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# Solving a bi-objective medicine distribution problem considering delivery to waste center using a hybrid clustering, mathematical modeling and NSGA-II approach

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**Abstract**

Proper transportation and distribution of commodities plays a pivotal role in the expenditures of supply chains. In this paper, a clustered vehicle routing problem with pick-up and delivery is studied. A fleet of distinct vehicles is concurrently responsible for distribution of medicines and collection of their wastes. Collected wastes should be sent to a waste center. To solve the problem, a bi-objective mathematical model is presented. Fairness of travelled distances among drivers and transportation expenses are two objective functions considered in the model. Since the proposed problem is NP-hard, a three-step hybrid approach is developed to solve the problem. First, K-medoids clustering algorithm allocates customers to subsets based on their coordinates. Second, a mathematical model is used for routing vehicles within each cluster. Third, NSGA-II is used to produce final result using the outcome of step 2. Extensive numerical results indicate the superiority of the proposed approach against the NSGA-II.

**Keywords:** VRP, Fairness, Delivery to Disposal Center, Clustering, NSGA-II

## 1-Introduction

Transportation and distribution of goods is a costly process for any business. To reduce transportation expenditures, miscellaneous mathematical models and methods have been developed. For distribution of medicines, companies utilize a fleet of vehicles. When medicines with hazardous wastes are deemed, they are often needed to be collected by the company and sent to specific disposal centers to be eliminated. This course of action mitigates the damage which is done to the environment and citizens. As a result, vehicles visiting customers should deliver products and pick-up wastes at the same time. In traditional VRPs, the fleet of vehicles is supposed to return to depot as they finish serving customers. However, under above circumstances, vehicles will not visit depot as their destination. Rather, they will be sent to a disposal center to deliver wastes.

Considering the equilibrium in the workload of drivers, they should be given fairly equal amount of job to do (distance to travel). This fairness is needed to create justice in terms of workload. Justice in workload has a paramount positive impact on drivers' attitude and feelings towards their jobs.

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In order to diminish the complexity of the problem, customers can be clustered before optimal routes are excavated. Methods existing in data mining area can be used for assigning demand points to subsets. As a result, clustering methods can be implemented to group customers based on their location. Next, vehicles' allocation can be done with respect to the outcome of clustering. Following this approach, if a vehicle enters a cluster, it should serve all customers belonging to it. In addition, a vehicle might be able to serve several clusters simultaneously. Consequently, a vehicle routing problem with pick-up and delivery of medicines to customers and disposal centers is presented in this paper. Furthermore, fairness of drivers' travelled distances and clustering of customers are considered.

The structure of this paper is organized as follows: In section 2, the problem literature is reviewed. Section 3 includes the definition of problem and the designed mathematical model. In section 4, the proposed solution methodology is described. Section 5 comprises numerical results and a case study. At last, the conclusion of the paper is in section 6.

## 2-Literature review

In this section, first, VRP papers with pick-up and delivery are reviewed. Second, routing problems which are designed for health care systems are briefly analyzed. At last, clustered vehicle routing problems are discussed.

Naccache et al. (2018) designed a new metaheuristic for solving Multi-Pickup and Delivery Problem with Time Window constraint (MPDTW). It was considered that a client node's request could be met by cargos picked-up from multiple nodes. An Integer Programming model was proposed. Avci and Topaloglu (2016) suggested a new hybrid heuristic for solving Vehicle Routing Problem with Simultaneous Pick-up and Delivery (VRPSPD) and heterogeneous fleet. A non-monotone threshold adjusting strategy was combined with Tabu Search (TS). This strategy equipped the solution procedure with the ability of self-tuning. Thus, unlike other metaheuristics, only one parameter related to tabu list length was required to be tuned and other parameters were not.

Belgin et al. (2018) proposed a hybrid heuristic approach for two-echelon VRPSPD which was combination of Local Search (LS) and Variable Neighborhood Decent (VND). First, vehicles reached the special nodes called satellites. Second, they were routed to customers. Validity of the model and heuristic were demonstrated by applying them in the supermarket chain in Turkey. Kalayci and Kaya (2016) proposed a hybrid heuristic combining ant colony and VND which could produce a near-optimal solution in a reasonable time for VRPSPD problem. In recent years, several papers offered various new approaches containing heuristics/meta-heuristic for this kind of VRP (Avci and Topaloglu, 2016; Sayyah et al., 2016; Wang et al., 2015; Polat et al., 2015; Pop & Chira, 2014). Ma et al. (2019) proposed a hybrid priority-based genetic algorithm to solve a VRP problem with simultaneous pick-up and delivery and time window. Shi et al. (2020) proposed a bi-structure based TS to solve similar problem to minimize the number of vehicle and transportation distance. Abdi et al. (2020) developed a green VRPSPD to minimize total cost and maximize customer service satisfaction. Furthermore, VRP with waste collection is getting more attention in the literature. Apart from routing, some studies considered locating disposal centers as well (See Rabbani et al., 2020; Rabbani et al., 2018).

Regarding health care issues, Shi at el. (2018) designed a stochastic model which considered simultaneous pick-up and delivery for Home Health Care (HHC) problems. Travel times were stochastic. Time window constraint for patients was taken into account. For evaluation of the model, firstly, the deterministic model was solved by five different approaches namely Gurobi Solver, Hybrid Genetic Algorithm (GA), Simulated Annealing (SA), Bat Algorithm, and Firefly Algorithm. Secondly, the stochastic problem was answered by a SA-based heuristic. Liu et al. (2013) suggested two mathematical models for medical distribution and collection of unused medicines or devices utilized for patients' care. Two metaheuristics namely GA and TS were implemented to address the mentioned problem. Asghari and Al-e (2020) developed a green VRPSPD for Home Hemodialysis Machines by considering sharing economy concepts.

En-nahli et al. (2015) studied resource assignment and routing with multiple objectives including minimizing total travel time, waiting time, and balancing workload. A number of constraints were deemed namely caregivers' break time, adequacy of their skills (in terms of providing a patient with appropriate service), patients' time window, and their preferences. A mathematical model was proposed. Decerle et al. (2018) proposed routing and scheduling problem in HHC by considering both

hard and soft time windows. Also synchronized visits were considered. The mathematical model was solved by a memetic algorithm and its performance was assessed by a case study in France. For more studies on routing and scheduling problems in HHC, see Fikar and Hirsch, (2017) and Cissé et al., (2017).

Regarding clustering, Osaba et al. (2019) proposed a new version of bat algorithm for solving VRP with pick-up & delivery. The algorithm was customized for medicine distribution and waste collection problem. Three features were considered. First, medical centers located in the same city were allocated to the same clusters. If a vehicle entered a city, it would provide service to all customers situated in that city. As a result, vehicle capacity was needed to be checked. Second, some roads were considered to be one-way or obstructed. Finally, a constraint prohibited the routs to be too long which implied fairness in the proposed model for caregivers. Pop et al., (2018) also considered Clustered VRP (CluVRP) and proposed a two-level model. At the first phase, each cluster was considered to be a single node and optimal route was designed for nodes. Next, a Travelling Salesman Problem (TSP) was solved for each cluster so that a vehicle would visit all nodes within a cluster. Aguirre-Gonzalez and Villegas (2017) suggested a mathematical model for collection of waste related to animal tissue in a Colombian company. In this model, various constraints were considered including frequency, heterogeneous vehicles and clustered customers. Eventually, a bi-level heuristic was designed. In the first phase, capacitated concentrator location problem (CCLP) was utilized to group nodes. In the second phase, a mathematical model was used to balance the number of the customers in each cluster.

Expósito-Izquierdo et al. (2016) designed a two-phase solution method to solve CluVRP. In the first step, Record-to-Record travel algorithm (RTR) was utilized for designing a route in cluster level. Second, three different solution methods namely Lin-Kernighan Heuristic, Algorithm of Christofides and MILP model were used for creating a path within each cluster. Ewbank et al. (2016) designed an algorithm in which unsupervised clustering was implemented for the grouping phase. Afterward, a mathematical model was proposed to solve the TSP problem in each cluster. Comert et al. (2018) offered a two-step algorithm. In the first step of the algorithm, clustering took place. Three different methods of clustering including K-means, K-medoids and choosing groups arbitrarily were used for this purpose. It should be noted that both distance and capacity of vehicles were deemed at this step. In the second phase, a TSP was solved using Branch and Bound (B&B). Additionally, drawing an analogy among grouping strategies illustrated that K-medoids outdid others.

Since CluVRP models are NP-hard, various studies focused on proposing a solution procedure for them, comprising hybrid GA (Marc et al., 2015) and hybrid Variable Neighborhood Search (VNS) algorithm (Hintsch and Irnich, 2018; Mestria, 2018; Defryn and Sörensen, 2017). Table 1 demonstrates studies which have utilized clustering as a part of their solution procedure for solving miscellaneous extensions of VRP. In addition, table 2 makes a comparison between papers studying VRP with waste collection, health care and clustering.

**Table.1** Various methods which are used for Clustered Vehicle Routing Problem

| Paper | Solution procedure | | |
|---|---|---|---|
| | Clustering | Routing Outside Clusters | Routing Inside Clusters |
| Osaba et al. (2019) | - | Bat Algorithm | Bat Algorithm |
| Pop et al. (2018) | - | GA | exact |
| Aguirre-Gonzalez & Villegas (2017) | CCLP | - | MIP model |
| Ewbank et al. (2016) | Unsupervised fuzzy clustering approach | - | MILP model |
| Marc et al. (2015) | - | GA | SA |
| Expósito-Izquierdo et al. (2016) | - | RTR | Lin-Kernighan Heuristic<br>Algorithm of Christofides<br>MILP model |
| Comert et al. (2018) | K-means<br>K-medoids<br>Arbitrary grouping | - | B&B |
| Hintsch & Irnich (2018) | - | MNS - VND | Balas-Simonetti Neighborhood |
| Mestria (2018) | - | LS - GRASP - VND | |
| Defryn & Sörensen (2017) | - | VNS | VNS |

To sum up, clustered capacitated VRP with collection and delivery of medical wastes to disposal centers is a gap in the literature. This is the case for a medicine production company that distributes medicines to customers. Afterwards, wastes produced by customers should to be collected. Such waste may contain hazardous materials for the environment. Hence, collected waste should be delivered to a disposal center. A heterogeneous fleet of vehicles is utilized. Moreover, since the total travelled distance may vary from one driver to another, rout lengths for drivers should almost be equal to ensure fairness of travelled distance among drivers. It is clear that the fairer the solution becomes; the more cost will be imposed on the cost function. As a result, a bi-objective model is suggested in which the first objective is reduction of costs and the second is creating justice among vehicles. To our knowledge fairness has never been included as an objective in the mathematical models existing in this arena.

**Table.2** Related literature on Vehicle Routing Problem

| Paper | Fairness | Pick-up & Delivery | Waste collection and sending to disposal center | Clustered | Heterogeneous Fleet | Vehicle Fixed Cost | HHC | Multi-Objective | Solution Procedure |
|---|---|---|---|---|---|---|---|---|---|
| Aguirre-Gonzalez and Villegas (2017) | ✓ | | | ✓ | ✓ | | | | CCLP-MIP |
| Belgin et al. (2018) | | ✓ | | | | | | | VND-LS |
| Decerle et al. (2018) | | | | | | | ✓ | | Memetic Algorithm |
| Avci and Topaloglu (2016) | | ✓ | | | ✓ | ✓ | | | Hybrid TS |
| En-nahli et al. (2015) | ✓ | | | | | | ✓ | ✓ | CPLEX |
| Kalayci and Kaya (2016) | | ✓ | | | | | | | AC-VNS |
| Liu et al. (2013) | | ✓ | | | | | ✓ | | GA - TS |
| Osaba et al. (2019) | ✓ | ✓ | | ✓ | | | ✓ | | Bat Algorithm |
| Naccache et al. (2018) | | ✓ | | | | | | | B&B - hybrid ALNS |
| Pop et al. (2018) | | | | ✓ | | | | | 2-level approach |
| Shi et al. (2018) | | ✓ | | | | | ✓ | | SA-based Heuristic |
| Shi et al. (2020) | ✓ | ✓ | | | ✓ | | | ✓ | TS |
| Asghari and Al-e (2020) | | ✓ | | | ✓ | ✓ | ✓ | ✓ | Self-learning NSGA-II |
| This paper | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | K-medoid - MM - NSGA-II |

Considering solution method, myriad researchers have combined clustering with routing problem (CluVRP) in the literature. In many studies two sub-problems have been solved namely the routing problem between clusters and within clusters. However, we aim at using a new three-step algorithm. Our approach implements clustering and mathematical modeling within clusters for yielding initial solutions and then uses these results for solving the whole problem with the NSGA-II. Therefore, in our approach, a clustering algorithm called K-medoid, a mathematical model, and a metaheuristic are combined. The initial solution obtained in our approach is near-optimal which will result in reduction of CPU time. Also our method improves the initial solution by implementing a metaheuristic.

## 3-Problem description

This study considers a vehicle routing problem with concurrent pick-up and delivery. Medicines are delivered to customers from a single depot using a heterogeneous fleet of vehicles. At the same time, medicine waste of each customer is collected as a vehicle visits the customer. After visiting all customers, a vehicle should visit a specific disposal center in which the hazardous wastes are eliminated. All trucks should return from the disposal center to the depot at the end of their tour. Since moving from disposal center to depot is predetermined for all trucks, this movement is not considered. Therefore, last visiting point in this problem is the waste center, not the depot. Figure 1 illustrates a simple example of the proposed problem. In this problem, there exist ten customers served by two vehicles with different capacities. Each customer has its medicine demand, and waste. Vehicles start from depot, serve customers which are assigned to them, and head to the waste center. Arriving at

each customer, the vehicle delivers demanded medicine and simultaneously picks medical waste. The second objective, which is fairness also, should be deemed among vehicles.

Two objective functions are considered. The first objective minimizes the routing and fixed cost of utilizing the fleet of vehicles. The second objective maximizes fairness and equilibrium of travelled distances among the crew of drivers. To handle this issue, the travelled distance by each vehicle is compared with that of the whole crew. It should be noted that the closer the distance travelled by each driver is to that of the others, the more they will be satisfied with fairness. Hence, they will sense more justice which has a positive impact on their mentality.

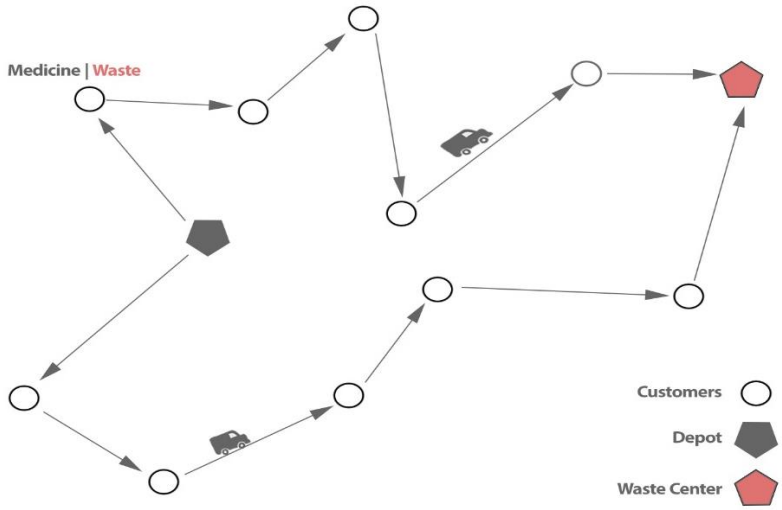


**Fig. 1.** A schematic view of presented problem

Clustering of customers is an efficient course of action for diminishing the feasible solution space of the problem. To do so, location of customers has been selected as the clustering criterion. Many methods exist for clustering customers in the field of data mining from which K-medoids method is selected. K-medoids enables the mathematical model to efficiently consider the prescribed clusters for allocation of the fleet rather than solely considering apparent transportation costs.

Clustering constraints, which are designed in this paper, limit the set of feasible solutions to an efficient smaller set which can remarkably improve the CPU time, particularly in large problems. Specifically, a smaller solution space is explored for each vehicle routing problem due to the clustering constraints. Each cluster can only be visited by one vehicle. However, a vehicle is able to travel through several clusters if its capacity constraint is not violated. Notation is as follows:

**Sets:**

| | |
|---|---|
| $i, j \in N = \{0,1,\ldots,n+1\}$ | All nodes including depot “0” and waste collection center “n+1” |
| $h \in H = \{1,2,\ldots,n\}$ | Customer nodes |
| $l, l' \in L = \{1,2,\ldots,m\}$ | Heterogeneous fleet of vehicles |
| $s \in S = \{1,2,\ldots,g\}$ | Clusters of customers |

**Parameters:**

| | |
|---|---|
| $Td_{ij}$ | Traveling distance from node $i$ to node $j$ |
| $Fc_l$ | Fixed cost related to using vehicle $l$ |
| $p_h$ | The amount of load which is required to be delivered to customer $h$ |
| $d_h$ | The amount of load which is required to be picked-up from customer $h$ |
| $q_l$ | Capacity of vehicle $l$ |
| $b_h^s$ | If customer $h$ is included in cluster $s$ |

**Variables:**

| | |
|---|---|
| $X_{ij}^{l}$ | If vehicle $l$ travels from node $i$ to $j$ it will be equal to 1, otherwise it will get 0. |
| $F_{ij}^{l}$ | The amount of load which is related to picked-up demands after providing node $i$ with service. |
| $E_{ij}^{l}$ | The amount of load which is related to delivered demands after providing node $i$ with service. |
| $Z_{s}^{l}$ | If cluster $s$ is assigned to vehicle $l$ it will be equal to 1, otherwise it will get 0. |
| $Y_l, Y'_l$ | Dummy variables for linearizing the second objective function |

$$\min \sum_{l\in L}\sum_{j\in N}\sum_{i\in N} Td_{ij}X_{ij}^{l} + \sum_{j\in N}\sum_{l\in L} Fc_l X_{0j}^{l} \tag{1}$$

$$\min \sum_{l\in L} Y_l + Y'_l \tag{2}$$

*s.t.*

$$\sum_{j\in N}\sum_{l\in L} X_{hj}^{l} = 1; \forall h \tag{3}$$

$$\sum_{i\in N} X_{ih}^{l} - \sum_{i\in N} X_{hi}^{l} = 0; \forall h, l \tag{4}$$

$$\sum_{j\in N} X_{0j}^{l} \leq 1; \forall l \tag{5}$$

$$\sum_{i\in N} X_{i(n+1)}^{l} \leq 1; \forall l \tag{6}$$

$$\sum_{j\in N} X_{j0}^{l} = 0; \forall l \tag{7}$$

$$\sum_{j\in N} X_{(n+1)j}^{l} = 0; \forall l \tag{8}$$

$$\sum_{i\in N} F_{hi}^{l} - \sum_{i\in N} F_{ih}^{l} = p_h; \forall h, l \tag{9}$$

$$\sum_{i\in N} E_{ih}^{l} - \sum_{i\in N} E_{hi}^{l} = d_h; \forall h, l \tag{10}$$

$$E_{ji}^{l} + F_{ji}^{l} \leq q_l X_{ij}^{l}; \forall i, j, l \tag{11}$$

$$\sum_{l\in L} Z_{s}^{l} = 1; \forall s \tag{12}$$

$$\sum_{j\in N} X_{hj}^{l} \leq \sum_{s\in N} b_h^s Z_s^l; \forall h, l \tag{13}$$

$$\sum_{i\in N}\sum_{j\in N} Td_{ij}X_{ij}^{l} - \sum_{i\in N}\sum_{j\in N} Td_{ij}X_{ij}^{l'} = Y_l - Y'_l; \forall l, l' \quad l \neq l' \tag{14}$$

$$X_{ij}^{l}, Z_{s}^{l} \in \{0,1\};\ \forall i, j, l, s, l \tag{15}$$

$$F_{ij}^{l}, E_{ji}^{l} \geq 0;\ \forall i, j, l \tag{16}$$

Equation (1) minimizes the total fixed cost of utilizing vehicles and their routing cost within the tour. Equation (2) describes that the total distance which is travelled by the vehicles should be the same, creating fairness and justice between the crew of drivers. Equation (3) describes that every customer is needed to receive service by the fleet. Equation (4) ensures that when a vehicle enters a node, it leaves those nodes for the next destination. Equation (5) ensures that if a vehicle is used, it should start its tour by leaving the depot point. Each vehicle can leave the depot only one time. Equation (6) makes sure that each vehicle is only allowed to enter the disposal center once in its tour. Equations (7) and (8) forbid a vehicle from either returning to depot or leaving the disposal center at the end of their tours. Equation (9) ensures that the amount of waste which is collected at each node is added to the amount already on-board. Likewise, equation (10) describes that the amount of on-board medicine decreases as a demand point is visited by a vehicle. Equation (11) checks the weight of freight to be less than the total capacity of vehicle on which it is loaded.

The next two equations are designed to include clusters in the mathematical model. Equation (12) guarantees that each group of customers (cluster) is visited only by one vehicle. Equation (13) shows that only if a vehicle is visiting a cluster, can it travel from one node within that cluster to another node. The destination node might either be inside that cluster or outside. Equation (14) calculates the difference in distance which is travelled by each pair of vehicles. This constraint is needed for the second objective function. Equations (15) to (18) describe the type of the decision variables.

## 4-Solution method

VRP is claimed to be an NP-Hard problem (Golden et al., 1981). As a result, VRP with pickup and delivery is an NP-hard problem as well. Due to the inherent complexity of this sort of problem, developing a proper solution method, specifically for medium and large-size problems, is of paramount importance. Therefore, in this section, a hybrid three-step solution method is proposed. As it was described earlier, assigning customers to clusters before starting the routing process is significant. Clustering will reduce the search space and improve the solution methodology's speed. For this purpose, the location of customers is considered as the criterion for clustering.

Consequently, in the first step of the proposed resolution, the clustering of customers occurs. To do so, K-medoids algorithm is used. In the second step, a vehicle capable of handling each cluster's collective order is randomly assigned to each cluster. Now, the routing problem in each cluster can be considered as a TSP and solved independently. A route starting at the depot and ending at the final point (waste center) is found for every cluster. It should be noted that at this phase, CPLEX solver in GAMS software is utilized for solving each TSP. Afterward, the optimal solutions produced by CPLEX solver are attached randomly to shape a complete answer. In the third step, the previous step's solutions are treated as initial solutions for the Non-Dominated Sorting Genetic Algorithm (NSGAII) algorithm. The NSGAII improves the quality of the initial solution by considering both objective functions. The output of NSGAII is the final solution to the problem. The comprehensive description of the above steps is as follows:

**Step 1: Clustering customers**

In the first step, customers are assigned to clusters using K-medoids algorithm. As it was discussed earlier, the coordinates of customers are considered for clustering. As a result, customers located near each other will be assigned to the same vehicle to be serviced, which aligns with the problem's objective, minimizing the transportation cost. It is worth mentioning that a specific car is required to serve each cluster; however, a vehicle may serve multiple clusters.

When it comes to determining the number of clusters before beginning the process, it can be initiated with the number of vehicles involved in the problem. However, later as the solution develops and the number of generations increases, the algorithm may merge some clusters. It means that some clusters may serve by the same vehicle, specifically those adjacent to each other. In that case, it may seem that fewer clusters are involved in the problem.

It should be noted that increasing the number of clusters, enlarges the feasible solution space of the problem. Therefore, the results will be closer the optimality. On the other hand, such course of action

necessitates more mathematical models to be solved. Hence, it might deteriorate the CPU time of the problem. A trade-off should be made regarding number of clusters.

**Step2. Routing clusters using mathematical model**

As each route comprises several customers, at this step, the optimal path for each cluster is found. This problem resembles the traveling salesman problem. It is assumed for each cluster that the routing starts at the depot and ends at the waste center. To start this phase, first, a vehicle from the fleet is assigned arbitrarily to each cluster. Afterward, the mathematical model is used for solving TSP in that cluster. This procedure is needed to be repeated until all the clusters are planned separately. As soon as all clusters are routed, these separate sequences are merged to provide a complete and valid initial solution. After allocating vehicles randomly to clusters, at this point, several clusters may share the same vehicle. Under such circumstances, those clusters with a shared vehicle will be merged in a random order before starting the next phase. As a result, an initial solution is obtained. It is worth mentioning that although the allocated vehicles and order of the merged clusters change during the next step, the clusters and the path inside each cluster remain the same through all the processes.

Considering the objective function of TSP and the second step in which clusters are routed, the fairness objective is not involved. Because at this point, a particular vehicle is assigned to each cluster and fairness cannot be calculated for a single vehicle. Therefore, the fairness of traveled distances cannot be compared between vehicles in the second phase. Also, all constraints of the mathematical model proposed in section 3 are considered in TSP except for the ones that refer to fairness. Figure 2 demonstrates the output of this phase for a simple problem with 15 customers and five vehicles. Besides, NSGAII chromosomes are precisely similar to this shape. Therefore, NSGAII can simply utilize this answer as an initial solution.

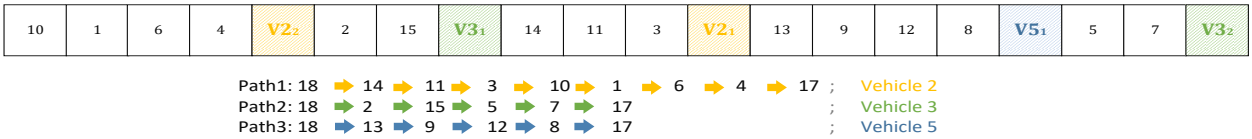


**Fig.2.** Chromosome design for hybrid NSGA-II algorithm

**Step3. Utilizing NSGA-II for finding ultimate solution**

At this step, NSGA-II algorithm is used for finding Pareto optimal solutions by taking both objective functions into consideration. The procedure described in the previous step is repeated as much as the number of the population. As each new population member is produced, both objective functions are calculated for it.

Considering the main loop, as the crossover takes place, two selected chromosomes are combined. To do so, the ending point of a random cluster is selected in each chromosome for performing the crossover procedure. It should be noted that crossovers are not allowed to alter the sequence within clusters. Since, aforementioned sequences represent optimal route which is obtained by solving a TSP inside that cluster. As the mutation takes place, the sequence within each cluster may be reversed. Since clusters are being merged with different orders, the reversion within each cluster may positively enhance the quality of the solution. In addition, a random vehicle in the sequence may be replaced by another one. The output of NSGA-II is a set of Pareto-optimal solutions one of which is the preferable choice for the company. The pseudo code of the proposed approach is provided below.

Hybrid 3-stage algorithm

```
Input: ℕ        // the population size
ℚ ⟵ ∅
P ⟵ ∅                    // initial population
ℂ ⟵K-medoid();           //Cluster Customers
For i:1 to ℕ
        For j:1 to Size(ℂ)
                P(i, j) ⟵ Exact_solution(ℂ(j))
        End
        P(i) ⟵ ∪_j P(i, j)
End
While not Termination_Condition() do
        Offspring ⟵ Crossover();
        Fitness_Function(offspring);
        Insert(offspring, ℚ);
        Mutated_Pop⟵Mutation();
        Fitness_Function(Mutated_Pop);
        Insert(Mutated_Pop, ℚ);
        ℛ ⟵ P ∪ ℚ
        Non-dominated_Sorting(ℛ);
        P ⟵Select_Best_Chromosomes(ℛ);
End
Return P;
```

## 5-Numerical results

In this section, firstly, an example is solved by our procedure and the CPLEX solver to demonstrate that our approach is valid in terms of finding Pareto optimal solutions. Secondly, a medium-size problem is depicted which is solved by our Hybrid three-stage algorithm. In addition, its non-dominated solutions are shown and compared with that of NSGA-II. Next, a comprehensive comparison is made among the results of our methodology and NSGA-II in 21 problem instances which are distinct in terms of size. A case study is illustrated in section 5.4 and sensitivity analysis is made.

### 5-1-Model validation

To validate the proposed methodology, the same problem is solved by an exact method and the proposed procedure. Since both methodologies are capable of producing almost the same Pareto fronts, then the proposed methodology is reliable. An example of 10 customers and 4 vehicles is designed to compare the solutions. The mentioned example is fairly small, since the CPLEX solver cannot solve larger instances in a reasonable time. The number of clusters is assumed to be 4 in both cases. The Pareto fronts of both methods are illustrated in figure 3. As it is shown, the answers are approximately the same which confirms the validity of the designed three-step procedure.

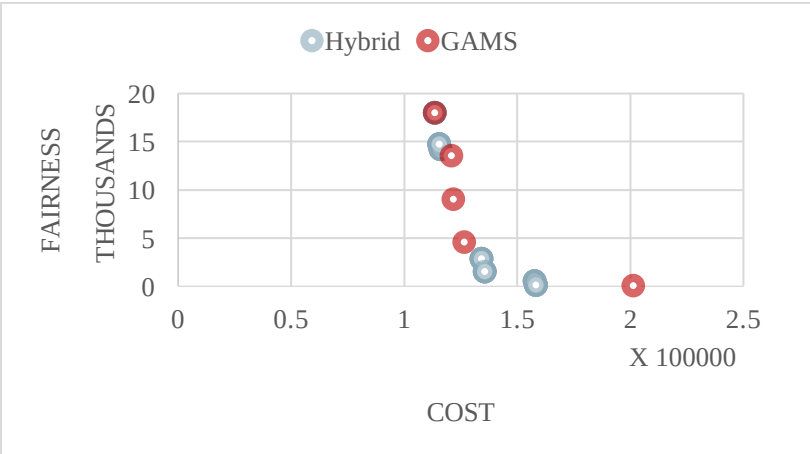


**Fig.3.** Pareto front of exact algorithm and Hybrid 3-stage methodology for example with 10 customers

## 5-2-A medium test problem

Trying to provide a better perception of the solution procedure, an example with 45 customers is illustrated in figure 4. As it is demonstrated, three vehicles are used for distribution of medicine and waste collection. Customers with same color belong to the same cluster. Additionally, some clusters are merged and served by the same vehicle. It is a noteworthy point that the starting point of each path is the depot and the ending point is the disposal center. Figure 5 demonstrates the Pareto front of the mentioned problem which is solved by both NSGA-II and our three-phase hybrid algorithm. It is crystal clear that the NSGA-II Pareto front is dominated by that of our methodology.

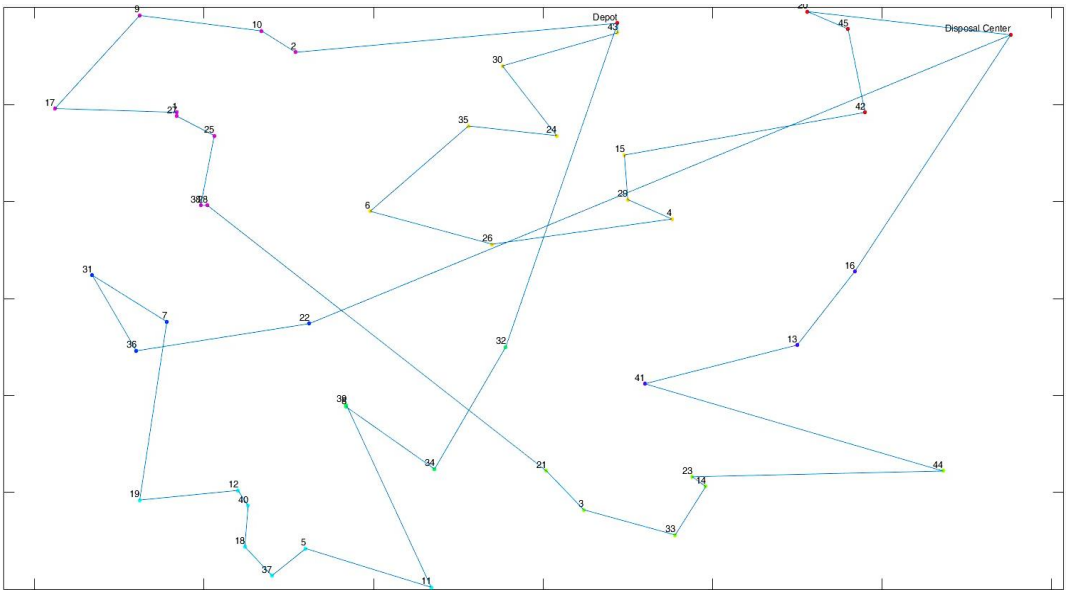


**Fig.4**. Solution of problem with 45 customers solved by proposed approach

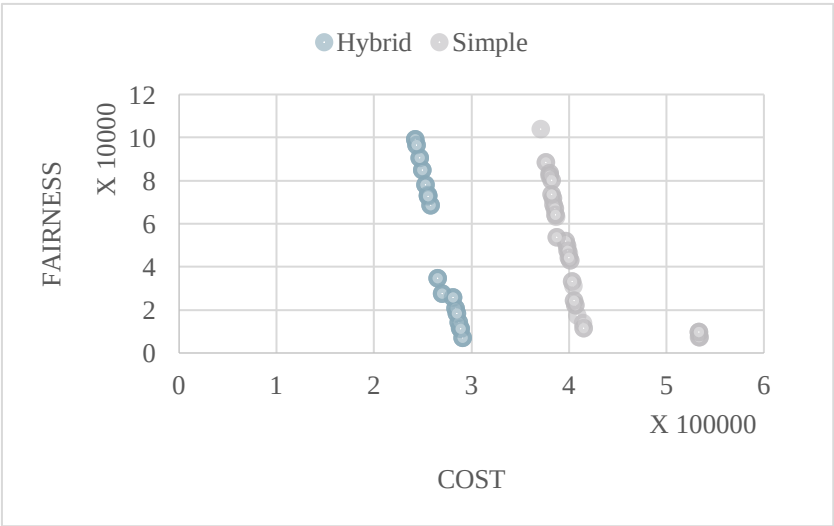


**Fig.5**. Pareto fronts of NSGA-II & 3-phase algorithm

## 5-3-Comparison measures of algorithms' performances

In order to evaluate the ability of the proposed algorithm in terms of finding efficient solutions for the bi-objective model in Section 3, extensive numerical examples are produced. All examples are solved by both, the three-phase approach and NSGA-II. Random problems of various sizes, ranging from 15 to 300 customers are produced utilizing python programming language. Based on the number of needed customers, coordinates are produced in proper ranges, along with random pick-up and delivery demands less than 10 for each point. Finally, these parameters are used as input data for the algorithm. In this paper, four criteria namely Quality Metric (QM), Mean Ideal Distance (MID),

Spacing Metric (SM) and Diversification Metric (DM) are utilized for comparing the performance of the proposed solution methodology with NSGA-II.

Table 3 shows the result of four comparison criteria for both algorithms as 21 problem instances are solved. It is worth mentioning that in some cases (examples with more than 220 customers), NSGA-II has been not capable of producing feasible solutions. Consequently, related fields are left empty in table 3. The hybrid approach outdoes the NSGA-II. Moreover, all the non-dominated points produced by this algorithm are feasible.

- Quality Metric (QM)

This metric represents the number of Pareto optimal solutions which are yielded by each algorithm (Rabbani et al., 2018). As it is demonstrated, Hybrid approach has a considerably higher amount of QM when it is compared with NSGA-II. Since this metric is the proportion of non-dominated solutions which belong to each algorithm in a combination of fronts (non-dominated solutions), bigger QM is translated to better performance of a metaheuristic.

- Mean Ideal Distance

When it comes to MID, it assesses the vicinity of points in a Pareto front to the ideal points for each objective (Karimi et al., 2010). Ideal point is translated to the point which has the best quantity in each goal among all methods which are compared.

$$MID = \frac{1}{n}\sum_{j=1}^{n}\sqrt{\sum_{k=1}^{m} f_{kj}^{2}} \tag{19}$$

In the equation (19), $n$ is the number of Non-dominated solution produced by each algorithm and $m$ represents the number of goals. Also $f_{kj}^{2}$ displays the normalized Euclidian distance of each point to ideal solution. In this paper, hybrid approach conspicuously outperforms NSGA-II by producing better results for this metric. Due to the fact that this metric measures proximity to ideal solutions, smaller MID is a sign of better performance of an algorithm.

- Spacing Metric (SM)

Considering SM criterion, it evaluates the distribution of the points comprising Pareto fronts (Schott, J. R., 1995; Suo et al., 2017). It is clear that the less the SM is, the more uniform the points are distributed which is a positive characteristic of an algorithm.

$$SM = \sqrt{\frac{\sum_{k=1}^{m}\left(d_k - \bar{d}\right)^2}{m-1}} \tag{20}$$

$$d_k = \min_{i \neq j}\left(\sum_{h=1}^{n} |f_h^j - f_h^i|\right) \tag{21}$$

In the equation (21), $h$ is the number of objectives. Based on the equation (20), minimum distance among points is related to those stay next to each other in the Non-dominated front. In our instance problems, there is a stiff competition between both algorithms. However, generally our approach outweighs NSGA-II in this metric as well. Since this metric calculates the distribution of efficient solutions, smaller amount is related to better performance.

- Diversity Metric (DM)

When it comes to DM metric, it represents the dispersion of points in a non-dominated set of solutions for each algorithm. In a simple parlance, it represents the vastness of the Pareto front. The formulation of this measure based on Zitzler, E., (1999) is as follow:

$$DM = \sqrt{\sum_{j=1}^{m} \max_{i}\left(\sum_{k=1}^{n}(f_k^j - f_k^i)^2\right)} \tag{22}$$

In the equation (22), $n$ is the number of objectives and $m$ is the number of points making up the Pareto front. The larger this metric is for an algorithm the better the performance of it will be. As it is displayed, hybrid approach outstandingly outperforms NSGA-II in this metric too. It should be noted that for calculating this measure, combined Pareto fronts of solutions resulting from both algorithms are considered.

Figures 6-9 provide results of table 3 using illustrative charts for better understanding. Trying to provide a brighter vision toward the performance of our methodology compared to NSGA-II, table 4 is provided which demonstrates the output of two sample t-test of each metric. When it comes to comparing the performance of our methodology with prevalent frequently-used metaheuristics in this field, we proved that our methodology certainly outperforms NSGA-II algorithm. Specifically, as the size of problem instance increases, the performance of our algorithm is by far better than NSGA-II.

**Table.3** Drawing analogy between proposed methodology & NSGA-II based on four criteria

| **Pop.** | **HYBRID** | | | | **SIMPLE** | | | |
|---|---|---|---|---|---|---|---|---|
| | QM | MID | SM | DM | QM | MID | SM | DM |
| 15 | **0.95** | **21702.38** | 1.710 | **22346** | 0.05 | 25826.41 | **0.470** | 0 |
| 30 | **0.79** | **32818.84** | **0.730** | **49182** | 0.21 | 42724.24 | 1.354 | 12216 |
| 45 | **1.00** | **274024.8** | **1.116** | **366100** | 0.00 | 416525.5 | 2.600 | 0 |
| 55 | **0.83** | **299384.7** | **1.370** | **929210** | 0.17 | 432948.9 | 1.729 | 678400 |
| 70 | **0.56** | **66648.15** | **1.521** | **150230** | 0.44 | 96178.89 | 2.367 | 108440 |
| 80 | **0.70** | **72213.92** | **2.450** | **253110** | 0.30 | 127880.1 | 2.873 | 237030 |
| 90 | **0.75** | **70359.72** | **1.202** | **233120** | 0.25 | 118594.9 | 2.292 | 96338 |
| 100 | **0.95** | **76406.26** | **0.858** | **88607** | 0.05 | 144736.1 | 1.255 | 18557 |
| 110 | **1.00** | **67940.94** | **0.694** | **49455** | 0.00 | 182175.8 | 2.260 | 0 |
| 120 | **1.00** | **74445.07** | 0.980 | **164690** | 0.00 | 189983.8 | **0.829** | 0 |
| 130 | **0.70** | **139979.9** | **1.021** | **9.75E+04** | 0.30 | 358696.8 | 1.405 | 56946 |
| 145 | **0.73** | **188131.5** | 2.454 | **4.52E+05** | 0.27 | 455895.2 | **1.105** | 374350 |
| 160 | **1.00** | **181368.8** | 1.710 | **266050** | 0.00 | 442035.3 | **1.682** | 0 |
| 170 | **0.94** | **190188.3** | 1.562 | **587900** | 0.06 | 571330.5 | **1.090** | 0 |
| 180 | **0.69** | **273208.3** | 4.072 | **1152400** | 0.31 | 813725.4 | **1.198** | 333400 |
| 200 | **0.83** | **307701.9** | 1.321 | **807860** | 0.17 | 903423.1 | **1.107** | 53908 |
| 220 | **1.00** | **291874.3** | **0.848** | **283980** | 0.00 | 975271.1 | 0.808 | 0 |
| 240 | **1.00** | **341719.1** | **0.964** | **548560** | 0.00 | - | - | - |
| 260 | **1.00** | **591154.5** | **2.711** | **2685500** | 0.00 | - | - | - |
| 280 | **1.00** | **1262652** | 1.836 | **485180** | 0.00 | - | - | - |
| 300 | **1.00** | **808820.5** | **0.833** | **1254200** | 0.00 | - | - | - |

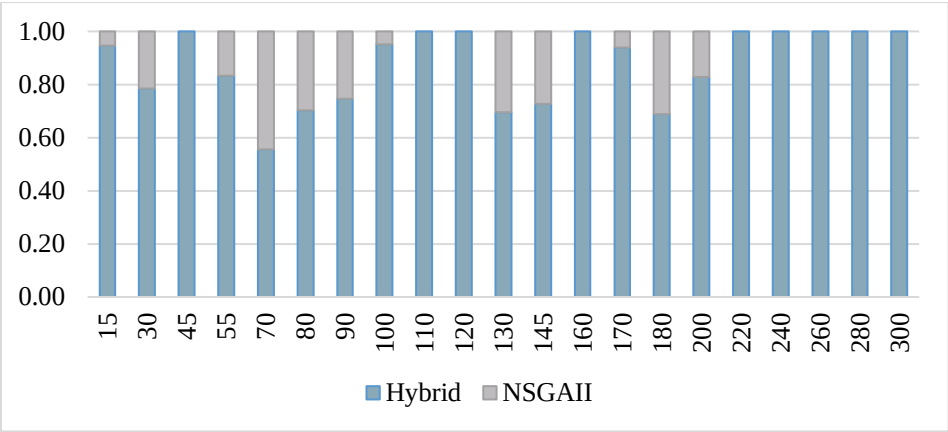


**Fig.6.** Analogy for QM between Hybrid three-stage approach & NSGA-II

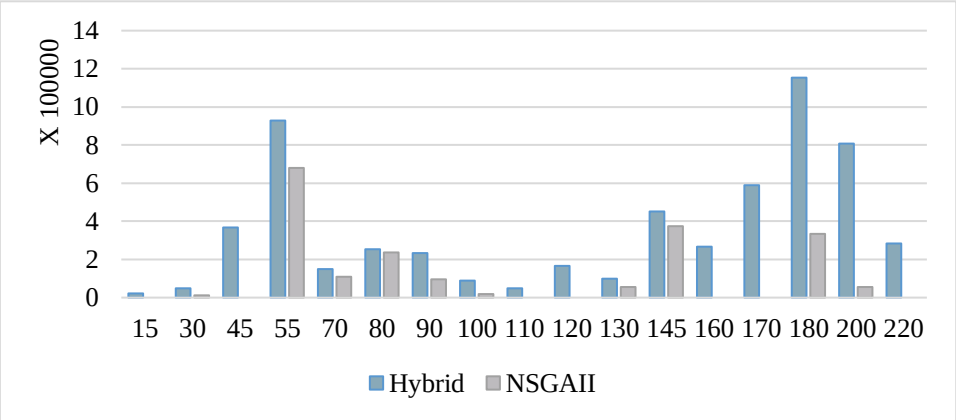


**Fig.7.** Analogy for DM between Hybrid three-stage approach & NSGA-II

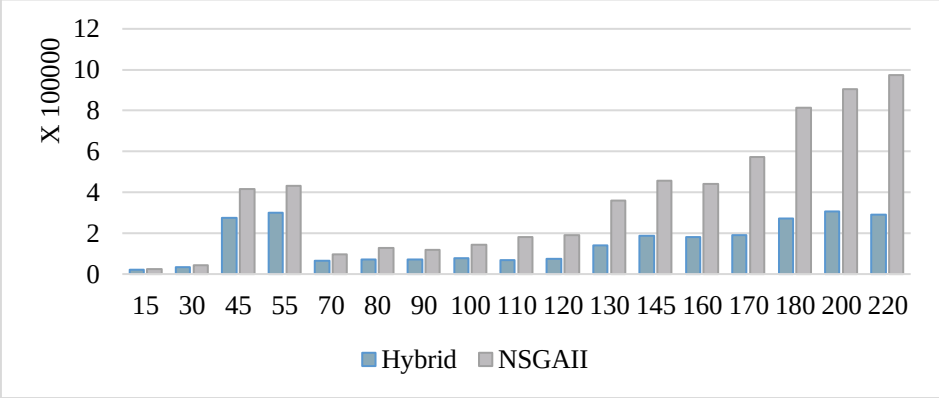


**Fig.8.** Analogy for MID between Hybrid three-stage approach & NSGA-II

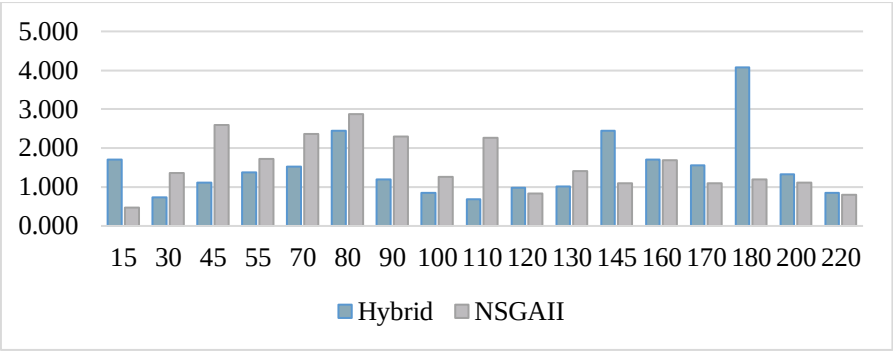


**Fig.9.** Analogy for SM between Hybrid three-stage approach & NSGA-II

**Table.4**. Result of two sample t-test comparing Hybrid methodology and NSGA-II

| Metric | **Superior approach** | Mean | | Output of t-test | | **Confidence (%)** |
|---|---|---|---|---|---|---|
| | | Hybrid | NSGA-II | Comparison result | P - value | |
| QM | **Hybrid** | 0.876 | 0.124 | $\mu_{hybrid}$ | 0 | **100** |
| MID | **Hybrid** | 268226 | 370468 | $\mu_{hybrid}$ | 0.152 | **84** |
| SM | **Hybrid** | 1.522 | 1.554 | $\mu_{hybrid}$ | 0.448 | **55** |
| DM | **Hybrid** | 520327 | 115858 | $\mu_{hybrid}$ | 0.004 | **99** |

## 5-4-Case study of a medicine distributing company

The proposed solution approach was validated in previous sub-sections using the mathematical model. Now, we carry out a case study on an Iranian medicine distribution company which specializes in distributing hazardous medicines. The company only covers districts 1 and 3 in Tehran, Iran. In addition, the company merely owns one depot. As company drivers complained, they suffered from lack of fairness in the distance that they were supposed to travel on a daily base. Based on company's research on organizational behavior, fairness and sense of justice are critical factors affecting workers spirit and attitude towards their occupation. Therefore, in order to organize their fleet and design their paths, our methodology was implemented.

The company had access to 13 different vehicles with different capacities and fixed expenses. Figure 10 shows a non-dominated solution resulting from the proposed solution methodology. In the non-dominated solution depicted in figure 10, four vehicles are utilized each of which starts its path from the depot and ends it at the waste center. Additionally, figure 11 displays the set of non-dominated solutions produced by hybrid methodology suggested in this research.

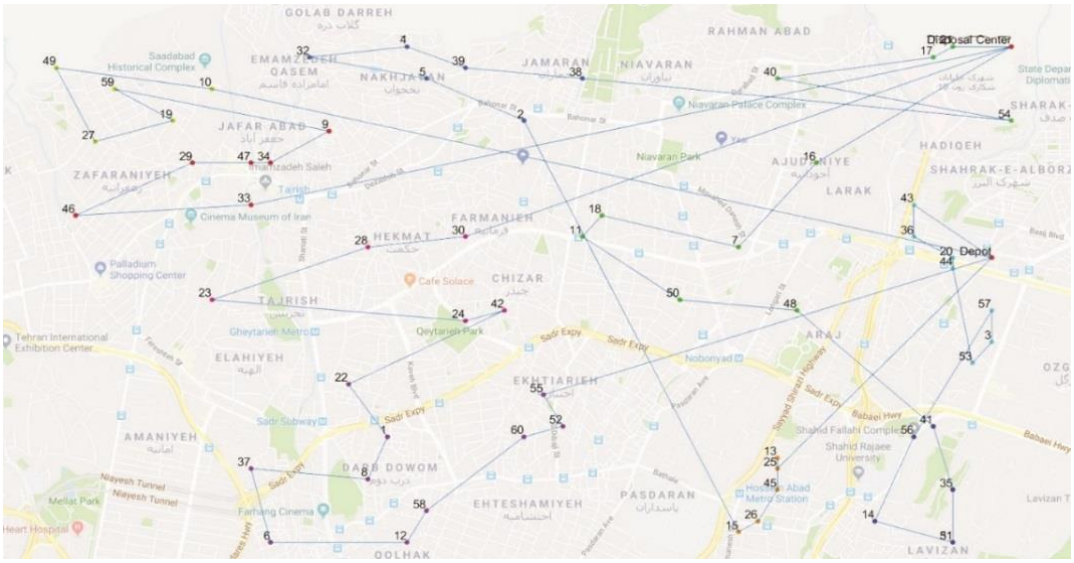


**Fig.10**. Suggested routes to the Iranian medicine distribution company of our case study

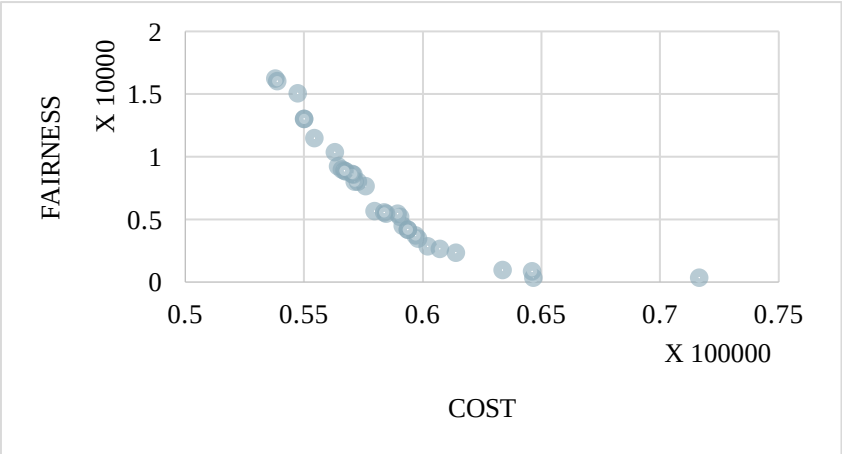


**Fig.11.** Set of non-dominated solution produced by Hybrid methodology

At this point, a better understanding of the model and its parameters is provided by carrying out a sensitivity analysis on the capacity of vehicles in above case study. Obviously, if a vehicle has higher capacity, it can visit more customers and clusters. Consequently, their capacity affects the number of utilized vehicles which has a direct impact on cost objective. In addition, changes in capacity may result in alterations in the number of customers and clusters which are visited. In other words, a change in capacity may lead to changes in length of the routes travelled by each driver. Consequently, the fairness objective is subject to change as the capacity parameter alters. Above description provides a better explanation on the importance of doing a sensitivity analysis regarding the capacity of vehicles.

Figure 12 demonstrates the results of the 7 versions of abovementioned problem with different capacities. As it are demonstrated, capacity changes from 60 percent of its initial value to 130 percent of it. Based on the description above, it is revealed that decreasing capacity deteriorates both objectives of the problem. Lower capacity necessitates usage of more vehicles which imposes additional fixed cost on the first objective. Furthermore, as the number of vehicles increases, creating fairness among the drivers gets more complicated which in turn worsens the fairness objective.

Similar to figure 12, figure 13 illustrate the changes in costs subject to changes in the amount of load to be delivered to each customer ($P_h$). There are 2 break points in the costs. As the amount of cargo to be delivered rises, more vehicles should be employed. Consequently, the costs suddenly sour as the fixed cost of new vehicles is added.

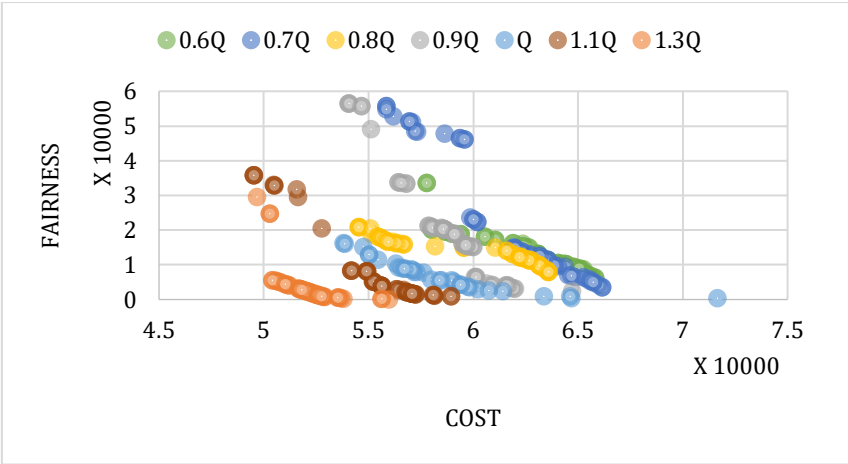


**Fig.12.** Sensitivity analysis in terms of capacity of vehicles

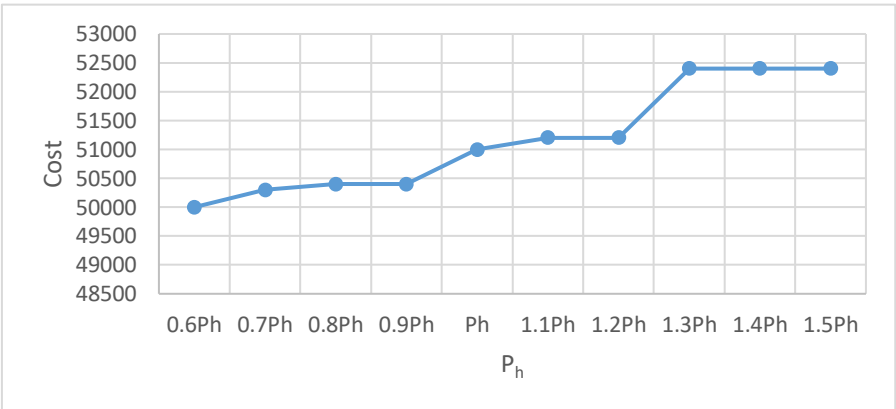


**Fig. 13.** Sensitivity analysis in term of amount of cargo to be delivered to customers

## 5-5-Managerial insight

Creating sense of satisfaction within an organization is a challenging target for the managerial board of any enterprise. Fairness of travelled distances among drivers is a prominent contributing factor to this goal. Presented approach in this paper, can enhance the situation regarding this matter to a great extent. Furthermore, diminishing expenditures of a distribution network is a significant objective for any company. Distribution expenses include the type of selected vehicles in terms of capacity and fixed costs along with vehicles' travelled path. The cost objective and appropriate constraints consider aforementioned costs to improve the insight which is provided by the output of the model. In addition, delivery to waste center is another obstacle medicine companies commonly deal with. Designed mathematical model in this research properly tackles this obstacle as it ensures that all collected wastes are delivered to a waste center.

## 6-Conclusion

In conclusion, in this paper a clustered vehicle routing problem with simultaneous pick-up and delivery was solved. A distinct fleet of vehicles was responsible for delivering medicines from a depot to customers. At the same time, customers' wastes were collected and delivered to a disposal center. Therefore, rather than conventional VRPs that consider the depot as the final destination, in this research, the disposal center was the destination. Prior to solving the problem, customers were clustered based on their coordinates to reduce the feasible solution space. To solve the proposed problem, a mathematical model was devised to minimize the costs while maximizing the fairness of travelled distance among vehicles for justice purposes. In addition, the mathematical model contained constraints to assign each predetermined cluster to separate vehicles.

Due to high level of complexity in this version of VRP, a hybrid three-step algorithm was introduced. In the first step, customers were clustered into distinct groups utilizing K-medoids algorithm to diminish the number of plausible solutions. The clustering took place with respect to coordinates of customers. Afterward, an exact solver called CPLEX was utilized for solving a TSP within each cluster of customers. At last, NSGA-II was used for finding Pareto optimal solutions considering both objectives. NSGA-II used the outputs of previous steps as an enhanced initial solution. Extensive numerical examples proved the efficiency of this approach in comparison with NSGA-II. Moreover, a thorough sensitivity analysis was carried out on vehicles' capacity which demonstrated the negative impact of decreasing capacity on both objectives of the problem. The impact of changes in customers delivery load on cost objective was also studied to analyze trend of changes in costs.

For future studies, new clustering criteria can be suggested and analyzed to further enhance the quality of solution. Such criteria can be excavated based on managerial specifications e.g. type of product, and type of required vehicle. Furthermore, other factors that influence employees' satisfaction are needed to be assessed and included in the mathematical model. In fact, fairness objective can be replaced by employee satisfaction to collectively include a variety of factors which might contribute their satisfaction with job.

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