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Genetic Algorithm for Solving Balanced Transportation Problem

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Abstract— A Transportation Problem is one of the most typical problems being encountered in many situations and it has many practical applications. Many researches had been conducted and many methods had been proposed to solve it. One of the most difficult challenge in solving the problem deals with inputting a very large volume of data. With the development of intelligent technologies, computers had already been used to solved this problem. This paper presents a method using Genetic Algorithm (GA) to provide a new tool that can quickly calculate the solution to the Balanced Transportation Problem.

The test results are compared with selected old methods to confirm the effectiveness of the use of GA. A mathematical model was used to represent the GA and be applied to solve it. Finally, the test results of the model were presented so show the effectiveness.

Index Terms— Genetic Algorithm, Transportation Problem

I. INTRODUCTION

Genetic Algorithm is a searching method used for choosing the best solution of the different problems, based on the mechanism of natural selection. That is, from the initial population, through several evolutionary steps, a set of new more appropriate solutions are achieved that led to the global optimal solution. GA is a useful tool for solving optimization problems, especially optimization problems with large search space [4].

Transportation Problem is one of the typical problems that can be applied in many situations and it has many practical applications. There are some methods used to solve it such as initial positive margin method and Volghen method [1]. However, in case of complex network traffic having a large number of delivery and received locations, old methods archived the global optimal solutions ineffectively. Therefore, GA are the appropriate methods to solve the problems.

II. TRANSPORTATION PROBLEM

A. Introduction of the Problem

Suppose that homogeneous goods (materials, food...) will be transported from m provided locations (hotspot). S_1, S_2... S_m to n are locations (points earned) and D_1, D_2…D_n where :

- The number of S_i is s_i (i=1..n)
- The number of D_j is d_j (j=1..m)
- The cost of moving a unit from S_i to D_j is C_{ij} (i=1..n, j=1..m)

The problem: Plan to move from one location to another provided that the total consumption of transportation cost is minimum and it satisfy transceiver. The problem is linear if the transport cost is proportional to the amount of freight.

B. Mathematical model

The x_{ij} is the amount of goods to be transported from Ai to Bj. Therefore,

$\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij}$: sum of cost transported, $\sum_{j=1}^{n} x_{ij}$: sum of amount from S_i ,

$\sum_{i=1}^{m} x_{ij}$: sum of mount D_j

So the mathematical model is: $f(X)=\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} \to \min$

With the terms:

$\sum_{j=1}^{n} x_{ij} = S_j$, $\sum_{i=1}^{m} x_{ij} = D_i$ and $x_{ij}>0$, i=i..m, j=1..n

C. Application of GA to solve the Transportation problem

C.1. GA and its parameters

The problem solved using GA has the following steps :

- Encoding: Each individual is a matrix m x n to show amount of goods from m delivered locations to n received locations. Value of each element in the matrix is a non-negative integer, representing the quantity of goods that needs to be moved from among delivered and received locations.
- Initial population: Population size is 100. Because each individual is a matrix m x n, then to create 100 individuals means using a three dimension matrix, where the first and second dimension show transportation among provided and new locations. The third dimension shows the order of individual in 100 individuals [6].
- Fitness function: Fitness of each individual in initial population is equal to the total transport cost. [5]

- The evolutionary process is as follows:

Parents are chosen by random for crossover to create offspring. Then, a crossover was done by choosing a row randomly. The corresponding column of the first offspring is from a mother, and the second offspring from a father. The other values in the matrix of the offsprings created randomly was used to satisfy the constraints of the problem.

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After creating the 2 offspring, fitness was also calculated to obtain the total cost. Offspring can compete with their parents. If parents are better than offspring that is, the total cost of parents are smaller than offspring, then fitness chose parents (one or both parents) to next generation, otherwise it is discarded [4]. Similarly, if the offspring (one or both) are better than parents i.e total cost of offspring is smaller than parents' fitness then we choose offspring (one or both) to next generation, and by contrast, it is discarded. Mutation process occurs with very small probability. Mutation was conducted by choosing randomly one individual in the population [5]. After that, a row and a column in the individual was chosen randomly and create randomly an integer number to replace the last value. Then, others rows and columns are changed to satisfy the individual constraints of the problem, then a new individual was generated after mutation. Fitness for the new individual was calculated. If the fitness of the new individual is smaller than old individual (the individual before mutation) then the new one was chosen, else the old individual was kept for the next generation [7].

- Parameters: The population size is 100, crossover probability is 0.1, and mutation probability is 10^{-4}. [2]
- The number of generation is 500 times i.e. after 500 generations, the best test result was chosen and compete with other methods.

C.2. Test results

A program was run on Matlab tool version 7.13.0.564. In particular, the algorithm was run 100 times and the program was checked for the best results to compare with initial positive margin method and Volghen method**.**

Input: m=3, n=4, s1=170, s2=200, s3=180, d1=130, d2=160, d3=120 and d4=140. Cost matrix Cij is given by the following table:

20	18	22	25
15	25	30	15
45	30	40	35

Table 1: Cost matrix C_{ij}

After running 100 times, the best result is 12596. It means, with such input, the transportation among locations is shown in Table 2, in which the lowest total cost of GA is 12596.

62	20	83	2
59	0	6	13
9	140	31	7

Table 2: The result of transportation among locations by GA

In there, with the same data input initial positive margin method and Volghen method, the results are 12950 and 12200. Details of the transport among the locations of the two methods is shown in Table 3 and Table 4.

0	160	10	0
130	0	0	70
0	0	110	70

Table 3: Results of initial positive margin method

70	0	100	0
60	0	0	140
0	160	20	0

Table 4: Results of Volghen method

To test the ability to solve large input of GA, a test program was conducted and run the data with larger data sets. Specifically, the number of places provided is m = 20, the number of sales locations is n = 30. In there, d1=730, d2=340, d3=600, d4=427, d5=1200, d6=500, d7=572, d8=427, d9=500, d10=530, d11=650, d12=500, d13=580, d14=550, d15=1250, d16=450, d17=520, d18=500, d19=500, d20=530, d21=465, d22=645, d23=315, d24=482, d25=858, d26=429, d27=616, d28=371, d29=480, d30=891, s1=935, s2=1022, s3=1176, s4=1100, s5=500, s6=785, s7=804, s8=862, s9=865, s10=904, s11=906, s12=930, s13=919, s14=877, s15=860, s16=932, s17=986, s18=914, s19=818,s20=1014.

The same applies to programming as described above, we get the value after 500 generations, we have the best individual show the transport among locations is shown in Table 5 below:

9	95	2	17	61	20	18	22	25	54	47	57	0	23	34	7	58	67	101	13
2	0	86	21	48	15	25	30	15	64	41	14	48	4	28	45	0	0	5	49
119	65	32	102	0	45	30	40	35	0	2	17	37	15	0	12	12	13	0	24
0	4	0	0	13	13	48	17	52	4	57	0	25	67	17	25	45	13	10	17
47	58	73	46	69	72	54	81	97	113	79	63	57	49	81	92	45	29	12	30
11	13	34	58	17	0	26	0	0	11	47	6	1	53	59	28	47	23	73	4

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46	12	48	0	45	36	21	11	3	6	49	101	23	50	17	0	29	4	28	89
103	7	91	17	1	3	5	2	7	18	0	0	27	46	25	73	11	42	5	47
1	75	82	14	2	4	35	4	5	25	17	68	91	2	13	1	5	9	31	17
12	72	96	8	15	23	11	42	44	5	1	7	12	13	15	71	31	23	25	16
49	9	95	2	17	61	20	18	22	25	54	47	57	0	23	34	7	58	67	34
23	2	0	86	21	48	15	25	30	15	64	41	14	48	4	28	45	0	0	14
17	119	65	32	102	0	45	30	40	35	0	2	17	37	15	0	12	12	13	4
29	0	4	0	0	13	13	48	17	52	4	57	0	25	67	17	25	45	13	150
0	47	58	73	46	69	72	54	81	97	113	79	63	57	49	81	92	45	29	45
89	11	13	34	58	17	0	26	0	0	11	47	6	1	53	59	28	47	23	16
47	46	12	48	0	45	36	21	11	3	6	49	101	23	50	17	0	29	4	16
19	103	7	91	17	1	3	5	2	7	18	0	0	27	46	25	73	11	42	22
4	1	75	82	14	2	4	35	4	5	25	17	68	91	2	13	1	5	9	47
25	12	72	96	8	15	23	11	42	44	5	1	7	12	13	15	71	31	23	29
17	61	20	18	22	25	54	47	57	0	17	0	26	0	0	11	47	6	1	53
21	48	15	25	30	15	64	41	14	48	45	36	21	11	3	6	49	101	23	50
102	0	45	30	40	35	0	2	17	37	1	3	5	2	7	18	0	0	27	46
0	13	13	48	17	52	4	57	0	25	2	4	35	4	5	25	17	68	91	2
46	69	72	54	81	97	113	79	63	57	15	23	11	42	44	5	1	7	12	13
58	17	0	26	0	0	11	47	6	1	17	61	20	18	22	25	54	47	57	0
0	45	36	21	11	3	6	49	101	23	21	48	15	25	30	15	64	41	14	48
17	1	3	5	2	7	18	0	0	27	102	0	45	30	40	35	0	2	17	37
14	2	4	35	4	5	25	17	68	91	0	13	13	48	17	52	4	57	0	25
8	15	23	11	42	44	5	1	7	12	46	69	72	54	81	97	113	79	63	57

TABLE 5: RESULT OF GA AFTER 500 GENERATIONS

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The results from table 2 and 3 show that, after 100 run times by GA, the results of the GA is better than initial positive margin method but worse than Volghen method. Simultaneously, with large input data sets, the GA is able to solve in the shortest time and for better results which was shown in table 5. This is a good remark that transportation problems can be solved by GA and have good results, especially with large data input. This is also a good sign that the GA can be applied to the other optimization problems with large search space and positive results. Although this is just a test problem more input data can be tested and good results can be realized, which is a very promising result.

III. CONCLUSION

On the basis of the results of this research on genetic algorithm and applying this algorithm to the balanced transportation problem, it was concluded that the GA is a useful tool to help solve the optimization problem especially optimization problems with large search space and will produce good results. However, this study had dealt only with specific applied problems which needs confirmation with the other math classes. In general, there must be a lot testing to be done on many other different problems. Further work may be used in combination with changes in population size, or defined "age" of the individuals involved to determine the evolutionary increase or decrease population size is the natural evolution.

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She had been in the teaching profession in more than 25 years and is the Dean of the College of Computer Studies of Lyceum of the Philippines University in Batangas for 12 years. She had presented research papers locally and internationally, one of which is Philippine government funded at San Diego California last March 2010. She had visited 9 countries in a period of 11 years during study tours and benchmarking visits. She had been the President of PSITE IV- Philippine Society of IT Education for 3 years and had been the PSITE National Secretary for another 3 years and is currently the National Treasurer this year.

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