply sources, and the demand by the demand centers, is known in advance.

In order to complete the requirements of the transfer form, we need to clarify the following:

1) The quantities available at supply sources and the quantities needed by the different demand centers must be known.
2) We assume that there are (m) supply sources (S1, S2,…,Sm) and the quantities available for each source are (a1, a2,…,am) and in general form:

$$S_i, i = 1,2, \dots, m \; a_i, i = 1,2, \dots, m$$

3) We assume that there are (n) demand centers (D1, D2, …, Dn) that need the quantities (b1, b2, …, bn) available at supply sources, in general form:

Dj, j=1,2,…,n

bj, j=1,2,…,n

4) There are also transportation costs. The cost of moving one unit from supply source (Si) to demand center (Dj) is (cij):

cij, i=1,2,…,m

j=1,2,…,n

5) We assume that the quantity transferred from the supply source to the demand center is xij.

6) The objective of the transportation model is to determine the number of units transferred from the supply source to the demand center so that the total transportation cost is as low as possible.

We can mathematically express the transport model that satisfies the above assumptions as follows:

$$Minimize\, z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

It expresses the objective function of the transfer process at the lowest possible cost. What is required is to find the values of (xij) that make the total costs (z) as low as possible, noting that there are limitations that should be taken into account when solving transportation-related models, namely:

$$\sum_{j=1}^{n} x_{ij} = a_i \sum_{i=1}^{m} x_{ij} = b_j$$

xij >0

In order for the solution reached to be basic, each model of the transportation problem must contain (m+n-1) variables. [31] Figure (1) shows a diagram of the transportation problem.

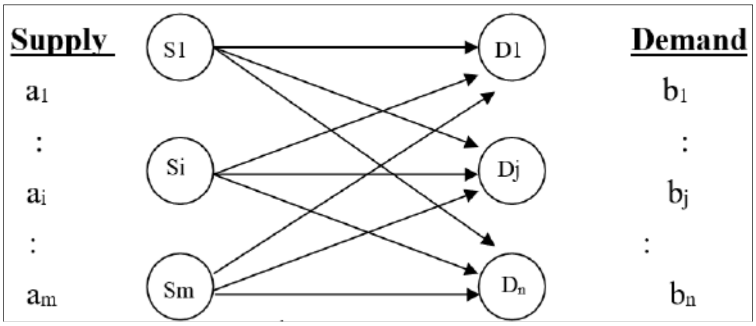

Fig 1: Scheme of the transportation problem

2.2 Genetic Algorithms

Genetic algorithms provide a generic approach to finding optimum solutions for complicated systems. The method disregards the objective function's differentiability and continuity and instead works directly with a coded set of the objective function's parameters. Therefore, the GA is a very effective optimization approach that may address issues that are hard for conventional algorithms to address (e.g., the steepest descent method). Three benefits of GAs were outlined by Chang *et al*. (2005) in comparison to more conventional optimization techniques.

GAs are used to produce a random starting population in a generation process. The GA then performs operations on the population, such as selection, crossover, and mutation, in order to generate new and, ideally, improved solutions. This procedure keeps running till the endpoint is reached. Pseudo code for a classic GA is shown in Figure 1.

2.3 Simulated Annealing Algorithm

The SA algorithm is a malleable optimization strategy motivated by metal annealing (Kirkpatrick *et al*. 1983). The SA randomly searches within the range using the Metropolis criterion. The SA's efficacy is directly proportional to the frequency with which it is allowed to cool down. By considering the cooling rate of the temperature and the neighbourhood structure, the SA's computational dependability and efficiency can be ensured.

2.4 Hybrid genetic algorithm and simulated annealing

Genetic algorithms may ensure a diverse population by saving the best members of each generation for the following generation's breeding process. The simulated annealing technique excels at local search and can break out of local minima. However, GAs often converge too quickly and become stuck on suboptimal solutions. The SA also has a higher computational cost. Thus, an enhanced genetic algorithm-simulated annealing method is given in this field by combining the two techniques.

It is a common associative method to use GAs as a nesting container for the SA. Repeat until L=Lt=t in Fig. 2 is met, as the SA iteratively improves each member of the GA population until the Markov chain length is approached. Therefore, a typical GA-SA takes longer to run than either GAs or the SA alone. The work here improves upon the GA-SA algorithm. When applied to a population of GAs, the enhanced method swaps out the best technique for the best individual. The enhanced technique reduces runtime even more than GA-SA. IGA-SA is more effective than competing optimization methods (see Section 5.4). The IGA-SA calculation is shown in Fig. 3.

3. Results and discussion

We tested our hybrid genetic algorithm on 15 benchmark examples. Unfortunately, Molla-Alizadeh-Zavardehi *et al*data .'s were unavailable. Our program ran 10 times each instance and captured the best value, average, and standard deviation.

Table 1 shows the findings. The first column shows the instance number (three per DC/customer combo). Column two shows the results for the Simulated annealing genetic algorithm alone and hybrid algorithm findings are in the following six columns. The problem's best remedy is bold.

According to Table 1, the hybrid method has shown the outperform other two algorithms in 14 of 15 cases, enhancing the best values and attaining the same best solution in the final instance. In 11 of 15 cases, incorporating the genetic algorithm with a local search technique enhanced solution quality.

Table 1: The experimental results

Case	No. sources	No. destination	Simulated annealing			Genetic algorithm			Hybrid algorithm		
			Best	Mean	Std	Best	Mean	Std	Best	Mean	Std
1	10	20	413	551	90.12	400	531	83.05	**300**	**351**	**30.22**
2	15	30	511	646	84.68	501	657	80.09	**402**	**447**	**29.56**
3	20	30	606	756	89.81	624	770	77.68	**500**	**555**	**31.25**
4	25	40	704	824	86.35	705	857	80.67	**600**	**646**	**29.11**
5	30	40	805	973	88.93	810	976	89.83	**702**	**757**	**30.48**
6	35	50	907	1049	89.74	900	1051	83.82	**800**	**851**	**31.22**
7	40	60	1001	1128	80.99	1004	1144	85.87	**900**	**946**	**27.05**
8	45	60	1121	1260	80.40	1102	1246	88.30	**1000**	**1052**	**33.15**
9	50	60	1207	1336	80.53	1202	1350	83.52	**1108**	**1155**	**27.26**
10	60	80	1302	1439	89.47	1305	1468	93.20	**1203**	**1249**	**31.50**
11	65	80	1400	1554	93.01	1402	1570	79.46	**1300**	**1361**	**28.06**
12	70	80	1500	1666	84.28	1501	1669	94.17	**1404**	**1454**	**26.38**
13	75	90	1601	1743	91.08	1601	1724	90.63	**1502**	**1551**	**27.94**
14	80	100	1701	1854	79.78	1702	1839	69.73	**1600**	**1652**	**27.91**
15	100	120	1808	1966	90.15	1814	1958	80.82	**1701**	**1742**	**27.19**

4. Conclusion

In this paper, a new algorithm based primarily on the genetic algorithm was proposed, and it was enhanced by a simulated annealing algorithm using developed local search techniques. Comparing the proposed algorithm to other algorithms on the basis of problems generated at random demonstrated its superiority.

In future studies, we intend to implement the proposed algorithm on an additional set of problems.

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