Periodic Distance-Constrained Multi-Perspective Clustered Open Vehicle Routing Problem

Timur Keskintürk

Department of Quantitative Methods, School of Business

Istanbul University, Istanbul, Turkey

tkturk@istanbul.edu.tr

Ayşen Yücel

Department of Quantitative Methods, School of Business
Istanbul University, Istanbul, Turkey

aysenycl@gmail.com

Abstract

The Vehicle Routing Problem (VRP) is one of the difficult combinatorial problems and aims to find optimum routes for vehicles with the constraint that beginning and ending at the depot. If vehicles are not required to return to the depot, this type of VRP is named as open vehicle routing problem (OVRP). VRP and OVRP have several variations and specializations. One of them is Distance constrained vehicle routing problem (DVRP) which all vehicles are identical and where the distance or time travelled by any vehicle, may not exceed a prespecified upper bound. Another variant of VRP is allocated customers into groups, Clustered vehicle routing problem (CluVRP). In this type, each cluster has to be visited once, and a vehicle entering a cluster cannot leave it until all customers have been visited. In this ongoing study both distance-constrained and cluster constraints are handled. Unlike the classical CluVRP, in our problem, clusters not formed due to one constraint, there are different sets of clusters formed from different perspectives. For instance, to determine the number of visits by representatives, doctors are divided into clusters and these clusters are generated separately for each medicine type. This paper aims to find optimum routes for the sales representatives with a real-world data with using a model of a new problem named as Distance Constrained Multi-Perspective Clustered Open Vehicle Routing Problem (DMPCluOVRP) by Genetic Algorithm. Our dataset is obtained from an international company operating in Istanbul, consisting of 61 doctors working in different 22 hospitals and 16 sales representatives.

Keywords
Vehicle Routing Problem, Meta-heuristics, Distance Constrained VRP, Clustered VRP

1. Introduction

The vehicle routing problem (VRP) is generally defined as finding the distribution or collection routes from one or more depots to geographically scattered customers by minimizing the total distance travelled by the vehicle fleet, under certain constraints. VRP is an NP-hard problem that was first introduced by Dantzig and Ramser in 1959 and it is an extension of the well-known travelling salesman problem (TSP). VRP is defined on a complete undirected graph G = (V, A). The set V = {0, …, n} is a vertex set which represents (n+1) nodes and A = {(i, j): i, j ∈ V; i < j} is the set of arcs. The "node 0" represents the depot and the remaining nodes correspond to the n customers. Each arc between i and j symbolizes the distance between these nodes and it has a non-negative travel cost $c_{ij} = c_{ji}$. This equation means, the problem is symetric. Classic VRP solution is the cluster of routes ensure that each routes starts and ends at the depot and each customer is visited once by one vehicle. The other common constraints are the capacity constraint, the maximum demand point in a route, the total time constraint of the vehicle and time window constraint.

Many variations of VRP have been suggested, but the main objective is to minimize the total routing cost while satisfying all customer demands and respecting the constraints of the vehicles. The Capacitated Vehicle Routing Problem (CVRP) is the most mentioned and studied type of VRP where the vehicles have a certain capacity they cannot exceed while serving the customers. Distance Constrained Vehicle Routing Problem (DVRP) is the version of CVRP, where for each route the capacity constraint is replaced by a maximum length or time constraint. In this type, while finding optimum routes for vehicles, customers might be visited in a certain time or distance. A variant of the CVRP is the Clustered Vehicle Routing Problem (CluVRP) which customers are grouped into clusters. The main difficulty of this problem is that when a vehicle serves a customer belonging to a given cluster, it has to serve all the customers of that cluster before it can enter another cluster or go back to the depot. Sevaux and Sörensen lately introduce Hamiltanion paths for clustered VRP in 2008. Recently, Vidal et. all, suggested a metaheuristic approach to CluVRP.

As it is seen from above the definition of the classical VRP construction, routes start and end at the central depot. In some special cases it is not an obligation that the tour must end at the central depot which is called Open Vehicle Routing Problem (OVRP).

In this ongoing study, the problem which the combination of DVRP, CluVRP and OVRP and problem specified multi-perspective constraint, will be explained in the next section, is discussed. This problem is named as Distance Constrained Multi-Perspective Clustered Open Vehicle Routing Problem (DMPCluOVRP). The combination of such a problem is not considered in the literature. The classical VRP is one of the most popular combinatorial optimization problem and the studies about it provide applicability various exact and heuristic techniques for its solutions. Like all VRP, this problem also types of combinatorial optimization problems. Since the data set is complicated, it is difficult to solve with exact methods. Because of that, in our problem the Genetic Algorithm meta-heuristic is used as a solution technique.

The problem definition and mathematical model are introduced in Section 2. In Section 3, the concept of Genetic Algorithm and the implementation of it to DMPCluOVRP is described briefly. A real life problem is considered in Section 4 while the conclusion is referred in Section 5.

2. Problem Definition and Mathematical Model

The studied problem named as Distance Constrained Multi-Perspective Clustered Open Vehicle Routing Problem (DMPCluOVRP). All the vehicles have predetermined total tour duration constraint. If the route duration that is performed by any vehicle, exceeds the time limit, the solution will become infeasible. The other feature of the problem is multi-perspective clustering that differs it from the literature. Different than the classical CluVRP, both customers and vehicles are classified among themselves according to some characteristics. Furthermore, for both customers and vehicles, there are more than one perspectives to group them. The customers which are in the same group according to first aspect, may not be together in the other group set that is formed according to different aspect. This situation is also valid for clusters of vehicles. The perspectives are divided in two groups. The first group of perspectives are effective for both vehicles and customers and the groups that formed by those perspectives are certain. The goal is to assign vehicles to the customers with best matching between clusters. Better matching assignments results better objective function value. In the second group of perspectives, the customers' clusters are formed depends on the vehicles' clusters. Therewithal, in the problem vehicles start their routes from the depot but they don't go back to the depot after they finish visiting the customers for all periods.

Taking into account all of these, before the mathematical formulation of the DMPCluOVRP, some basic terminologies from graph theory is introduced below.

Definition 1. G is a complete undirected graph symbolized as G = (V, E) where V = {0, 1, 2, ..., n} is the set of vertices which represents nodes for VRP problems, and E = {(i, j) |i, j ∈ V, i≠j} is the set of edges that represents unordered pairs of distinct vertices.

Definition 2. G = (V, E) is referred as a connected graph if there is a path between all vertices.

As previously noted, G is an undirected graph corresponding to a vehicle routing problem where "vertex 0" states the central depot and vertex *i* corresponds to customer *i*, for $1 \leq i \leq n$. The other variables are defined as in 2.1 Variables.

2.1. Variables

$\boldsymbol{n}$: Number of customers where V = {0, 1, 2,..., *n*}

$\boldsymbol{p}$: Number of periods where P={1,2,…,*p*}

$\boldsymbol{r}$: Number of vehicles where R={1,2,…,*r*}

$\boldsymbol{c_{ij}}$: Cost between customer *i* and *j*

$\boldsymbol{h_i}$: Service time for customer *i*

$\boldsymbol{T}$: Maximum travel time per period

$\boldsymbol{K_l}$: A sequence $(\pi_{0,}\, \pi_{1,}\, \ldots, \pi_{k,})$ corresponding a route of vehicle *l*, so number of nodes that vehicle *l* has visited, is *k*. Such that $(\pi_{j,}\, \pi_{j+1}) \in$ E, for all 1 ≤ j ≤ k.

$$C(K_{lt}) = c_{\pi_0,\pi_1} \; + \; h_{\pi_1} \; + \sum_{i=1}^{k-1} c_{\pi_i,\pi_{i+1}} \; + \; h_{\pi_{i+1}}$$

is the total travel time for route K_l in period *t*.

A solution S is a collection of routes $K_1, K_2, \ldots, K_l$ and the DMPCluOVRP can be formulated as the following optimization problem [11];

$$Min\ C(S) = \sum_{l \in R} \sum_{t \in P} C(K_{lt})$$

With a constraint of a distance (time);

$$C(K_{lt}) \leq T$$

3. Genetic Algorithm for DMPCluOVRP

The Genetic Algorithm (GA) is a population based metaheuristic that introduced by John Holland in 1975. GA is a search and optimization technique that uses natural selection methods to perform optimal/local searches. It can work only by using an objective function, without assumptions and preliminaries. Problem variables are represented in the sequences which are called chromosomes by using genes.

In general, genetic algorithm includes implementation of selection, crossover and mutation operators to the population consisting of the sequences. The steps of algorithm are explained as follows: In genetic algorithm the encoding format is decided firstly, means shaping the specific information into the form that the genetic algorithm will use. Generally, binary encoding, permutation encoding and real-valued encoding are used. The group of solutions are encoded as sequences from all possible solutions in the search space. Usually, this process is implemented randomly and the initial population is created. Then, fitness value is calculated for each chromosome. It shows the quality of solutions. After that, the selection operator is implemented. The aim is to replicate better individuals in the population and to eliminate individuals with low fitness value. There are several selection methods: The roulette wheel selection, tournament selection, stochastic sampling and sequential selection are examples of these. After a selection, crossover and mutation operators are implemented with predefined probabilities. The crossover operator is used to increase the potential of the existing gene pool and to create better qualified generations than previous ones. For implementing crossover operator, two chromosomes are selected randomly and crossover exchange is implemented. Thus, producing higher convenient alternative solutions is ensured. The other operator mutation consists of alterations that are made on any random gene by using low probability ratio due to maintain protection against loss of chromosomes that have high fitness value. It Increases the ability to produce new candidates. After these operators, new population is replaced with the previous population. This process continues until termination criterion is satisfied and the most feasible chromosome is selected as a final solution. It is an iterative search, optimization and adaptive machine learning technique premised on the principles of natural selection and they are capable to finding good solutions to NP hard problems.

The real life vehicle routing problems are usually large problems that exact methods can not be used to solve them in appropriate time. For the past two decades, the emphasis on metaheuristics which are methods that used to find good solutions in a reasonable time, is experienced.

Laporte is one of the first researchers to refer GA and other heuristic methods as efficient solution approaches for VRP and his paper is one of the pioneers for other researches for implementing GA to VRP.

Han and Tabata, developed a Hybrid-Genetic Algorithm to improve the accuracy of the results. They found that using Sweep Heuristic with Genetic Algorithm may give better results and there is an important research-space for hybrid-GA approach.

Pereira et. all, presented a new genetic evolutionary approach to the VRP. Their two-level representational scheme is more effective to VRP, which finds new best solutions for several instances belonging to well-known benchmarks. Moreover, results show that this method is both robust and scalable.

Mohammed et. all, shows that GA is efficient for solving Capacitated Vehicle Routing Problem (CVRP) and finding approximate solution as it is capable of solving many other problems in real life. The strength of the GA stems from its ability to be adapted to solve any problem through combining with other algorithms or by modifying its techniques according to the problem.

In this study, genetic algorithm intended to be used and the model is designed for solving the problem as follows.

3.1. Chromosome Representation for DMPCluOVRP

In our problem vehicles are sales representatives who work for pharmacy company to introduce different types of medicines to customers. Customers are doctors in our problem that work in different hospitals and we consider 10day period of visiting them by the representatives.

Chromosome structure is composed of two sub-chromosomes which are interrelated. The first sub-chromosome represents the assignment of sales representatives to doctors in relevant period. It consists of ***m*** unit pages which are referred to medicines and each page is formed as a matrix which has ***n*** unit columns and ***p*** unit rows. In the matrices, columns represent doctors and rows represent periods. Besides that, there are ***r*** number of sales representatives which are defined in separate sets for each page and as a result of the necessary assignment process that the algorithm is performed, they should take place as matrix data. These assignments perform by considering two perspectives. The first one is personality color which refers general character of person, related to which sales representative should visit which doctor. The personality colors of doctors and sales representatives are inputs of the problem by which wanted the matching of doctors and sales representatives have same color. These color matching also determine the service time of sales representatives for related doctor. The other perspective for assignment is related to number of visits per doctor. Doctors are clustered into different groups by their medication potential to related medicine. All clusters have criteria for visiting number and it is checked by summing the positive number values of each column. After the initial assignment on the first sub-chromosome, all datum of each row of all pages is taken into second sub-chromosome which represents the routing process. Accordingly, the second sub-chromosome also formed as $\boldsymbol{p}$ unit pages which represents a day. Each page structure is matrix form and has $\boldsymbol{r}$ unit rows that are sales representatives and the number of $\boldsymbol{max\ \pi_k}$ columns. $\boldsymbol{max\ \pi_k}$ represents the maximum number of visited doctors per day and it may change in all days and for all iterations. In regard to first sub-chromosome, the second sub-chromosome matrix' data includes ordered doctors' information for each sales representative daily. Figure 1 shows the chromosome structure basically.

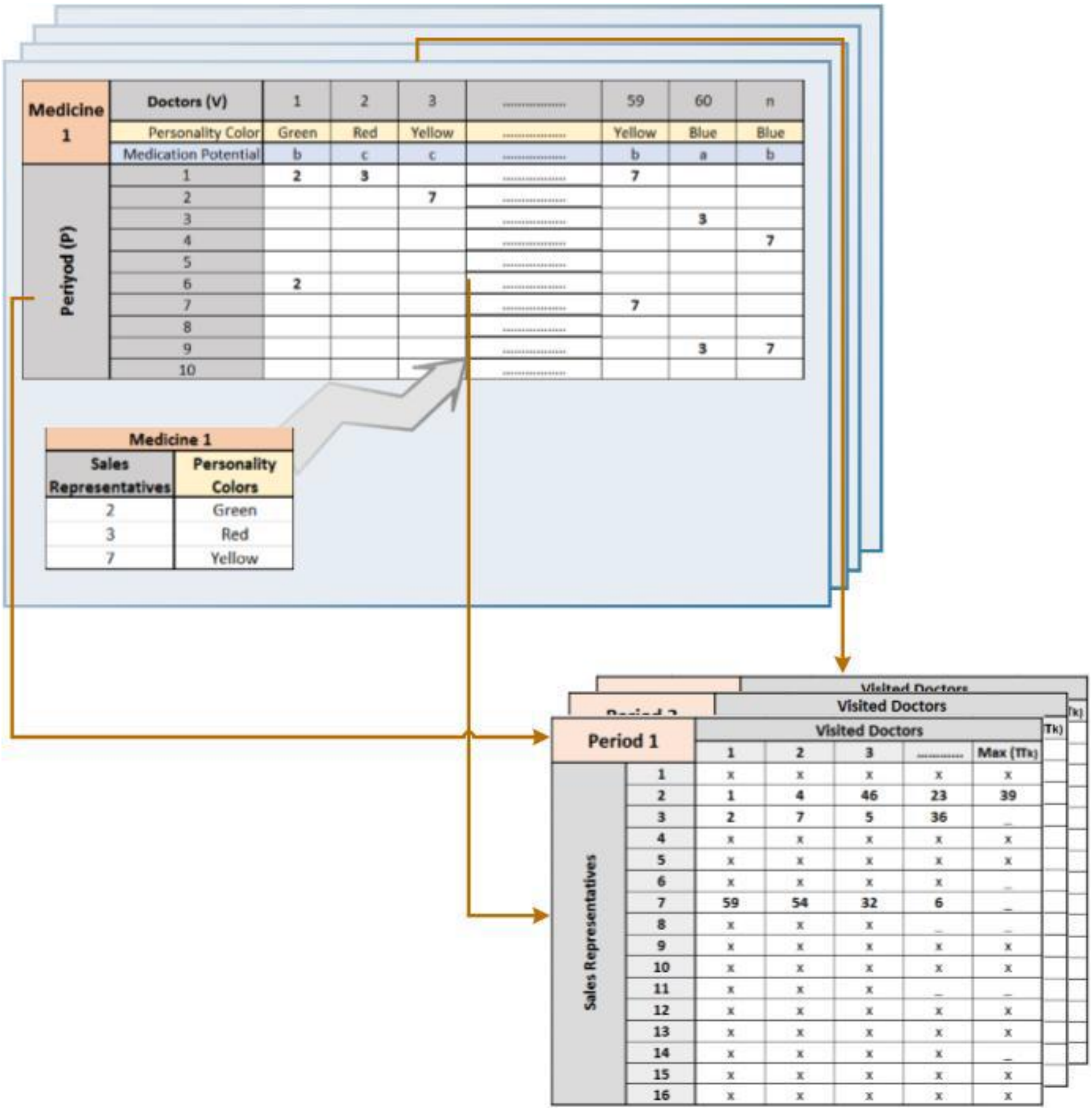

Figure 1. Chromosome representation for pharmacy application of DMPCluOVRP

After getting the initial datum on second sub-chromosome, algorithm applies the selected Travelling Salesman Problem (TSP) method for routing based on distance (time) constraint. While routing each salesman, the duration datum between doctors' locations that the same salesman visits in a day is used as a cost value. It is obtained from cost matrix that includes durations between all hospitals. In addition to this, the time that is spent by sales representative in hospital while visiting the doctor, is also used as another cost value. As mentioned before, the service time varies by personality color matching. These data obtained from service time matrix. After these operations, in consideration of genetic algorithm, fitness value of the problem is calculated.

3.2. Fitness Value

Fitness Value of the problem belongs to both two sub-chromosomes. The calculation of fitness value is sum of all sales representatives' route durations for all periods and service time of representatives for each visit. This value is evaluated for each iteration as the following:

For p=1, r=1, ordered doctors that are visited in this day, their personality colors and duration between related doctors' locations whether as in Figure 2.

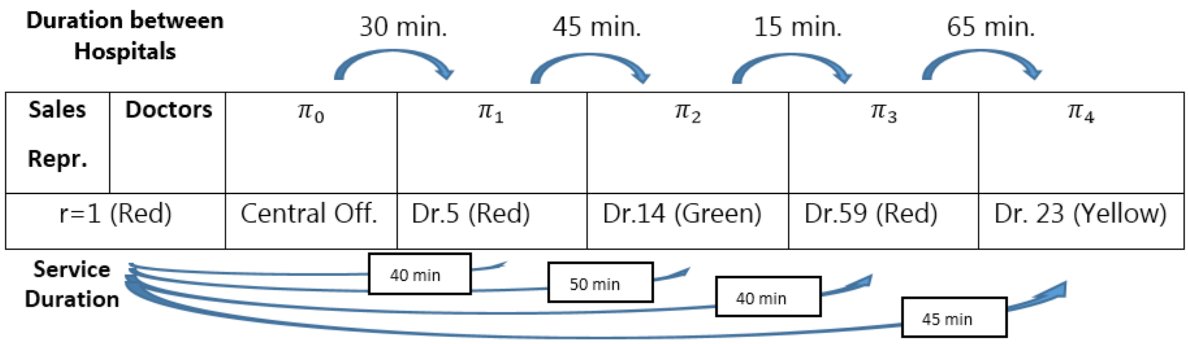

Figure 2. Calculation of Fitness Value

The total route duration of sales representative 1 for period 1 is:

30+40+45+50+15+40+65+45 =**330**

These values for all days and for all sales representatives are calculated and they are summed. This total gives us fitness value of the chromosome.

3.3. Genetic Operators

The well-known roulette wheel selection method is used in our genetic algorithm. The crossover operator is carried out by changing the first sub-chromosomes' pages which are belong to same medicine. In the other word, the pages with same ***m*** number. Random exchange mutation is implemented by changing the gens on first sub-chromosome.

These steps are implemented for all iterations until the termination criterion is satisfied. The general flowchart of genetic algorithm for DMPCluOVRP as in Figure 3.

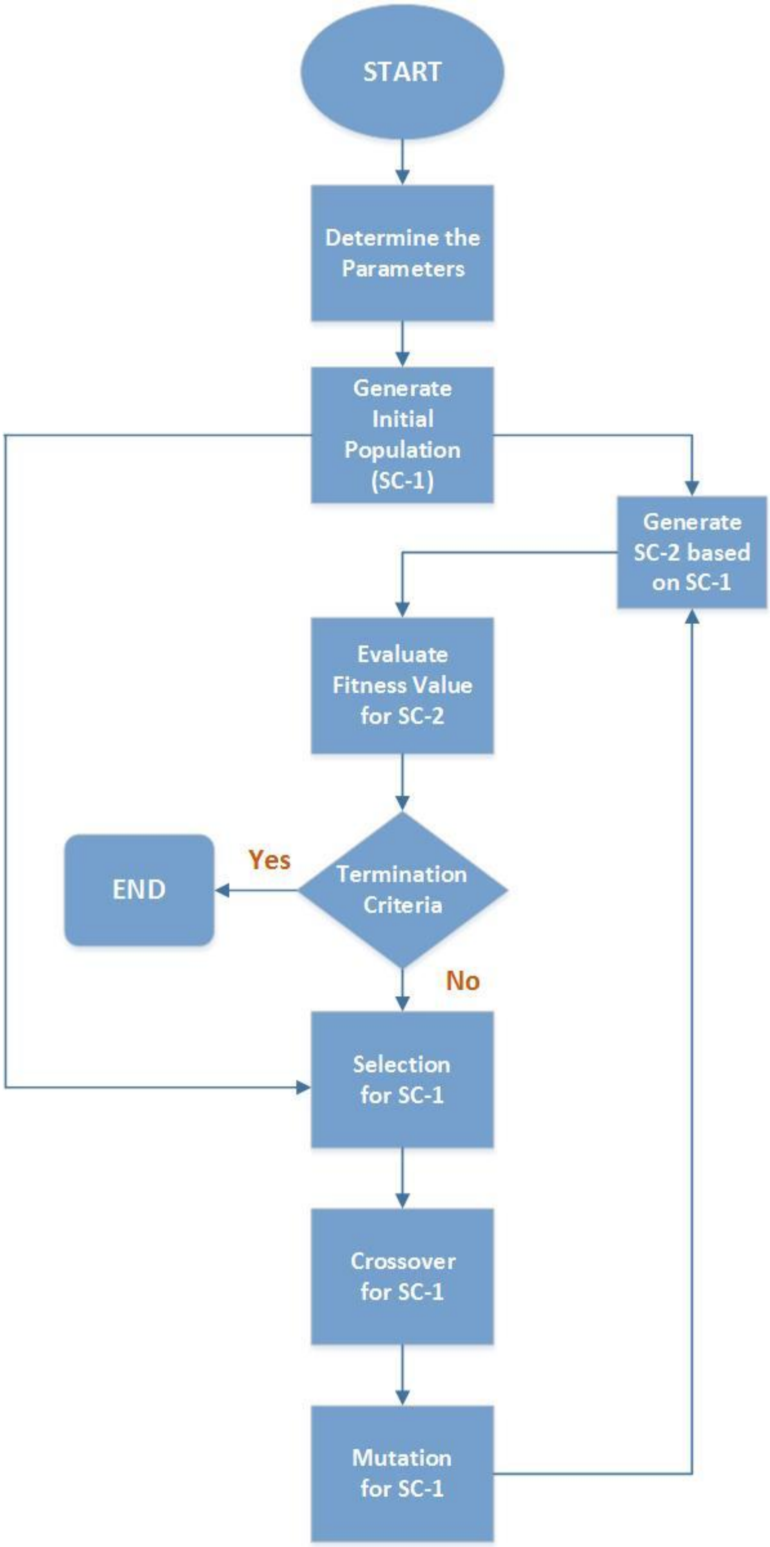

Figure 3. The general flowchart of Genetic Algorithm for DMPCluOVRP

4. Application

In our application problem, there are several sales representatives who work for introducing some medicines to related doctors. The data set is obtained from an international pharmacy company which is also operating in Istanbul. According to that, there are 8 different types of oncology medicines that are required to be presented by 16 sales representatives to 61 doctors which work in 22 different hospitals. The map in Figure 4 shows the locations of the hospitals.

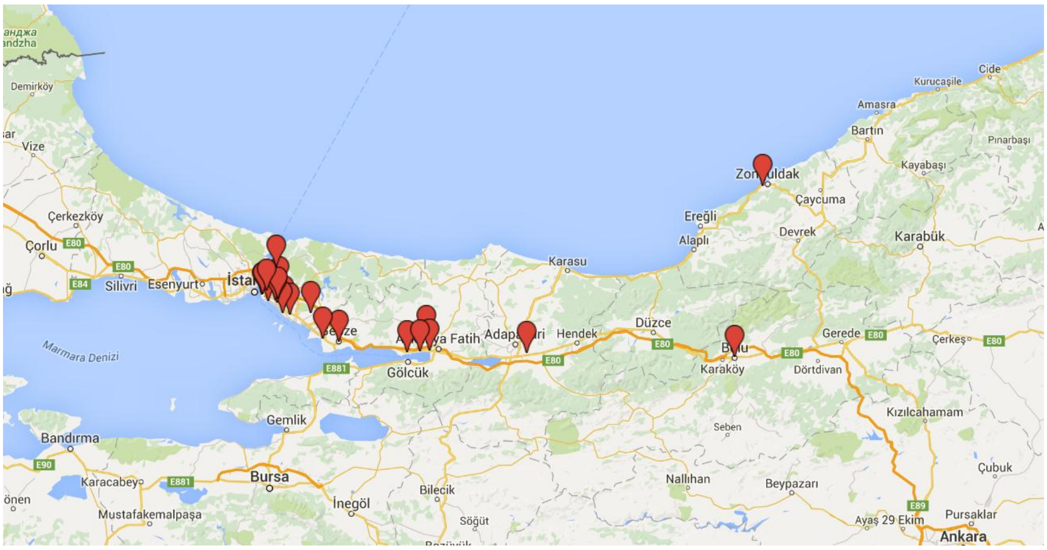

Figure 4. Locations of Hospitals

The total visiting period refers clear working days of two weeks and there is 380 minutes time limit for each route in a single day for each representative. All doctors should be visited at least once every two weeks to present all medicines. Each representative can work on prespecified medicines and the representatives who work with same medicines are grouped in a same cluster. Namely, each representative could make visitation just for her/his medicine. However, if there are multiple representatives that working for the promotion of a same medicine, only one of them can visit a particular doctor. The question that who will visit which doctors in the cluster is determined according to some criteria. One of them is personality colors that describe characteristics of people and the harmony between colors provides more successful and shorter negotiations between representatives and doctors. Shortly, there are four personality colors that describe them and the negotiations between which have the same color are more desirable. In addition to this, service time which describes the time that is spent while visiting the doctor, is determined by color matchings and it is added the routing time. The personality colors of doctors and sales representatives are known in advance. The service times according to colors are shown in Figure 5.

Service Time (according to colors)				
min.	Red	Yellow	Green	Blue
Red	40			
Yellow	70	40		
Green	50	60	40	
Blue	60	50	70	40

Figure 5. Service Time Matrix

The other criterion is visiting number of each doctor in a specified period by representatives. This number is determined by the medication potential of doctors. Medication potential is the level of doctors' suffiency and expertise about related medicine. If the medicine's pharmaceutical domain is related with the doctor's field of working, this doctor's medication potential will be higher. So, the doctors which have more medication potential for related medicine, they should be visited for this medicine more than the others. Due to the medication potential of doctors changes based on medicines, all doctors are grouped differently under the medicines. For example; while the doctor is in first group for medicine x, it can be in another group for medicine y because of the differences between medicines' pharmaceutical domain. Under this information, doctors are grouped in three clusters as A, B and C. The doctors which are in Cluster A, have most medication potential for related medicine and they should be visited twice in a total period. Also, the doctors which are in Cluster B, have potential more than Cluster C doctors and while the visiting number of Cluster C doctors should be one, if it is possible Cluster B doctors should be visited twice, otherwise once. The medicines, groups of sales representatives and their personality colors are shown in Figure 6.

Medicines			
Medicine Code (m)	Pharmaceutical Domain	Related Sales Representatives (r)	Personality Colors
1	Lung cancer	Sales Represantative 1	Blue
2	Colon-Ovarian cancer	Sales Represantative 2	Red
		Sales Represantative 3	Blue
		Sales Represantative 4	Green
3	Breast-Colon-Stomach cancer	Sales Represantative 5	Blue
		Sales Represantative 6	Yellow
		Sales Represantative 7	Red
4	Side effect inhibitor	Sales Represantative 8	Green
		Sales Represantative 9	Yellow
5	Skin cancer	Sales Represantative 10	Blue
		Sales Represantative 11	Blue
6	Lymphoma	Sales Represantative 12	Red
		Sales Represantative 13	Green
7	Breast cancer	Sales Represantative 14	Red
		Sales Represantative 15	Green
8	Diagnosis	Sales Represantative 16	Blue

Figure 6. Medicines and Sales Representatives

The last assignment criterion is the distance between doctors' locations. After assigning the sales representatives to doctors based on personality colors and visiting numbers, algorithm routes sales representatives daily and evaluates the routing costs. This cost calculation is made each sales representative per day by adding durations between hospitals and service times. Figure 7 shows these durations between hospitals.

Duration Between Hospitals		Zonguldak Bülent Ecevit Üni. Hast.	Bolu İzzet Baysal Üni. Hast.	Sakarya Eğitim Araşt. Hast.	Kocaeli Üni. Hast.	Kocaeli Devlet Hast.	Kocaeli Acıbadem Hast.	Kocaeli Derince Devlet Hast.	Gebze Medikal Park Hast.	Gebze ASM Hast.	EMSEY Hos.	Marmara Üni. Hast.	Kartal Lütfi Kırdar Eğ. Araş. Hast.	Süreyya Paşa Hast.	Maltepe Üni. Hast.	Yeditepe Üni. Hast.	Hisar Hos.	Life Med.	Kozyatağı Acıbadem Hast.	GATA	Haydarpaşa Numune Hast.	Paşabahçe Devlet Hast.	Ataşehir Memorial Hast.
	min.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Zonguldak Bülent Ecevit Üni. Hast.	1	1	133,58	152,32	181,45	180,35	193,3	188,13	202,78	207,23	217,07	224,93	230,47	232,17	231,23	231,72	230,92	229,37	231,38	233,05	234,15	240,77	227,15
Bolu İzzet Baysal Üni. Hast.	2	133,58	2	75,77	104,9	103,8	116,75	111,6	126,23	130,7	140,52	148,38	153,93	155,62	154,68	155,17	154,37	152,82	154,57	156,5	157,6	164,22	150,6
Sakarya Eğitim Araşt. Hast.	3	152,32	75,77	3	44,82	43,73	56,68	51,52	66,17	70,62	80,45	88,3	93,85	95,53	94,62	95,1	94,3	92,75	94,48	96,43	97,52	104,15	90,53
Kocaeli Üni. Hast.	4	181,45	104,9	44,82	4	12,98	15,28	22,4	44,28	48,75	58,57	66,43	71,98	73,67	72,73	73,23	72,42	70,87	72,88	74,55	75,65	82,27	68,65
Kocaeli Devlet Hast.	5	180,35	103,8	43,73	12,98	5	26,07	18,15	40,03	44,48	54,32	62,17	67,72	69,4	68,48	68,97	68,17	66,62	68,35	70,3	71,38	78,02	64,4
Kocaeli Acıbadem Hast.	6	193,3	116,75	56,68	15,28	26,07	6	36,15	65,05	69,52	79,33	87,2	92,75	94,43	93,5	94	93,18	91,63	93,38	95,32	96,42	103,03	89,42
Kocaeli Derince Devlet Hast.	7	188,13	111,6	51,52	22,4	18,15	36,15	7	30,77	35,23	45,05	52,92	58,47	60,15	59,22	59,72	58,9	57,37	59,38	61,03	62,13	68,75	55,13
Gebze Medikal Park Hast.	8	202,78	126,23	66,17	44,28	40,03	65,05	30,77	8	12,32	28,55	33,08	35,55	41,7	36,32	43,78	42,4	40,85	44,8	44,53	45,63	52,25	38,63
Gebze ASM Hast.	9	207,23	130,7	70,62	48,75	44,48	69,52	35,23	12,32	9	25,08	26,23	28,7	34,85	29,45	36,93	38,93	37,38	37,93	41,07	42,15	48,78	35,17
EMSEY Hos.	10	217,07	140,52	80,45	58,57	54,32	79,33	45,05	28,55	25,08	10	12,87	24,47	30,4	25,95	33,42	32,48	30,93	32,95	34,62	35,7	42,33	28,72
Marmara Üni. Hast.	11	224,93	148,38	88,3	66,43	62,17	87,2	52,92	33,08	26,23	12,87	11	12,07	18	14,42	21,9	23,9	22,35	22,9	26,03	27,12	33,75	20,12
Kartal Lütfi Kırdar Eğ. Araş. Hast.	12	230,47	153,93	93,85	71,98	67,72	92,75	58,47	35,55	28,7	24,47	12,07	12	19,07	13,67	21,15	29,28	26,2	22,15	28,82	29,92	39,13	25,52
Süreyya Paşa Hast.	13	232,17	155,62	95,53	73,67	69,4	94,43	60,15	41,7	34,85	30,4	18	19,07	13	12,48	12,43	24,9	18,95	15,98	21,57	22,65	34,75	19,83
Maltepe Üni. Hast.	14	231,23	154,68	94,62	72,73	68,48	93,5	59,22	36,32	29,45	25,95	14,42	13,67	12,48	14	17,22	28,23	22,27	17,93	24,9	25,98	38,08	24,77
Yeditepe Üni. Hast.	15	231,72	155,17	95,1	73,23	68,97	94	59,72	43,78	36,93	33,42	21,9	21,15	12,43	17,22	15	12,47	6,52	8,53	9,13	10,23	22,32	9,02
Hisar Hos.	16	230,92	154,37	94,3	72,42	68,17	93,18	58,9	42,4	38,93	32,48	23,9	29,28	24,9	28,23	12,47	16	14,7	16,72	17,37	18,47	21,65	13,17
Life Med.	17	229,37	152,82	92,75	70,87	66,62	91,63	57,37	40,85	37,38	30,93	22,35	26,2	18,95	22,27	6,52	14,7	17	3,48	10,98	12,08	23,08	9,77
Kozyatağı Acıbadem Hast.	18	231,38	154,57	94,48	72,88	68,35	93,38	59,38	44,8	37,93	32,95	22,9	22,15	15,98	17,93	8,53	16,72	3,48	18	14,55	11,5	22,5	14,13
GATA	19	233,05	156,5	96,43	74,55	70,3	95,32	61,03	44,53	41,07	34,62	26,03	28,82	21,57	24,9	9,13	17,37	10,98	14,55	19	1,08	31,33	15,83
Haydarpaşa Numune Hast.	20	234,15	157,6	97,52	75,65	71,38	96,42	62,13	45,63	42,15	35,7	27,12	29,92	22,65	25,98	10,23	18,47	12,08	11,5	1,08	20	30,25	14,73
Paşabahçe Devlet Hast.	21	240,77	164,22	104,15	82,27	78,02	103,03	68,75	52,25	48,78	42,33	33,75	39,13	34,75	38,08	22,32	21,65	23,08	22,5	31,33	30,25	21	23
Ataşehir Memorial Hast.	22	227,15	150,6	90,53	68,65	64,4	89,42	55,13	38,63	35,17	28,72	20,12	25,52	19,83	24,77	9,02	13,17	9,77	14,13	15,83	14,73	23	22

Figure 7. Duration between Hospitals

Although, it is wanted that the sales representative visits the doctors which work in nearby locations for lower cost, the problem has other criteria for this assignment as mentioned before. Because of that, algorithm tries to find best solution that covers all wishes by evaluating all criteria.

5. Conclusion

In this ongoing study, a new VRP model is introduced: Distance Contrained Multi Perspective Clustered Open Vehicle Routing Problem (DMPCluOVRP). This problem differs from the literature with using different constraints together and has developed for assignment of sales representatives to doctors and routing them. The genetic algorithm that has extensive usage, is selected as a solution method. The chromosome structure of genetic algorithm is designed specific to the problem. The real data set is identified and a better planning for assignment and routing will be tried to get by the recommended model for real life pharmacy problem. After the application, the obtained results will be shared with the company on behalf of improving their performance.

References

1 Kumar, S. N., & Panneerselvam, R. (2012). A survey on the vehicle routing problem and its variants. *Intelligent Information Management*, *4*(3), 66.

2 Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80-91.

3 Laporte, G., & Nobert, Y. (1987). Exact algorithms for the vehicle routing problem. *Surveys in Combinatorial Optimization*, *31*, 147-184.

4 Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, *59*(3), 345-358.

5 Toth, P., & Vigo, D. (Eds.). (2014). *Vehicle routing: problems, methods, and applications* (Vol. 18). Siam.

6 Barthélemy, T., Rossi, A., Sevaux, M., & Sörensen, K. (2010, June). Metaheuristic approach for the clustered VRP. In *EU/MEeting: 10th Anniversary of the Metaheuristics Community-Université de Bretagne Sud, France*.

7 Izquierdo, C. E., Rossi, A., & Sevaux, M. (2013, February). Modeling and solving the clustered capacitated vehicle routing problem. In *Proceedings of the 14th EU/ME workshop, EU/ME 2013* (pp. 110-115).

8 Sevaux, M., & Sörensen, K. (2008, October). Hamiltonian paths in large clustered routing problems. In *Proceedings of the EU/MEeting 2008 workshop on Metaheuristics for Logistics and Vehicle Routing, EU/ME* (Vol. 8, pp. 411-417).

9 Vidal, T., Battarra, M., Subramanian, A., & Erdoğan, G. (2015). Hybrid metaheuristics for the clustered vehicle routing problem. *Computers & Operations Research*, *58*, 87-99.

10 **Handbooks in Operations Research** and **Management Science** Volume 14, Pages 1-784 (2007). **Transportation**. Edited by Cynthia Barnhart and Gilbert Laporte.

C. Barnhart and G. Laporte (2007). (Eds.), Chapter 6: Vehicle Routing. *Handbook in OR & MS.* (Vol. 14, pp. 367-428)

11 Chang, Y., & Chen, L. (2007). Solve the vehicle routing problem with time windows via a genetic algorithm. *Discrete Continuous Dynamical Systems*, (Supplement), 240-249.

12 Panchal, G. & Panchal, D. (2015). Solving NP hard Problems using Genetic Algorithm. *International Journal of Computer Science and Information Technologies,* (Vol. 6 (2), pp. 1824-1827).

13 Bjarnadóttir, Á. S. (2004). *Solving the vehicle routing problem with genetic algorithms* (Doctoral dissertation, Technical University of Denmark, DTU, DK-2800 Kgs. Lyngby, Denmark).

14 Sangheon, H. A. N., & Tabata, Y. (2002). A hybrid genetic algorithm for the vehicle routing problem with controlling lethal gene. *Asia Pacific Management Review*, *7*(3).

15 Pereira, F. B., Tavares, J., Machado, P., & Costa, E. (2002). GVR: a new genetic representation for the vehicle routing problem. In *Artificial Intelligence and Cognitive Science* (pp. 95-102). Springer Berlin Heidelberg.

16 Mohammed, M. A., Ahmad, M. S., & Mostafa, S. A. (2012, June). Using Genetic Algorithm in implementing Capacitated Vehicle Routing Problem. In *Computer & Information Science (ICCIS), 2012 International Conference on* (Vol. 1, pp. 257-262). IEEE.