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Minimization of Transportation Cost: Genetic Vs Traditional

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Abstract—*In recent years there has been a dramatic increase in the use of technology in supply chain related activities. Now-a-days, there is a growing need for services that can analyze and optimize transportation possibilities to determine the responsive, economic and efficient strategies for movement of goods from one location to another. In this paper, a novel and efficient approach using genetic algorithm has been developed, which clearly determines an optimal compromise solution of multi-objective transportation problems. The developed approach and solution is compared to the traditional optimization methods to indicate the effectiveness of the former.*

Keywords*: Transportation network, Optimization, Vogel's approximation method, Genetic algorithm, Mutation.*

1. INTRODUCTION

Supply chain management can be described as an integral process wherein several entities of diverse nature work in an alliance so as to ensure proper production and distribution of the products (or services) in the right quantity at the right time while satisfying the quality standards and service level requirements. The process can be broadly divided into three main areas: purchasing, manufacturing, and transport. From end to end this results about which input materials to use, size of production batches, inventory levels, distribution network configuration, and transportation for both the input materials and the finished products [1]. Today, international trade is commonplace and hence, it is safe to say goods are rarely consumed where they are produced, and transportation services are the essential link between all of the elements of the supply chain. Effective, cost-efficient transportation network can be a real point of competitive differentiation.

Though globalization has made the world shorter, it hasn't made it any simpler. With transportation being the most volatile element of a supply chain, it is bound to face most of the challenges, some of which are discussed below:

- Fuel Costs – As the fuel costs keep on changing, it becomes quite difficult to estimate the exact cost of running the transportation system. This challenge is more prominent when we are talking about transportation across the borders.
- Technology – With a new technology emerging every day, taking advantage of new opportunities might sound enticing but adoption and on boarding can be quite overwhelming.
- Improved Customer Expectation –In this modern era of cut-throat competition, the customers want full transparency about where their product is at all times. The increased cost of adding visibility increases the overall cost of transportation.
- Increasing Regulations – Various governmental rules and regulations are imposed to create a clear and legal functioning of supply chains. Regulations on the hours of service of drivers, compliance, safety, and accountability are vital requirements. Fulfilling all of them without falling victim to legal complications is a real hassle.
- Expansion in 3PL / 4PL Providers - 3PL and 4PL providers are third party and fourth party logistics company which manage part or the complete supply chain distribution. Extra expenses of third party service providers have to be dealt with in order to cope up with trends in the market.

1.1 Multiple Objective Transportation Problem

The transportation problem is an optimization problem which minimizes the cost of transporting some products that are available at *m* sources (supply nodes) and required at *n* destinations (demand nodes). The source parameter (sij) may be production facilities, warehouse, etc., whereas the destination parameter (dij) may be a warehouse, sales outlet, etc. The penalty (aij) that is, the coefficient of the objective functions, could represent transportation cost, delivery time, number of goods transposed, unfulfilled demand, and many others.

Most of the real-life transportation problems are multi-objective problems which mean that the problems involve multiple, conflicting and incommensurable objective functions. The resulting outcome is a set of optimal solutions with varying degree of objective values. Hence, it would be better to compute the final solution as the compromise solution of two optimum solutions.

The mathematical model of multi-objective transportation problem can be stated as below

$$(MOTSP)\ Z_K(x) = \sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}^{k} x_{ij}$$

$$Subject\ to \sum_{j=1}^{n} x_{ij} = s_i, i = 1,2,3,\dots m$$

$$\sum_{i=1}^{m} x_{ij} = d_j, j = 1,2,3,\dots n$$

$$x_{ij} \geq 0\ \forall\ i,j$$

1.2 Traditional Methods to Optimize Transportation Network

There are three mostly used traditional methods to determine the solution for balanced transportation problems, namely

1. Northwest Corner method
2. Minimum cost method
3. Vogel's approximation method

The three methods differ in the quality of the starting basic solutions they produce. Better starting solution yields a smaller objective value. The advantage of North-West corner method is a quick solution because its computations take shorter time but yields a bad solution because it is very far from optimal solution. Vogel's approximation method and Minimum-cost method are used to obtain the shortest road. The advantage of Vogel's approximation method and Minimum-cost method is that they yield the best starting basic solution and gives initial solution very near to optimal solution [2]. The cost of transportation with Vogel's approximation method and Minimum-cost method comes out to be lesser than the North-West corner method.

1.3 Genetic Algorithms

Genetic Algorithms (GAs) are adaptive heuristic search algorithms which belong to the larger part of evolutionary algorithms. Genetic algorithms are based on the ideas of natural selection and genetics. They are the intellectual manipulation of random search provided with chronological data to direct the search into the region of improved performance in solution space. They are commonly used to create high-quality solutions for optimization problems and search problems.

Genetic algorithms mimic the process of natural selection which means the species which can adapt to changes in their environment are able to survive and reproduce and go to the next generation. In simple words, they simulate "survival of the fittest" among individual of sequential generation for solving a problem. Each generation consist of a population of individuals and each individual represents a point in search space and possible solution. Each individual is represented as a string of character/integer/float/bits. This string is akin to the Chromosome.

1.4 Foundation of Genetic Algorithms

Genetic algorithms are based on a resemblance with genetic structure and behavior of chromosome of the population. Following is the foundation of GAs based on this analogy –

1. Individuals in population compete for resources and mate
2. Those individuals who are successful (fittest) then mate to create more offspring than others
3. Genes from "fittest" parent propagate throughout the generation that means sometimes parents create offspring which is better than either parent.
4. Thus each successive generation is more suited for their environment.

The Genetic Algorithm flow chart is shown in Fig. 1.

Fig. 1: Genetic algorithm flow chart

Search space

The population of individuals is maintained within the search space. Each individual represents a solution in search space for the given problem. Each individual is coded as a finite length vector (analogous to chromosome) of components. These variable components are analogous to Genes. Thus a chromosome -(individual) is composed of several genes (variable components).

Fig. 2

Chromosomes (or Phenotypes)

In genetic algorithm, chromosomes are the set of variables which define the proposed solution of the problems that are to be solved. It works by building a population of chromosomes. Within a generation of a population, the chromosomes are randomly altered in hopes of creating new chromosomes that have better evaluation scores.

1.5 Operators of Genetic Algorithms

Once the initial generation is created, the algorithm advances the generation by using the following operators –

1. **Selection Operator:** Inclination is given to the individuals which have good fitness scores and their genes are allowed to get passed to the successive generations.
2. **Crossover Operator**: This represents mating between individuals. Two individuals are selected using selection operator and crossover sites are chosen arbitrarily. The genes at these crossover sites are then exchanged (using single point, two point or uniform crossover operators) thus creating a completely new individual (offspring). The process is shown in Fig. 3:

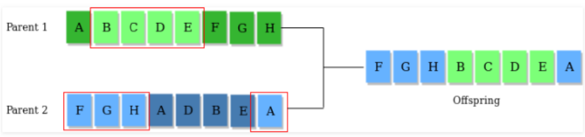

Fig. 3: Crossover operation

3. **Mutation Operator:** The purpose of mutation operation is to change the genes of the offspring and to increase the diversity of the population. This process enables GAs to jump out of local or suboptimal solutions [3]. Koza, et. al. put it best: "The exploitation of small differences in fitness yields major improvements over many generations in much the same way that a small interest rate yields large growth when compounded over decades [4]."
   Some of the commonly used mutation operators are:
   - Bit String Mutation Operator
   - Flip Bit Mutation Operator
   - Boundary Mutation Operator
   - Uniform Mutation Operator
   - Non Uniform Mutation Operator

2. NUMERICAL EXAMPLE

In order to demonstrate the application of the proposed approach for optimizing the MOTSP, a simple problem with four depots and fifteen customers in three states (A, B and C) is given on the assumption that each customers' demand must be served by only one depot. Moreover, a depot's capacity is sufficient to serve a customer. The cost (in hundreds of rupees) of transportation from each depot to each state is given in the matrix as xij where ij represents the cost of supplying from the respective depot to the customer.

$$\boldsymbol{A} = \begin{bmatrix} 10 & 13 & 10 & 7 & 10 \\ 8 & 4 & 8 & 8 & 6 \\ 7 & 6 & 10 & 12 & 4 \\ 7 & 9 & 12 & 3 & 3 \end{bmatrix} \boldsymbol{B}$$

$$= \begin{bmatrix} 3 & 10 & 9 & 2 & 5 \\ 2 & 10 & 10 & 6 & 3 \\ 9 & 2 & 9 & 5 & 6 \\ 2 & 9 & 7 & 10 & 9 \end{bmatrix} \boldsymbol{C}$$

$$= \begin{bmatrix} 3 & 5 & 7 & 4 & 7 \\ 5 & 9 & 5 & 10 & 3 \\ 6 & 4 & 6 & 4 & 7 \\ 7 & 10 & 7 & 4 & 2 \end{bmatrix}$$

Maximum supplies from each depot: a1 - 6, a2 - 5, a3 - 3, a4 – 10.

Demands of customers in each state: b1 - 5, b2 - 5, b3 - 7, b4 - 3, b5 - 4

Solution-

2.1 Initial Allocation (Parent Solution)
(Computed using VAM)

$$A1=\begin{bmatrix}0&0&6&0&0\\0&5&0&0&0\\3&0&0&0&0\\2&0&1&3&4\end{bmatrix}\quad B1=\begin{bmatrix}0&2&1&3&0\\0&0&1&0&4\\0&3&0&0&0\\5&0&5&0&0\end{bmatrix}\quad C1=\begin{bmatrix}2&4&0&0&0\\0&0&5&0&0\\0&1&2&0&0\\3&0&0&3&4\end{bmatrix}$$

Cost value (in Hundreds)

A1=148

B1=108

C1=108

2.2 Two Point Crossover

Two-point crossover has been performed to the parent matrices.

- The first crossover point is after the first column.
- The second crossover point is before the fifth column.

By using crossover operator, a second generation population of the solution is obtained from the above parent solution as following:

$$\mathbf{A2}=\begin{bmatrix}0&2&1&3&0\\5&0&0&0&0\\0&2&0&0&0\\0&0&6&0&4\end{bmatrix}\quad \mathbf{B2}=\begin{bmatrix}0&5&1&0&0\\0&0&1&0&4\\0&0&0&3&0\\5&0&5&0&0\end{bmatrix}\quad \mathbf{C2}=\begin{bmatrix}5&0&0&1&0\\0&5&0&0&0\\0&0&3&0&0\\0&0&4&2&4\end{bmatrix}$$

Cost value (in Hundreds)

A2=135

B2=106

C2=164

2.3 Mutation

Mutation alters one or more gene values in a chromosome from its initial state. In mutation, the solution may change entirely from the previous solution. In the given example some points have been randomly chosen and are then replaced with some other elements within the same matrix. This has been done at three points in each matrix. After that genetic algorithm has been applied. Hence the solution by GA can be further optimized by using mutation. The result obtained after applying both mutation and genetic is obtained as follows:

$$\mathbf{A3}=\begin{bmatrix}0&0&6&0&0\\5&0&0&0&0\\0&3&0&0&0\\0&2&1&3&4\end{bmatrix}\quad \mathbf{B3}=\begin{bmatrix}1&5&0&0&0\\1&0&0&0&4\\3&0&0&0&0\\0&0&7&3&0\end{bmatrix}\quad \mathbf{C3}=\begin{bmatrix}5&0&1&0&0\\0&5&0&0&0\\0&0&0&3&0\\0&0&6&0&4\end{bmatrix}$$

Cost value (in Hundreds)

A3=104

B3=85

C3=88

3. DISCUSSION OF RESULTS

The cost of transportation encountered in supplying the product to state A, B and C obtained from various optimizing techniques are shown in Fig. 4:

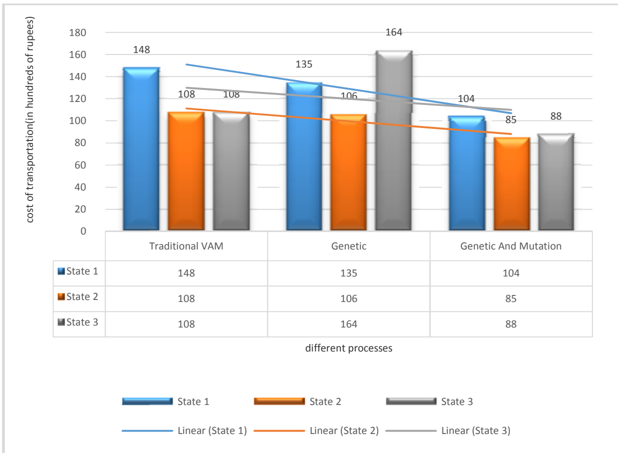

Fig.4: Comparison of Different Methods

From the above bar charts, it is quite evident that for optimizing the transportation network the process of genetic and mutation is the best.

The allocations (in units) for optimized cost of transportation which are obtained by using genetic algorithm along with mutation are shown in Table 1.

Table 1: Optimal allocations

Supplier	Demand of														
	State A					State B						State C			
A1	0	0	6	0	0	1	5	0	0	0	5	0	1	0	0
A2	5	0	0	0	0	1	0	0	0	4	0	5	0	0	0
A3	0	3	0	0	0	3	0	0	0	0	0	0	0	3	0
A4	0	2	1	3	4	0	0	7	3	0	0	0	6	0	4

Genetic Algorithm when used with mutation has provided us with not only the minimum individual costs for each state but also the overall cost of the project has been minimized.

4. CONCLUSION

The paper deals with the optimization of a multi-objective transportation problem using genetic algorithm. The result has been compared with several numbers of traditional cost minimizing transportation techniques and it is found that the proposed approach of using genetic algorithm yields comparatively a better result in a much shorter period of time. It is also found that genetic algorithm, when used along with mutation helps to improve the result by altering one or more genes in the initial solution. This will help the industries to achieve the target of minimizing transportation costs and maximizing their profit while functioning under the specified constraints.

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