Session 008

The Use Of The Genetic Algorithm To Solve Large Transshipment-Location Problems

Puneet Bhatia

Mechanical Engineering Department,
University of Louisiana at Lafayette

Dr. Terrence. L Chambers

Mechanical Engineering Department,
University of Louisiana at Lafayette

Summary

The Transshipment-Location problem has been solved using various different algorithms and programs such as the capacity scaling algorithm and infinitesimal perturbation analysis (IPA), however, it has never been solved using the Genetic Algorithm. This work reports on the progress of an effort to solve large Transshipment-Location problems using the Genetic Algorithm.

Abstract

This paper describes a two-phase stochastic procedure based on the Genetic Algorithm, to minimize the total transportation cost in transporting a product from sources to destinations through intermediate nodes (transshipment nodes). The Genetic Algorithm phase minimizes the total cost by modifying the transshipment node locations. The Linear Programming phase optimizes the allocations from the source locations to each intermediate node, and from each intermediate node to the destinations.

The proposed algorithm has been used to solve a small the Transshipment-Location problem using a binary representation. In the future, suite of 19 small test problems (from 2 X 2 X 4 to 2 X 2 X 7), and two large test problems (8 X 8 X 16 and 12 X 12 X 16) will be tested. The problems will be constructed in such a way that the exact solution will be known. In addition, the Genetic Algorithm will be tested on this suite of problems using both a binary and real-valued representation for the transshipment node locations.

Introduction

A Transportation Location problem is a problem in which both optimal source locations and the optimal amounts of shipments from sources to destinations are to be found. In the recent years, several researchers have attempted to solve these types of multi-modal objective problems. Some of the approaches to solve these problems are outlined below.

Cooper (1972)[2] formulated the transportation – location problem, which was a generalization of both the Hitchcock "Transportation Problem" and the "Location - Allocation" problem with unlimited constraints. He proposed an exact algorithm, which is considered to be exact and relatively simple in concept, but its use is limited to relatively small problems. A heuristic algorithm called the "Alternating Transportation – Location Heuristic" was also developed by Cooper (1972). This algorithm involved an iterative search technique to find the optimum. The steps are iterated until the amount of improvement in the objective value is reduced to within some tolerance. This algorithm was of limited utility, because it tended to get stuck in local minima.

The need for short computation time, and the increased complexity in the optimization problems lead to the search for more efficient methods, such as the heuristic Simulated Annealing algorithm (SA), and the Genetic Algorithm (GA), which produce more nearly globally optimum solutions in reasonable amount of time.

Liu et al. (1994)[4] have applied Simulated Annealing to solve large-scale Location-Allocation problems with rectilinear distances. The results showed high solution quality and computation time.

Gonzalez – Monroy et al. (2000)[3] have compared the use of Simulated Annealing with use of the Genetic Algorithm for the optimization of energy supply systems. The results inferred that for small problems, the Genetic Algorithm was more efficient than Simulated Annealing and for large problems, the reverse was true.

Chowdhury et al. (2001)[5] used a two-phase Simulated Annealing method for solving large – scale Transportation – Location problems with good results. Later Nallamotu et al. (2002)[6] extended that work by using the Genetic Algorithm in place of Simulated Annealing to solve large – scale Transportation – Location problems.

The present work builds upon the work of Nallamotu [6], by using the Genetic Algorithm to solve Transshipment-Location problems. The same problems will be solved, except adding transshipment nodes. Here the results will also compare the use of binary and real representations.

Problem Statement

Although the general Transshipment – Location problem refers simply to "sources", "transshipment nodes," and "destinations," for clarity's sake, we will solve a particular example of a Transshipment – Location problem, namely, identifying the optimal location of power plants to supply the new (or future) energy demands of a certain number of cities, given the location of certain coal mines. The objective of this problem will be to minimize the total power distribution cost from the mines to the plants, and the plants to the cities. The power distribution cost is the sum of the products of the power distribution cost (per unit amount, per unit distance), the distance between the mine and the plant, and the plant and the city, and the amount of power supplied from the mine to the plant, and the plant to the city, for all mines, plants, and cities. For each plant and city, we will constrain the total amount of energy supplied by all mines and plants to be equal to the total demand of that plant and city respectively. And for each mine and plant we will constrain the total amount of energy supplied by the mine and the plant to be less than or equal to the total capacity of the mine and plant respectively.

The mathematical form of the problem can be written as,

$$Min.Cost\,(C) = \sum_{i=1}^{S}\sum_{j=1}^{N}\phi_{sn}\delta_{ij}v_{ij} + \sum_{j=1}^{N}\sum_{k=1}^{D}\phi_{nd}\delta_{jk}v_{jk} \qquad Eqn.\ 1$$

subject to;

$$\sum_{i=1}^{S} v_{ij} = d_j \qquad for \qquad j = 1, N$$

$$\sum_{j=1}^{N} v_{ij} \le c_i \qquad for \qquad i = 1, S$$

$$\sum_{j=1}^{N} v_{jk} = d_k \qquad for \qquad k = 1, D$$

$$\sum_{k=1}^{D} v_{jk} \le c_j \qquad for \qquad j = 1, N$$

Where

ϕ_{sn} =	*transportation cost per unit amount per unit distance, from the source to the intermediate node*
ϕ_{nd} =	*transportation cost per unit amount per unit distance, from the intermediate node to the destination*
δ_{ij} =	*distance from source i to intermediate node j*
δ_{jk} =	*distance from intermediate node j to destination k*
v_{ij} =	*amount supplied from source i to intermediate node j*

v_{jk} = *amount supplied from intermediate node j to destination k*
S = *number of sources*
N = *number of intermediate nodes*
D = *number of destinations*
x_i , y_i = *X & Y coordinates of the source i*
x_j , y_j = *X & Y coordinates of the intermediate node j*
x_k , y_k = *X & Y coordinates of the destination k*
d_j = *demand of the intermediate node*
c_i = *source capacity*
d_k = *demand of the destination*
c_j = *intermediate node capacity*

Notice that the Euclidean distance term, δ_{ij} *or* δ_{jk}, can be calculated using Eqn. 2 and Eqn. 3 below.

$$\delta_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad \textit{Eqn. 2}$$

$$\delta_{jk} = \sqrt{(x_j - x_k)^2 + (y_j - y_k)^2} \qquad \textit{Eqn. 3}$$

Method

A two- phase method is implemented to solve the Transshipment-Location problem. In phase 1, the Genetic Algorithm technique minimizes the transportation cost by varying the transshipment locations. Phase 2 includes a Linear Programming technique to allocate the amount shipped from the sources to the transshipment nodes and from the transshipment nodes to the destinations, in accordance with the constraints. A summary of the method is given below.

Phase 1

1. The representation (binary or real); the number of generations; locations and demands for each city; the lower and upper limits for the mine locations; the mine capacities; the lower and upper limits for the plant locations; the plant capacities; and the population are specified. The upper and lower limits are used to create the initial random population of the source and transshipment locations.

2. The objective function (Eqn. 1) is evaluated for the population of plant locations by calling the phase 2 subroutine, which optimally allocates the amounts shipped from the sources to the intermediate nodes, and from the intermediate nodes to the

destinations. The function also insures that the constraints are satisfied and reports the overall transportation cost.

3. The X and Y locations of all of the plants of the initial population are converted to base 10 integers. And further they are converted to their binary forms.

4. The selection of mating parents is done by roulette wheel selection, in which a probability that any individual(s) will be selected to mate is given by the following equation:

   Pi = fi/(f1+f2+f3..) where Pi = Probability of an individual, and fi = fitness values, which are proportional to the overall transportation costs. Mating parents are then randomly selected, based on this probability.

5. The parents thus selected are caused to mate using the single point crossover method. The children thus obtained form a new population. The binary version of the new population is converted to base 10 integers and then to real values.

6. In order to maintain the diversity in the population, random mutation is included at low level of probability. Mutation is the random change of a gene from 0 to 1 (or) 1 to 0.

7. Elitism is performed, which is the procedure by which the weakest individual of the current population is replaced by the fittest individual of the just previous population.

8. Steps 2 - 5 are repeated until the desired number of iterations has been performed.

9. The final cost, the final X and Y locations of the plants, are reported.

Phase 2

In Phase 2, the proposed locations of the plants are received from Phase 1 and are solved as two linear transshipment problems using the simplex algorithm. The simplex algorithm optimizes the cost for allocation of power from the plants to the cities to a minimum. The optimal cost value, which is the objective function value in Genetic Algorithm, is passed to Phase 1.

Results

So far, the method described above has only been applied to small problems with a binary representation. The results are promising, but more work is needed before any conclusions can be drawn.

Conclusion

A new two phase Genetic Algorithm for the solution of Transshipment-Location problems has been described. Initial results look promising, but more work on a larger set of test problems will be required before any certain conclusions can be reached. This work will also eventually include a comparison of binary and real representations within the Genetic Algorithm.

References

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PUNEET K. BHATIA
Puneet Bhatia is scheduled to receive his Master of Science in Mechanical Engineering in the Summer 2004 from the University of Louisiana at Lafayette. Her research interests include Artificial Intelligence, Programming, and Engineering Optimization. She received his Bachelor of Science in Electrical Engineering from University of Oklahoma, Norman in December 2001. She is a student member of the ASME and SWE.

TERRENCE CHAMBERS
Dr. Terrence Chambers currently serves as an Assistant Professor of Mechanical Engineering at the University of Louisiana at Lafayette. His research interests include engineering design and optimization, artificial intelligence, genetic algorithms and genetic programming, engineering software development, and numeric and symbolic solutions to engineering problems. Dr. Chambers is a registered Professional Engineer in Texas and Louisiana