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The Modeling of Optimization and Decline Transportation Costs in Supply Chain System

National Iranian Oil Products Distribution Company (n.i.o.p.d.c)

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Abstract— **This paper presents a new model and solution for multi-objective vehicle routing problem (VRP).This paper, using goal programming with specific constraints and this model solve with genetic algorithm, that in which decision maker specifies optimistic aspiration levels to the objectives and deviations from those aspirations are minimized. The proposed algorithms have been successfully implemented and deployed for the real life problems in National Iranian Oil Products Distribution Company. The objective is to minimize the distance in each travel and minimize the number of vehicle without being tardy or exceeding the capacity or travel time of the vehicles. In this paper we describe goal programming, a genetic algorithm heuristic for solving the VRP. The synergy between goal programming and genetic algorithm lead to a best solution for VRP. The VRP plays a central role in the fields of physical distribution and logistics. There exist a wide variety of VRPs and a broad literature on this class of problems. The purpose of this paper is to minimize distance between pair of node and reduce the number of vehicle for each route.**

Keywords:supply chain management, transportation, goal programming,Genetic algorithm.

I. INTRODUCTION

Throughout the world, physical distribution has been developing rapidly during recent decades, while demands for customers have been increasing. A number of distribution centers have emerged and expanded under these circumstances. Fast delivery makes a logistics company more competitive, and the distribution cost is an essential problem it concerns. Therefore, vehicle routing is a problem of undeniable practical significance in logistics distribution. The vehicle routing problem (VRP) is one of visiting a set of customers using a fleet of vehicles, respecting constraints on the vehicles, customers, drivers, and so on. The goal is to minimize the costs of operation, which normally involves reducing a combination of the number of vehicles and the total distance travelled or time taken. The vehicle routing problem (VRP) was first proposed by Dantzig and Ramser (1959). It is an extension of the travelling salesman problem. During the past five decades, the VRP models have been developing rapidly and many other new models have derived from this original model [4].This paper is based on the vehicle routing problem (VRP), where a set of vehicles with limited truckload are to be routed from a distribution center to a set of geographically dispersed customers with known demands.VRP is not only a theoretical conundrum in Operations Research, but also a useful practical problem. It is not enough to get the distribution routes only by theoretical algorithms with certain conditions. In recent years, computer simulation is widely used on studies in logistics distribution. The simulation technology supplies the research of complicated distribution system with direct and effective analysis methods. *Local search* is the most frequently used heuristic technique for solving combinatorial optimization problems. It is also the basis for modern met heuristics, like, e.g. Taboo Search, and Variable Neighborhood Search. The paper introduces *sequential search* as a generic technique for the efficient exploration of local-search neighborhoods [5].The paper is structured as follows. In Section 2, we define the VRP and VRPTW and review classical and some recent papers on this problem. Section 3 introduces the goal programming and VRP modeling and define variable the constraints of model. In Section 4, the general principles of genetic algorithm and two operators (cross over and mutation) are applied and in order to show effectiveness of GP and GA using real data in National Iranian Oil Products Distribution Company (n.i.o.p.d.c).In section 5 final conclusions are given in Section.

II. LITERATURE REVIEW

Routing and scheduling problems are important elements of many logistics systems. A lot of research has been done to solve these complex combinatorial problems in an effective way. One of the major research topics has been the Vehicle Routing Problem (VRP) that involves the design of a set of minimum-cost vehicle routes, starting and ending at a central depot, and servicing a set of orders of customers with a fleet of vehicles. Each

Customer has a given demand that has to be serviced using only one vehicle. A vehicle cannot service more customers than its capacity enables it to. In this paper we focus on a variant of VRP, where each customer has an allowable delivery time period [13].In this section; we briefly review the literature on VRP, especially heuristic methods. VRP is one of the most attractive topics in operation research and deals with determination of the least cost routes from a central depot to a set of geographically dispersed customers. Vehicle routing problems (VRPs) are well known combinatorial optimization problems arising in transportation logistic that usually involve scheduling in constrained environments. In transportation management, there is a requirement to provide goods and/or service from a supply point to various geographically dispersed points with significant economic implications. Because of many applications of different kinds of VRP, many researchers have focused to develop solution approaches for these problems. Byung-In Kima, Seongbae Kimb, Surya Sahoob,2005, address a real life waste collection vehicle routing problem with time windows (VRPTW) with consideration of multiple disposal trips and drivers lunch breaks. Solomon's well-known insertion algorithm is extended for the problem, While minimizing the number of vehicles and total traveling time is the major objective of vehicle routing problems.[8] in a their article present a unified heuristic, which is able to solve five different variants of the vehicle routing problem: the vehicle routing problem with time windows (VRPTW), the capacitated vehicle routing problem (CVRP), the multi-depot vehicle routing problem (MDVRP), the site dependent vehicle routing problem (SDVRP) and the open vehicle routing problem (OVRP). They present a mathematical formulation of the VRPTW problem. The mathematical model is used to describe the heuristic in details in later sections and to describe how the considered VRP variants are transformed to the VRPTW.[9] present a mixed -integer formulation of the vehicle routing problem with time window constraints. Their formulation is based upon the model defined by Solomon. That research shows that genetic search can obtain good solutions to vehicle routing problems with time windows compared to traditional heuristics for problems that have tight time windows and a large number of vehicles with a high degree of efficiency. The adaptive nature of the genetic algorithms is exploited by GIDEON to attain solutions that are of high performance relative to those of competing heuristics. This methodology is potentially useful for solving VRPTW's in real time for routing and scheduling in dynamic environments. [10] Shows that Heuristic algorithms for the VRP can often be derived from procedures derived from the TSP. He nearest neighbor algorithm, insertion algorithms and tour improvement procedures can be applied to CVRPs and DVRPs almost without modifications. However, when applying these methods to VRPs are must be taken to ensure that only feasible vehicle routes are created. [11] Use a local search method we term Large Neighborhood Search (LNS) for solving vehicle routing problems. LNS mesh well with constraint programming technology and is analogous to the shuffling technique of job-shop scheduling. The technique explores a large neighborhood of the current solution by selecting a number of customer visits to remove from the routing plan, and re-inserting these visits using a constraint-based tree search. [12] Study a variant of the multi-depot vehicle routing problem where depots can act as intermediate replenishment facilities along the route of a vehicle. This problem is a generalization of the Vehicle Routing Problem (VRP).

III. GOAL PROGRAMING

The VRP specification requires a minimization of both the number of vehicles and total distance traveled. From a theoretical point of view, this may be impossible to realize, because instances of the VRP may have many non-dominated solutions. Some solutions may minimize the number of vehicles at the expense of distance, and others minimize distance while necessarily increasing the vehicle count. If one scans the literature, however, most researchers clearly place priority on minimizing the number of vehicles. Although this might be reasonable in some instances, it is not inherently preferable over minimizing distance. Minimizing the number of vehicles affects vehicle and labor costs, while minimizing distance affects time and fuel resources [14]. Therefore, the VRP is intrinsically a Multiple Objective Optimization (MOP) problem in nature, and it recognizes these alternative solutions. Now we want introduce a new model from VRP that it can minimize two objectives. One objective is minimizing of distance and another objective is minimizing number of vehicle.

For gain this two objective we define goal programming. And then this model solve with genetic algorithm. Than we apply a real data from National Iranian Oil Products Distribution Company (n.i.o.p.d.c) to solve the model.

A. Model Formulation

The vehicle routing problem (VRP) is given by a special node called depot, a set of customer (C) to be visited and a directed network connecting the depot and the customers. Also homogeneous fleet of vehicles is available. They are located at the depot, so they must leave from and return to the central depot. It is assumed that there is no limitation on the number of vehicles that can be used, but in order to facilitate the model formulation the maximum possible size of the fleet is denoted by K. The actual number of vehicles will be found after solving the model that it would be equal to the number of routes in the traffic network. Let us assume there are N+ 1 customers, C= {0, 1, 2, . . .,N} and for simplicity, depot is denoted as customer 0.

Each arc in the network corresponds to a connection between two arcs. A route is defined as starting from depot, going through a number of customers and ending at the depot. A distance d_{ij} and travel time t_{ij} are associated with each arc of the network. Every customer in the network must be visited only once by one of the vehicles. Since each vehicle has a limited capacity q_k (k = {1,..., K}), and each customer has a varying demand m_i, q_k must be greater than or equal to the summation of all demands on the route travelled by that vehicle k. The model has two types below variables:

For each arc (i, j), where $i \neq j$, $i, j \neq 0$, and each vehicle k, the decision variable x_{ijk} is equal to 1 if vehicle k drives from vertex i to vertex j and 0 otherwise. The decision variables, In order to formulate the model, other following notations are defined:

The objective of the VRPTW is to serve all the C customers such that the following objectives are met and the following constraints are satisfied.

Objectives are:

• Minimize the distance traveled by the vehicles.

• Minimize the total number of vehicles used to serve the customers.

Constraints are:

• Vehicle capacity constraints are observed.

• Time window constraints are observed.

• Each customer is served exactly once.

• Each vehicle starts its journey from depot and ends at the depot.

Therefore, after establishment of target levels which represent optimistic aspiration levels for each objective, this multi-objective problem is formulated as a goal programming model. Hence, the following goals, in accordance with the above mentioned objectives are defined:

$$(1) Goal(1): \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=0}^{N} d_{ijk} x_{ijk} \le b_1$$

$$(2) Goal(2): \sum_{k=1}^{N} \sum_{j=0}^{N} x_{ijk} \le b_2 \qquad For\, i = 0$$

$$(3)\, s.t: \vec{x} \in \Delta \text{ (feasible space)}$$

$$(7) \sum_{j=1\ j\neq i}^{N} x_{ijk} = \sum_{j=1\ j\neq i}^{N} x_{jik} \le 1 \quad For\, i = \{0,\dots,N\}, K = \{1,\dots K\}$$

$$(8) \sum_{k=1}^{K} \sum_{j=0\ j\neq i}^{N} x_{ijk} = 1 \quad For\, i = \{1,\dots,N\}$$

$$(9) \sum_{k=1}^{N} \sum_{j=0\ j\neq i}^{N} x_{ijk} = 1 \quad For\, j = \{1,\dots,N\}$$

$$(10) \sum_{i=1}^{N} m_i \sum_{j=0\ j\neq i}^{N} x_{ijk} \le q_k \quad For\, k = \{1,\dots,k\}$$

$$x_{ijk} \in \{0,1\} \quad For\, i,j = \{1,\dots,N\}$$

$$P_1, P_2, P_3, P_4, b_3, b_4 \ge 0 \quad For\, i = \{1,\dots,N\}\ ,,\ k = \{1,,,,k\}$$

Formula (4) at subject function formulation minimizes the undesired deviations from the aspiration level of the objectives Constraints (5) and (6) refer to goals 1 and 2. They indicate the difference between what is aspired and what is accomplished with respect to the objectives. It does not make any sense for both deviational variables to take non-zero values simultaneously. Constraint (7) secures every route starts and ends at the central depot. Constraints (8) and (9) define that every customer node is visited only once by one vehicle. Constraint (10) is the capacity constraint. There is no need of any additional constraint for each goal. Since the suggested solution approach (that will be described later) does not require objective functions to be differentiable, the aforementioned objective function could be used. Since there is a way to convert a goal programming problem into an equivalent multi-objective problem, a multi-objective genetic algorithm could be used to solve it. The multi-objective genetic algorithm is described in the following section.

The first and second goals in relations (1) and (2) indicate the aspiration levels of objectives (1) and (2). b_1 and b_2 are the target values associated with the desired levels of the objectives (1) and (2) which control the distance traveled by vehicles and the total number of vehicles used to serve the customers.

In order to treat the goals, two mathematical equations (5) and (6) are written and added to the constraints using the non-negative deviational variables (P_i for i = 1,2,3,4) which measure the deviation from the target values. Therefore the objective of the model is to minimize the undesirable deviations P_1 and P_2.Given the above defined goals, target levels, deviational variables and decision variables, the problem is formulated as follows:

(4) Minimize P_1

Minimize P_3

Subject to:

$$(5) \sum_{i=0}^{N} \sum_{j=0, j\neq i}^{N} \sum_{k=1}^{N} d_{ijk} x_{ijk} - p_1 + p_2 = b_1$$

$$(6) \sum_{k=1}^{k} \sum_{j=1}^{N} x_{ijk} - P_3 + P_4 = b_2 \qquad For\, i = 0$$

B. Genetic Algorithm

Genetic Algorithms is an iterative procedure that maintains a population of _ candidates (solutions). The population members can be seen as entities of chromosomes. Each chromosome has a value describing the goodness" of the solution. Variation into the population is introduced by cross-over and mutation. Cross-over is the most important operator. Mutation prevents loss of important information by randomly mutating (inverting) bits in the chromosomes. The termination criterion is usually a certain number of iterations [1].

The results presented below are based on the following parameters:

• Population size = 12

• Generation number = 250.

• Crossover rate = 0.50.

• Mutation rate = 0.10

IV. RESULTS ANALYSIS

For solve this model we collect below data from n.i.o.p.d.c:

1) Distance matrix between depot and costumer and Costumer with each other

2) Vehicle capacity

3) Demand of costumer

4) Cost level decision maker

5) All distance between costumer and depot that all vehicles

We have 16 customers that serviced with 7vehicles.

We coded this data with genetic algorithm in m

MATLAB software. For solving multi-objective VRP with GAs, it is usual to represent each individual by just one chromosome, which is a chain of integers, each of them representing a customer. In this representation each vehicle identifier (gene with index 0) represents in the chromosome a separator between two different routes, and a string of customer identifiers represents the sequence of deliveries that must cover a vehicle during its route. Each route begins and ends at the depot. If there is a solution that shows two vehicle identifiers in consecutive manner with no customer identifier in between, it would be understood that the route is empty and, therefore, it will not be necessary to use all the vehicles available. This representation allows the number of vehicles to be manipulated and minimized directly for multi-objective optimization in VRP. It should be noted that most existing routing approaches consider an individual objective such as cost of traveling distance due to the fact that the number of vehicles is incontrollable in their representations. Fig (1) shows a initial solution by 12 population and 25 generation.

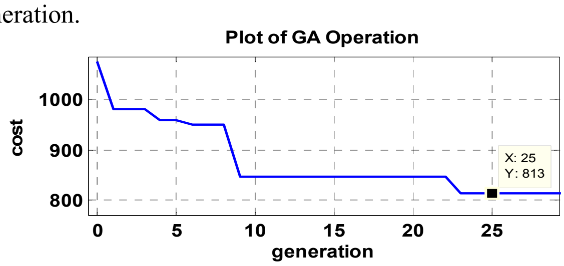

Figure1. 25generation, 813km for subject function

Fig (1) shows 813 for subject function whereas in real data distance between costumers is 820.

Fig (2) shows 60 generation with 755.5km between costumers and 6 vehicles.

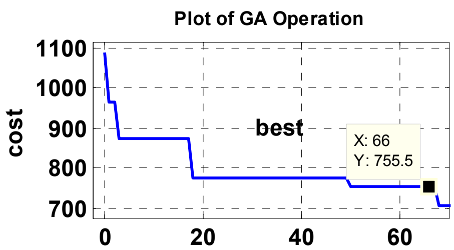

Figure2. 60generation with 755.5km subject function

And final fig (3) shows best solution for this problem. Subject function is 685 and number of vehicles is 5.

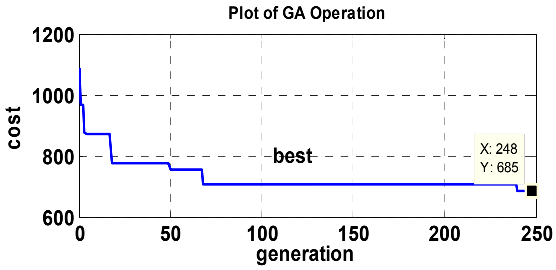

Figure3. 250generation with 685km subject function

TABLE1. shows best solution in 250 generation.

[illegible]	Routes Genes.																N. vehicle	Cost
1	6	2	9	13	3	8	5	12	11	4	10	14	7	15	16		5.	665
2	5	12	11	14	10	4	9	13	15	16	7	3	8	2	6		6	840
3	1	12	5	4	16	10	7	3	14	6	8	15	13	2	9		6	933. 5
4	1	12	5	15	16	6	4	3	10	2	8	7	9	14	13		6	963. 5
5	3	12	13	11	14	4	6	5	15	16	7	10	8	2	9		5.	1008
6	5	8	4	13	14	9	12	3	15	10	7	16	6	2	11		6.	1030. 5
7	3	12	4	13	10	11	8	5	15	16	7	6	14	2	9		5.	1032
8	3	12	2	13	10	4	8	5	15	14	6	16	7	11	9		6.	1047. 5
9	11	12	2	15	16	10	7	14	8	6	4	3	13	5	9		6.	1061
10	10	12	6	13	5	15	8	3	11	7	14	16	4	2	9		6.	1109
11	7	12	5	13	10	4	16	2	15	3	11	14	8	9	6		7.	1245. 5
12	5	12	3	13	10	4	9	11	15	16	14	7	8	2	9		6.	4 .1280

TABLE2.

6	2	9	13	3	8	5	12	11	4	10	14	7	15	16
vehicle 1		vehicle 2		vehicle 3				vehicle 4			Vehicle 5			

Table(2)shows that 16 costumer dividend between 5 vehicles in 5 different routs.

V. CONCLUSION

This paper suggested a new model and solution for multi objective vehicle routing (VRP), using goal programming and genetic algorithm. This paper considered the VRP as a multi-objective problem that in which fleet size of vehicles and total travelling distance are minimized.

This paper formulated Multi-Objective VRP mathematically as MOV-GP (I) formulation with the approach of goal programming. In this idea the decision maker specified optimistic aspiration levels to the objective functions of the problem and deviations from these aspiration levels were minimized. Then an efficient multi-objective genetic algorithm was suggested for solving this model. The proposed genetic algorithm used a string of customer identifiers which represented the sequence of deliveries that must cover a vehicle during its route and each vehicle identifier represented a separator between two different routes. At the end, the algorithm was applied to solve the problem of n.i.o.p.d.c. According to the produced results, the suggested approach was quite sufficient as compared to the best published results and the average GA performance was adequate.

REFERENCES

[1] Jesper Larsen. Parallelization of the Vehicle Routing Problem with Time Windows.(1999).

[2] Keivan Ghoseiria,b , Seyed Farid Ghannadpour. Multi-objective ehicle routing problem with time windows using goal programming and genetic algorithm,(20101).

[3] Gilbert Laporte, The Vehicle Routing Problem: An overview of exact and approximate algorithms,(2005).

[4] Wenhui Fan, Huayu Xu and Xin Xu,Stefan Irnicha, , Simulation on vehicle routing problems in logistics distribution,(

[5] Birger Funkeb, Tore Grünertb, Sequential search and its application to vehicle-routing problem,(2005).

[6] Stefan Ropke,David pisinger, A general heuristic for vehicle routing problems,(2005).

[7] Byung-In Kima,∗, Seongbae Kimb, Surya Sahoob, Waste collection vehicle routing problem with time windows,(2005).

[8] David Pisinger ,tefan Ropke, A general heuristic for vehicle routing problems,(2005).

[9] Sam R. Thangiah, Vehicle Routing with Time Windows using Genetic Algorithms,(2007).

[10] Gilbert Laporte, The Vehicle Routing Problem: An overview of exact and approximate algorithms,(1991).

[11] Using Constraint Programming and Local Search Methods to Solve Vehicle Routing Problems Paul Shaw,(1998).

[12] Benoit Crevier, Jean-Franc¸ois Cordeau, Gilbert Laporte, The multi-depot vehicle routing problem with inter-depot routes,(2004).

[13] Ollibraysy,Geirhasle, , Systematic divercification metaheuristic for the vehicle rutingg problem with time windows,(2007).