Raising Fairness Issue of Vehicle Routing Problem

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***Abstract*—Since fairness deals with the quality of distributing the jobs and creates an ambience that is free from any discrimination, any distribution management problem must take fairness issue into consideration. Again, since the *Vehicle Routing Problem (VRP)* is also a distribution management problem, any *VRP* solving algorithm must consider the fairness when solutions are explored. However, most of the proposed *VRP* solving algorithms do not take this issue into consideration. In this paper, we raise this issue with sufficient evidences. In this course of action, following contributions are made in this paper: *i)* fairness issue is raised analytically, and to support this, an extensive simulation campaign is performed, *ii)* the *VRP* is discussed through a practical application, namely *Garbage Collection Problem (GCP)*, and later it is mathematically formulated, *iii)* a *Genetic Algorithm (GA)* is employed to explore feasible solutions for the given application (i.e., *GCP*), and *iv)* some future research directives are noted, which will help the researchers to extend this work.**

Keywords-vehicle routing problem, capacitated vehicle routing problem, garbage collection problem, fairness, genetic algorithm.

I. INTRODUCTION

The *Vehicle Routing Problem (VRP)* is a distribution management problem, which envisions to explore the optimum collection or delivery routes of a fleet of vehicles that commences from a depot and returns back to the origin after visiting a set of intermediate cities or nodes. The route optimizations in the *VRP* are subject to several parameters, namely travel time, mileage, capital cost, personnel cost, and several side constraints. Although, this problem has been studied over a century; however, researchers still pay immense attention to it due to changing constraints over time or due to emerging new practical applications. Some notable practical applications of this problem are: print press scheduling, crew scheduling, school bus routing, interview scheduling, mission planning, hot rolling scheduling, design of global navigation satellite system surveying networks, garbage collection, and so forth [1], [2].

In the 1800s, the mathematical formulation of a similar kind of problem was addressed by the Irish mathematician W. R. Hamilton and by the British mathematician Thomas Kirkman, called *Traveling Salesman Problem (TSP)* [3]. The *TSP* is a special case of the *VRP*, where a single vehicle has to visit all the cities and has to return back to the origin following the shortest possible path. Over time, the *TSP* evolves and arises in several different forms due to the variety of constraints encountered in practice. In contrast to the *TSP*, the *VRP* takes into account of a fleet of vehicles. Again, the *VRP* that takes capacity into consideration is called *Capacitated Vehicle Routing Problem (CVRP)*, which is more in-line with the practical applications. Note that, the terms, *VRP* and *CVRP*, *city* and *node*, and *collection* and *delivery* are used interchangeably in this paper.

At present, several *Exact Solution Algorithms (ESAs)* are proposed that can resolve the *TSP* for thousands and more number of nodes [4]. Similarly, some *ESAs* are also proposed for the *VRP* that are based on mathematical programming formulations in several literatures [2], [5]-[9]. However, these *ESAs* are only compatible for a small number of nodes; whereas, there is no *ESA* proposed that can explore optimum solutions for a large number of nodes (e.g., hundreds or more). Consequently, this problem falls under the *NP-hard* problem class. For this class of problems, the *MetaHeuristic (MH)* based solutions are deemed efficient due to their competency to explore optimum or near-optimum solutions within considerable time duration. Hence, several *MH* based algorithms are proposed in the last decade. For instance, in [10] and [11], the authors propose *tabu search*-based algorithms, where the basic principle is to use a local or neighborhood search procedure to iteratively move from one potential solution s to an improved solution s' in the neighborhood of s, until some stopping criterion has been satisfied. Again, since *Genetic Algorithms (GA)* are the most applied modern *MH* based approach, several algorithms are also proposed based on the *GA*, such as in [12] and [13]. In this paper, a *GA* based algorithm is employed to explore feasible solutions, which is discussed in Subsection III-C in details.

Although, there exist a considerable number of algorithms that explores optimum solutions for the *VRP*; however, to the best of our knowledge, no one yet raises the fairness issue of these algorithms. Conversely, any unfair distribution of jobs may lead to dissatisfaction among the employees. The solutions offered by the most of the existing algorithms are seldom fair. This paper raises this issue evidently through analytically (in Section II}) and using simulation campaign (in Section V).

The rest of the paper is organized as follows. The fairness issue of the *VRP* is raised analytically and discussed in details in Section II. Section III presents the system model of an application where the *VRP* subsists, and the problem is mathematically formalized in Subsection III-B. The simulation scenarios that are taken into account to support

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the claim described in Section IV; whereas the results are presented and analyzed in Section V. In Section VI, the future directions of the research are detailed, and the paper ends with the concluding remarks in Section VII.

II. Problem Definition

For any distribution management problem, fairness remains an important issue, since it deals with the quality of distributing the jobs and created an ambience that is free from any discrimination. Again, discrimination may generate dissatisfaction, and due to the later cause, an organization may not be able to extract the best out from an employee. In addition, it may work as a negative force to the growth of an organization. This proposition is also applicable to most of the *VRP* based applications. Unfortunately, most of the *VRP* solving algorithms never take this issue into consideration while they are exploring solutions. The primary objective of these algorithms is to provide optimum solutions based on certain given conditions. However, we would like to argue that the optimum solutions that are calculated based on certain given conditions may not be viable solutions in terms of fairness. In our following discussions, this issue is detailed evidently.

Let us assume that in a *VRP*, there is a set of nodes, $N = \{N_1, N_2, ..., N_n\}$, and $|N| = n$ is fixed. A *VRP* solving algorithm explores m optimum routes for a fleet size of m vehicles, i.e., $S = \{S_1, S_2, S_3, ..., S_m\}$, where $S_i \subset N$, and $S_i = \{N_1, N_2, ..., N_k\}$. If $k = n$ and $|N| = |S_i|$, this is a *TSP*; otherwise this is a *VRP*. Again, all the solutions are computed sequentially, i.e., $S_i \in S$ is computed before $S_j \in S$ since $i < j$ and $i \neq j$, by following the common constraints of the *VRP* that are mentioned in [6]. In this circumstance, following propositions can be derived.

Proposition 1: In a solution set S, there could be only one global optimum solution, S_φ, if no two distances are identical.

Proof: Let us assume that there are two global optimum solutions present in S, namely $S_i = S_\varphi$ and $S_j = S_\varphi$, S_i is computed before S_j or vice versa, and $i \neq j$. Again, for our further discussions, assume that S_i is computed prior to S_j. Since a node can be visited only once, all the nodes in S_i will be absent in S_j , i.e., $S_j \subset N \setminus S_i$, and hence, $S_j \neq S_\varphi$. Therefore, there could be only one S_φ in S.

Proposition 2: For the analogous scenario in *Proposition 1*, except S_φ, all other solutions in S, i.e., $S \setminus S_\varphi$, are local optimum solutions.

Proof: As in *Proposition 1*, it has been proved that there could be only one S' in S; hence, the other solutions, i.e., $S \setminus S_\varphi$, are local optimum solutions.

Proposition 3: If all the nodes are placed at equal distance from the depot, and all the concerned constraints are identical, then $\forall S_i \in S$, $S_i = S_\varphi$.

Proof: If $\forall S_i \in S$, $S_i = S_\varphi$ is not true, then let us assume that there is at least one $S_j \in S$ such that $S_j \neq S_\varphi$. Again, since all the nodes are placed at equal distance from the depot, and all the concerned constraints are identical, S_j is an optimum solution, i.e., $S_j = S_\varphi$, which admits the true sense of the proposition.

However, in reality, the nodes are placed at arbitrary locations, and the probability of having identical distances for all the nodes is insignificant. Hence, *Proposition 3* is impractical; whereas, *Proposition 1* and *Proposition 2* represent practical scenarios. As mentioned in those propositions, if there is only one S_φ and the rest are local optimum solutions, there must be some deviations exist in the solutions. The fairness of these solutions becomes an issue when the deviations are substantially high. One may argue that it is possible to ensure fairness by taking a single parameter into consideration. For instance, if the duration of the travel time is set fixed or if the distance is set fixed, it is possible to ensure fairness. In counter argument, it can be mentioned that since in the *VRP*, the capacity of the vehicles also plays an important role; and fixing those parameters may reduce the utilization of the vehicles. Hence, the management cost increases that is against the objective of the *VRP*. Therefore, fairness remains an important issue for the existing *VRP* solving algorithms.

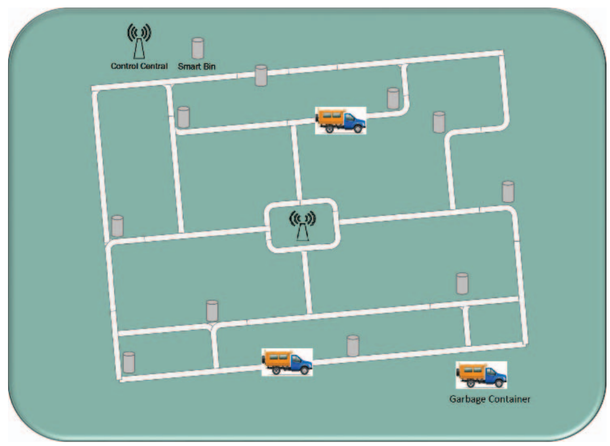

Figure 1. An architecture of the *GCP*, which is a practical implementation of the *VRP*.

III. System Model

This section is divided into three subsections. In Subsection III-A, an application is discussed in details where the *VRP* subsists, called the *Garbage Collection Problem (GCP)* [2]. This problem is then mathematically formalized in Subsection III-B. Finally, this section ends with discussing a *GA* based approach in Subsection III-C, which is utilized to explore feasible solutions from the given application scenario.

A. VRP over GCP

Waste collection is an immensely vital public service that is conducted by the municipal corporation. In the past, this service was carried out without analyzing the demand and calculating the feasible routes; whereas, the latter was left over to the drivers. However, with the expansion of urbanization, the importance of an effective collection system appeared more evidently to all concerns. Especially for large towns and cities, the operation cost rises substantially. Subsequently, people start thinking about an efficient garbage collection system that involves operational, tactical, and strategic decisions to provide better service with minimum operating cost. It is also getting considerable attention from the researchers due to its impact on the society and on the environment. One of the primary concerns of the researchers is to reduce the operating cost of the *GCP* through: *i)* minimizing the vehicle fleet, *ii)* maximizing the vehicle utilization, and *iii)* minimizing the travel time.

The *GCP* is a practical application of the *VRP*, where a fleet of *Garbage Containers (GCs)* with identical capacity involved in unloading *Garbage Bins (GBs)* of a particular area at a minimum management cost. Generally, a *GC* starts from a single depot, then it unloads multiple *GBs* before it unloads itself at a disposal area and return back to the depot. Generally, the *GBs* are placed arbitrarily beside the roads to ease the garbage collection process, and the position is known. Again, the capacity of the *GCs* are also pre-known. Hence, a competent algorithm must utilize these known factors to explore feasible solutions, which demand a considerable amount of computational activities. A *Control Center (CC)* can be installed inside the depot to support these computational activities. The primary task of the *CC* is to compute feasible solutions periodically with respect to one or more pre-selected parameters. At a later time, it will deliver these solutions to the *GCs* so that the garbage collection can be performed in the most efficient manner. These optimum solutions reduce operation and management cost by minimizing the requirements of the *GCs*, or by minimizing the traveling distance by offering shortest path that in turns reduce fuel consumptions, or by minimizing the requirement of employees, or so forth.

B. Mathematical Formulation

The *GCP* can be represented in a graph, $G = \{N, E\}$, where N is the set of *GBs*, $|N| = n$, and E is the set of edges, i.e., roads. Let $C = C_{ij}$ is a non-negative distance matrix for the edge between $i \in N$ and $j \in N$, and $i \neq j$. Based on the context, C_{ij} can be interpreted as a travel cost or as a travel time matrix. Again, when $C_{ij} = C_{ji}$ and $\forall (i, j) \in E$, the matrix C is said to be symmetric, and otherwise asymmetric. Let us assume that the depot is the node 0, i.e., N_0, and N number of *GBs* to be unloaded by m number of *GCs*. Let us also assume a decision variable, δ_{ij}^m, such that:

$$\delta_{ij}^m = \begin{cases} 1, & if\ m^{th}\ GC\ travels\ from\ GB\ i\ to\ j \\ 0, & otherwise \end{cases} \tag{1}$$

The GCP can be formulated using following objective functions and constraints as in [14]:

$$min \sum_{m=1}^{M} \sum_{i=0}^{N} \sum_{j=0}^{N} C_{ij}^m \delta_{ij}^m \tag{2}$$

Subject to:

$$\sum_{m=1}^{M} \sum_{i=0}^{N} \delta_{ij}^m, \qquad where\ j = 1, 2, \dots, N \tag{3}$$

$$\sum_{m=1}^{M} \sum_{j=0}^{N} \delta_{ij}^m, \qquad where\ i = 1, 2, \dots, N \tag{4}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} C_{ij}^m \delta_{ij}^m \leq \lambda_m, where\ m = 1, 2, \dots, M \tag{5}$$

$$\sum_{j=0}^{N} \delta_{0j}^m, \qquad where\ m = 1, 2, \dots, M \tag{6}$$

$$\sum_{i=0}^{N} \delta_{i0}^m, \qquad where\ m = 1, 2, \dots, M \tag{7}$$

In this formulation, constraints 3 and 4 ensure that each *GB* is unloaded exactly once. Constraint 5 shows that the total demand of any route must not exceed the capacity, λ_m, of the m^{th} *GC*, where $0 \leq m \leq M$. Constraints 6 and 7 ensure that each *GC* is utilized no more than once in a session.

C. GA Based GCP Solving Approach

Similar to its predecessor (i.e., *VRP*), the *GCP* is also an *NP-hard* problem. For this type of problem, it is argued that it is impossible to find an exact solution in polynomial time when the number of nodes are large. In other words, exact algorithms or linear programming based approaches are incapable of exploring solutions within feasible time duration for a large number of nodes. Conversely, metaheuristics based approaches are competent for these scenarios, and can explore optimum or near optimum solutions within a substantial time duration. Consequently, several metaheuristics based approaches are proposed in the last decade. Among them, *GA* is the most utilized metaheuristics based approach. Hence, several *GA* based algorithms are also proposed for solving the *VRP*, such as [13], [15]. Likewise, in this paper, a *GA* based approach is employed to find out the viable solutions, as because a large number of nodes are set in some scenarios in the simulation campaign.

The basis of the *GA* is to imitate the mechanisms of evolution of natural genetics, and take into consideration of the survival of the fittest among individuals over consecutive generation for solving a problem. Generally, the *GA* utilizes a set of *populations*, and creates several *generations* to solve a particular problem. Again, a *population* consists of a set of *solutions*, *a.k.a*, *chromosomes*; whereas a *chromosome* contains the solution in the form of *genes*. For reproduction of the new *generation*, two prime operations are performed on *populations*, namely *crossover* and *mutation*. At first, a *crossover* operation is performed for the reproduction of new *chromosomes*, and then a *mutation* operation is performed on the new *chromosomes* through making random changes in them. Afterward, a selection procedure selects only fittest solutions as a parent, which is then utilized by the *crossover* operation to create other fit solutions, also called *offsprings*.

At the end of each iteration, a new *generation* is produced from the combination of the old *generation* and the new *offsprings*. However, since the size of the new *generation* is larger than the previous one, it is reduced by placing only the fittest nodes in the population. On the other hand, the fittest node is selected based on a function, called *Fitness Function (FF)*. To achieve the objective function given in Equation 2, the following *FF* in Equation 8 is applied in this paper.

$$F(i) = \frac{1}{1 + (\ C_{0,j} + \sum_{j=1}^{\varrho} C_{j,j+1} + C_{\varrho,0}} \tag{8}$$

where *F(i)* is the fitness of a solution *i*, which has ϱ number of genes, 0 is the identification number of the depot, and *j* is the index of a *GB* in a chromosome. In this scenario, since the volume of *GBs* is random against a fixed capacity container, the size of the chromosomes or solutions may vary, and that makes this implementation more challenging.

IV. SIMULATION SCENARIO

In the simulation campaign, the *GA* based algorithm discussed in III-C is representing all those algorithms that do not take fairness into consideration. To investigating the fairness, a Euclidean 2D-area of variable size is considered, which may vary within the range of 500 m × 500 m to 5000 m × 5000 m. In favor of selecting this simple scenario, we would like to argue that if a *GCP* solving algorithm cannot ensure fairness in this scenario, it will also fail to do so in practical scenarios. The *GBs* are deployed in arbitrary location within the given area following a uniform probability distribution. A variable number of *GBs* are taken for the investigation that ranges from 10 to 80. Every *GB* has a unique identification number, and in this process, 0 is consider as the identification number of the deport. A random volume of waste is assigned to every *GB*, which is not higher than the bin capacity, β_c, and every container can contain waste volume $\leq \zeta_c$, where ζ_c is the container capacity. To stress the simulation, all the GBs are considered having waste volume, υ_j , where $j = 0, 1, 2, \ldots, N,$ higher than the half of β_c, which is calculated as follows:

$$\upsilon_j = \frac{\beta_c}{2} + \frac{\beta_c}{2} \times \rho \tag{9}$$

where ρ is a random number, and $0 \leq \rho \leq 1$. The distance between two nodes, d_{ij}, where $i, j \in N$, are calculated using Euclidean distance formula. In the simulation, traffic congestion is considered negligible; and hence, we assume that the *GC* that travels the shortest distance has performed the task in minimum time.

Among various variants of the *GA*, 1-opt *crossover* and 1-opt *mutation* is utilized in our simulation campaign. In addition, several other parameters are also taken into consideration throughout the simulation campaign, such as $\zeta_c = 1000$, $\beta_c = 200$, *generation* = 50, *sizeof(population)* = 2 × *N*, *mutation rate* = 0.1, and *crossover rate* = 0.25. The length of the chromosomes may vary from $\lfloor \zeta c/\beta c \rfloor$ to $\left\lfloor \zeta c/(\frac{\beta c}{2}) \right\rfloor$. Both the simulation scenario and the *GA* based searching approach have been implemented using C++, and all the acquired results are saved in a plain text file. Every scenario has been run with twenty five (25) different seed values, and then they are averaged before plotting on the graph.

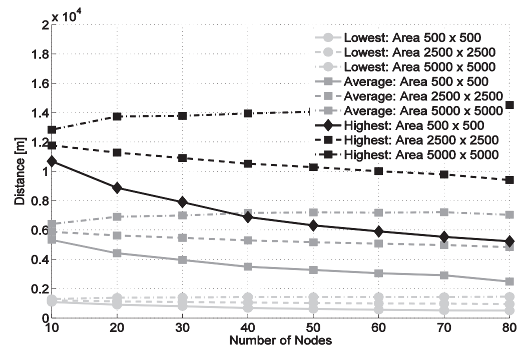

Figure 2. Travel distance for S_l, S_a, and S_h, with respect to various number of nodes and various coverage areas

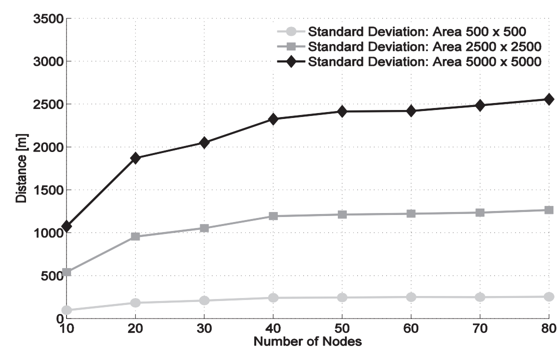

Figure 3. Standard deviations with respect to various number of nodes and various coverage areas

V. RESULT ANALYSIS

After every simulation, the *GA* based algorithm produces *S* solutions, where $|S| = m$, for a fleet size of *m* vehicles. Since *S* contains *m* different solutions, the acquired results are further analyzed to discover the lowest, $S_l \in S$, average (i.e., mean of all the solutions), $S_a \in S$, and the highest, $S_h \in S$, distances in *S*. Then, these results are plotted in Fig. 2. From this figure, it could be observed that when the coverage area is considerably small, $\forall S_i \in S$ offer distances with minimum deviations with respect to any number of nodes. However, the differences become prominent, i.e., $S_l \leq S_a \leq S_h$, with increasing coverage areas, and it is the highest for the coverage area of 5000 m × 5000 m. The reasons of increasing the differences are: *i)* as discussed in Section II is that *S* could have only one S_φ, and the rest, $S \setminus S_\varphi$, are local optimum solutions with respect to the given scenario, and *ii)* when the area to be covered is higher, the GBs are also deployed with higher inter-distance between themselves. Again, it also could be observed from the figure is that when the nodes are uniformly sparsely distributed, the differences are lower; whereas, the differences appear more significantly when the nodes are uniformly densely distributed. In former case, since all the *GBs* are sparsely distributed within a given area, all the *GCs* have to travel a considerably long distance to cover the area; whereas, in latter case, since the nodes are densely distributed, an algorithm can explore some solutions with shorter distances and some solutions may experience longer distances. Consequently, the highest difference could be observed between S_l and S_h, when N = 80 and the coverage area is 5000 m × 5000 m, and that is around 9.3 *km*. This distance will become prominent in the practical scenario where the area to be covered is substantially high, sometimes even several hundreds of *kms*.

In Fig. 3, standard deviations of various solutions are illustrated. Alike Fig. 2, the deviation increases with increasing coverage areas and increasing number of nodes. The minimum deviation could be found when the number of nodes are lower, and the *GBs* are deployed sparsely within the given area. In dense scenario, there could be several solutions that have minimum distances, and some solutions experience longer distances. This is because of the similar reasons that are discussed previously. Again, similar to Fig. 2, the highest deviation could be observed, when N = 80 and the coverage area is 5000 m × 5000 m, and that is around 2.5 *kms*. It would be substantially more in the practical scenario where a city could span more than several hundreds of *kms*.

Fig. 1 and 2 provide evidence of the discrimination among the solutions. By observing these figures, one can easily identify that fairness is not ensured by this algorithm. When the coverage area is larger and number of nodes are higher, the solutions are substantially deviated from each other, and may create dissatisfaction. Although, we employ a *GA* based algorithm in this paper; however, this observation is also correct for other algorithms that do not take fairness into consideration. A practical implementation of these algorithms in any organization may introduce dissatisfaction among the employees in it. Therefore, to extract the best out of the employees, it is necessary to distribute the jobs in such a manner that it is free from any discrimination. Hence, a *VRP* solving algorithm must take fairness issues into consideration whenever the solutions are computed.

VI. FUTURE WORKS

This paper apprise the fairness issue of the algorithms that are proposed for the *VRP*. It open up the possibilities of several other researches, e.g., *i)* investigate the fairness of other existing algorithms, *ii)* enhance the existing algorithms through incorporating fairness issues, *iii)* propose a new algorithm that take fairness into consideration, *iv)* incorporating *Nash-equilibrium* or *Game Theory* with an existing algorithm to ensure substantial fairness, and so on.

VII. CONCLUSIONS

In this paper, the fairness of the existing *VRP* solving algorithms is raised evidently through analytically and using an extensive simulation campaign. Although, the fairness is an important issue for any distribution management problem; to the best of our knowledge, there is no *VRP* solving algorithm that considers this issue as a parameter when they explore the optimum solutions. In this course action, we employ the *VRP* in the *GCP*, which is a practical application of it. Then, the *GCP* is mathematically formulated, and a *GA* based *GCP* solving algorithm is proposed, which represents the class of algorithms that does not take fairness into consideration. Afterwards, an extensive simulation campaign is conducted to investigate the fairness of the explored solutions by the proposed algorithm, and then the acquired results are scrutinized. From the investigation, it is confirmed that the fairness need to be taken into account while exploring viable solutions.

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