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ON MULTIPLE CRITERIA GENETIC APPROACH TO HIGHLY CONSTRAINT VRPs

Abstract

The literature provides numerous examples of either rich[*] or multi-criteria Vehicle Routing Problems (VRPs). Practitioners claim, however, that real-life problems need effective methods for VRPs which are both rich and multiobjective. In the paper we investigate whether such problems can be efficiently handled by standard metaheuristics – genetic algorithms. The answer is affirmative. Additionally, the analysis conducted supports the thesis that it is purposeful to adjust components of metaheuristics so that they take advantage of the multiobjective nature of the problems they solve.

Keywords

Multiple Criteria Optimization, Genetic Algorithms, Vehicle Routing Problems.

Introduction

The Vehicle Routing Problem (VRP henceforth) consists in determination of the optimal transportation plan to be performed by a fleet of vehicles in order to serve a collection of clients. It was introduced by Danzig and Ramser [4] and can be perceived as an extension of the classical transportation task. Customers in the VRP are geographically distributed, hence, this problem can also be perceived as an extension of the traveling salesman problem. This indicates that VRPs are NP-hard problems – their complexity growths rapidly with the number of clients to be served, which makes them far more complex

[*] VRPs are called rich if they impose an elaborate restriction structure on numerous objects involved in the problem.

than classical transportation tasks. Toth and Vigo [17] point out that VRPs are among the most intensively studied combinatorial optimization problems. This is mainly due to practical needs – effective transportation management can save a considerable proportion of a logistic company's distribution costs as a consequence of better resource allocation: fewer trucks and fewer drivers travel together a shorter total distance, costs of storing goods decrease, more deliveries are performed on time and customers don't wait long for their orders.

VRPs constitute a diverse family of problems. However, they can all be defined in the language of graphs. Let us define a graph G = (V, E) with a set of vertices (which represent clients) $V = \{v_1, \ldots, v_n\}$ and a set of edges (which represent routes) $E = \{(v_1, v_j) : i \neq j,\ v_1, v_j \in V\}$. Selected vertices (a subset V_d of V) represent depots – places where vehicles are located and commodities are stored. Clients place orders for commodities to be delivered to them by the available fleet of vehicles. If there is only one depot and one vehicle with unlimited capacity and all clients can be visited only once, the VRP boils down to the traveling salesperson problem*. This constitutes a starting point for extensions. Assume there are more vehicles, though they are still identical. One can impose constraints on their capacity. This is the capacitated VRP. If customers impose constraints on time intervals within which they can be served, this is a VRP with Time Windows. Both capacity and time window constraints complicate the matter, since the feasibility of solutions has to be verified within each iteration of the procedure**. Going a step further, one assumes that consumers can both demand and supply commodities, which means that vehicles have to both deliver goods and pick them up along the route. Such VRPs, which depend on further assumptions, are called VRPs with Backhauls or VRPs with Pickup and Delivery. A further complication comes from the fact that vehicles can vary with respect to capacity and other technical specifications. Such problems are called Heterogeneous or Mixed Fleet VRPs. At the end of this (selective) list of VRPs, an instance, in which customers can place multiple orders, we have. This is known as a VRP with Multiple Orders.

Enlisted VRPs (summarized in Table 1) add a significant amount of complexity to the simplest VRP framework. However, as we put forward in the next section, these VRPs are still not complex enough for practitioners, who request further extensions – both in the single and in the multicriteria directions.

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* Under the assumption that the graph G is connected.
** If this procedure does not allow to explore the search space through infeasible solutions.

Table 1

Typical VRP characteristics

1. Size of available vehicle	– One or more vehicle, limited or unlimited fleet
2. Vehicle capacity constraints	– Limited or unlimited capacity
3. Type of available fleet	– Homogeneous or heterogeneous fleet Special vehicle types – e.g. fridge
4. Housing of vehicle	– Single depot, multiple depots
5. Time restrictions	– With and without time windows
6. Consumers actions	– Declare demand or demand and supply

1. Routing problems and multiple objectives

The classes of VRPs which we referred to in the last section are subjects of intensive studies. This list covers the most important VRP instances in the deterministic framework. Practitioners, nonetheless, indicate a need for development of these frameworks, so that they take into account such elements of the problem as drivers and their characteristics*; elaborate, more detailed constraints on vehicles and customers; hierarchical treatment of customers; optimal positioning of transported goods in vehicles etc. These issues generate additional complexity in the already existing VRPs, either by the inclusion of more time consuming feasibility verification routines (enrichment of restriction structure), or by the need of inclusion of subroutines that solve, on-the-fly, subproblems added to the original framework. These extensions are mainly of a single criteria nature, or, at least, can be naturally defined without referring to multicriteria concepts.

The second direction along which practitioners requirement to extend the VRP formulation reflects *explicitly* the multicriteria nature of real-life VRPs. Jozefowicz, Semet and Talbi [8] point out, in their state-of-the-art survey, that multi-objective routing problems are utilized mainly for three purposes:

1. To extend classic academic problems in order to improve their practical application.
2. To generalize classic problems,

* In fact, in practice the treatment of drivers is very similar to the treatment of vehicles.

3. To study real-life cases in which the objectives have been clearly identified by decision-makers and are dedicated to a specific real-life problem or application.

We will concentrate on the first and the last points of this list. Here are the examples:

1. Lee and Ueng [10] propose a VRP in which the balance of route lengths is considered in order to increase fairness of solutions. When drivers compare their schedules and discover disparities, they complain. Since drivers constitute a vital element of the transportation company, their welfare is important.
2. Sessomboon et al. [15] add objectives to a VRP with time windows to improve customer satisfaction with regard to delivery dates.
3. Ribeiro and Lourenco [14] take into account diverse objectives, including cost, balancing, and marketing. They claim that the relationship between the customer and the driver is very important for improving sales and the reputation of the company.
4. Several researchers have studied the multi-objective traveling salesman problem in which several costs are associated to each edge. Problems of this kind are used to model networks for which two or more objectives must be computed simultaneously (e.g. the cost of the solution and the time required to execute the orders placed).
5. Chitty and Hernandez [3] define a dynamic stochastic VRP in which the total mean transit time and the total variance of transit time are minimized simultaneously.
6. Murata and Itai [12] define a bi-objective VRP which seeks to minimize both the number of vehicles and the maximum routing time.
7. El-Sherbeny [6] worked on a problem with eight objectives defined by the company. The fleet was heterogeneous, consisting of both covered and uncovered trucks. There was no capacity constraint.
8. Bowerman et al. [2] consider a problem where a set of students living in different areas must have access to a public schoolbus to take them from their residences to their school and back. The problem is to find a collection of routes that will ensure a fair distribution of services to all eligible students. The authors proposed a multi-objective model with four objectives: minimization of the total length of routes, minimization of the total student walking distance, fair distribution of the load (i.e., the number of students transported), and fair division of the total distance traveled among the buses.

9. Corberan et al. [1] and Pacheco and Marti [13] examined methods for transporting students from home to school and back. The transportation had to be accomplished as safely as possible, while still considering economic aspects as well as comfort. The time constraint ensured that students would not spend too much time on the bus and that there would be no glaring inequities between the first student picked up on the tour and the last one.
10. In Lacomme et al. [9] trash has to be collected and delivered to a waste treatment facility. The trucks leave the factory at 6 a.m. and have to return to the factory before a given hour since the workers have to sort the waste afterwards. The authors consider two objectives: the minimization of the total route length and the minimization of the longest route.
11. Zografos and Androustsopoulos [18] have proposed modeling hazardous product distribution as a bi-objective routing problem in which objectives of minimizing the route length and minimizing risk are considered simultaneously.
12. Doerner et al. [5] attempt to deal with the fact that developing countries frequently face a dilemma engendered by a growing population and very restrictive budget limitations for healthcare expenditures. The purpose of the study is to propose cost-effective routing for mobile healthcare facilities, thus providing access to health services for a large proportion of the population. The problem involves selecting the stops and the routing for the mobile facility, while also considering the following three objectives: (1) efficiency of workforce deployment, as measured by the ratio between the time spent on medical procedures and total time spent, including travel time and facility setup time, (2) average accessibility, as measured by the average distance that the inhabitants need to walk to reach the nearest stop on the tour, and (3) coverage, as measured by the percentage of inhabitants living within a given maximum walking distance to a tour stop.

The examples listed reflect the practitioners' growing need for the analysis of multicriteria VRPs, since the specification of such VRPs better corresponds to what they encounter in everyday business or policy activity. VRPs involving diverse types of heterogeneous objects (e.g. vehicles, drivers, customers, loading spaces), on which a rich structure of restrictions is imposed and many type of interactions are allowed to arise between the objects involved with reference to the notion of time, distance and geographical location, are called rich VRPs. Practitioners lead us therefore to the consideration of what is called a rich VRP with multiple objectives. In the simulation section we focus our attention on instances of such problems. Before we proceed to the solution method and simulations, multicriteria representation of VRPs considered will be presented.

2. MCDM Problem Formulation

Let us consider, for simplicity, the bi-objective case. We start from the assumption that solutions to multiobjective VRPs (i.e. *transportation plans*) are represented by collections ϕ of vectors $\mathbf{x_i}$ from the space $\mathbf{R}^n$, $\mathbf{x_i} \in \mathbf{R}^n$, $\phi = \{\mathbf{x_i}, I = \{1,2,...,p\}\}$. Since vectors $\mathbf{x_i}$ can be stacked to form a single vector $\mathbf{x} \in \mathbf{R}^N$, where N equals pn, we assume that the solutions are represented by vectors $\mathbf{x} \in \mathbf{R}^N$. The set $\mathbf{X}_d$ of feasible solutions is assumed to be bounded and constrained:

$$\mathbf{X}_d = \{\mathbf{x} \in \mathbf{R}^\mathbf{N} \mid \mathbf{g(x) = b}\},$$

$$\mathbf{b} \in \mathbf{R}^\mathbf{k},$$

$$\mathbf{g} : \mathbf{R}^\mathbf{N} \to \mathbf{R}^\mathbf{k},$$

Let us assume that the evaluation of the transportation plan $\mathbf{x}$ is done with respect to m criteria f_i, i.e. the functions $f_i : \mathbf{X}_d \to \mathbf{R}$, i=1,2, …,m. The mapping $\mathbf{f}(\mathbf{x}) = [f_1, f_2] : \mathbf{X}_d \to \mathbf{R}^2$ is called a bi-objective function and the direct image $\mathbf{Y}_d = \mathbf{f}(\mathbf{X}_d)$ is called a feasible bi-evaluation space.

Let us consider the set $\mathcal{C}$ of convex cones $\mathcal{C}$, $\mathcal{C} = \{ \mathbf{y} \in \mathbf{R}^2 : \mathbf{y} \in \mathcal{C} \Rightarrow \mathbf{ay} \in \mathcal{C}, a > 0\}$ and the family $\mathcal{S} : \mathbf{R}^2 \to \mathcal{C}$. The family $\mathcal{S}$ defines the preference structure as follows. Given $\mathbf{y} \in \mathbf{R}^2$, the dominance relation $\rho_\mathbf{y}$ for the evaluation $\mathbf{y}$ is defined by the formula:

$$\mathbf{y} \rho_\mathbf{y} \mathbf{y'} \Leftrightarrow \mathbf{y'} - \mathbf{y} \in \mathcal{S}(\mathbf{y}) \Leftrightarrow \mathbf{y'} \in \mathbf{y} + \mathcal{S}(\mathbf{y});$$

the symbol "+"stands here for the vector sum of a vector and a set. Thus, by moving the cone $\mathcal{S}(\mathbf{y})$ to the point $\mathbf{y}$, we obtain the *dominance set* $\mathbf{Y}^{\mathbf{pref(y)}} = \mathbf{y} + \mathcal{S}(\mathbf{y})$ *for* $\mathbf{y}$. The dominance set consists of such evaluations $\mathbf{y'}$ which remain in relation $\rho_\mathbf{y}$: $\mathbf{y} \rho_\mathbf{y} \mathbf{y'}$. If $\mathbf{Y}^{\mathbf{pref(y)}} \cap \mathbf{Y}_d = \{\mathbf{y}\}$, then $\mathbf{y}$ is said to be nondominated in the set $\mathbf{Y}_d$. The set $\mathbf{Y}_d^{ND}(\mathbf{Y}, \mathcal{S})$ denotes the set of all nondominated evaluations (of transportation plans) for all evaluations from the set $\mathbf{Y}_d$.

The dominance relation in the feasible evaluation set $\mathbf{Y}_d$ which is defined by the cone family $\mathcal{S}$ can be transferred to the feasible set of transportation plans $\mathbf{X}_d$. Let us consider the transportation plan $\mathbf{x} \in \mathbf{X}_d$ and the relation $\wp_\mathbf{x} \subset \mathbf{X}_d \times \mathbf{X}_d$. defined by the formula:

$$\mathbf{x} \wp_\mathbf{x} \mathbf{x}' \Leftrightarrow \mathbf{f(x)}\rho_{f(x)}\mathbf{f(x')}.$$

If $\mathbf{x}\ \wp_\mathbf{x} \mathbf{x}'$, then we say that the transportation plan $\mathbf{x}'$ is preferred to the plan **x.** The transportation plan is said to be *efficient* when its evaluation is not dominated. The set of efficient transportation plans is denoted by X_d^E; $\mathbf{X}_d^E = \mathbf{f}^{-1}(Y_d^{ND})$. For simplicity we consider constant preference defined by $\mathcal{S}_0 : \mathbf{R}^2 \to \mathcal{C} : \mathcal{S}_0(\mathbf{y}) = \mathbf{R}^- \times \mathbf{R}^-$, $\mathbf{y} \in \mathbf{Y}_d$. Thus we have:

$$\mathbf{y}\rho_\mathbf{y}\mathbf{y}' \Leftrightarrow \mathbf{y}'-\mathbf{y} \in \mathcal{S}_0(\mathbf{y}) \Leftrightarrow \mathbf{y}'-\mathbf{y} \in \mathbf{R}^- \times \mathbf{R}^- \Leftrightarrow y_1' \le y_1 \wedge y_2' \le y_2.$$

Thus we assume that both evaluations are to be minimized (e.g. cost of routes and the number of time windows violated).

The bi-criteria problem is to find a unique, most preferred transportation plan with respect to the dominance relation $\wp_\mathbf{x}$, i.e. it requires identification of an efficient solution from the set X_d^E, or to determine the entire efficient frontier. We conduct simulations for both of these cases. The set $\langle \mathbf{f}, \mathbf{g}, \mathbf{b}, \mathcal{S}_0 \rangle$ represents the problem in the sense that **g** and **b** represent actions and technological issues (here, transportation infrastructure), the functions **f** represent the evaluation of transportation plans and the family of cones $\mathcal{S}_0$ describes the decision maker's preference. However, there may exist infinitely many maximal elements with respect to the preference defined above*. Thus the natural definition of the solution of the problem – the efficient set – although satisfactory from the formal point of view, sometimes may not be sufficient from the practical point of view as the decision maker is left with many solutions. Moreover, the method of presentation of X_d^E to the decision maker is not an obvious issue.

When a solution method has to yield a unique solution, it has to involve a procedure which contracts the X_d^E to a unique solution. The MCDM theory lists a series of approaches aimed at the identification of unique solutions (using e.g. weights, trade-offs, lexicographic orders, reference points and others). Let us focus our attention on weighting approach to show general problems which

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* The definition of the solution can be rephrased using the relation theory terminology: viz. the option **x** is a solution if the set $\mathbf{Y}_d$ of feasible outcomes contains the maximal element with respect to the partial order $\le$ in $\mathbf{R}^2$ (Yu, 1995).

are not specific to the approach in scalar evaluated transportation tasks. Leaving aside very serious doubts on the decision maker's ability to define reliable weights, we finally arrive at scalar objective functions.

3. Genetic Approach

Not only rich, but also standard VRPs are most often approached by means of optimization metaheuristics: simulated annealing, taboo search, ant colony optimization techniques and genetic algorithms. To solve the multi-criterial VRP we employ the genetic approach, which turned out to be useful in this respect. As pointed out by Tan et al. [16], genetic algorithms tend to be stable over a wide range of VRP instances, which gives rise to the assumption that they should also give satisfactory results when applied to diverse rich multicriteria VRPs (since these constitute a mixture of diverse VRP classes). Secondly, genetic algorithms give better results than simulated annealing and taboo search over a wide range of diverse VRP problem sets, while being positioned on average between these heuristics in terms of computation time.

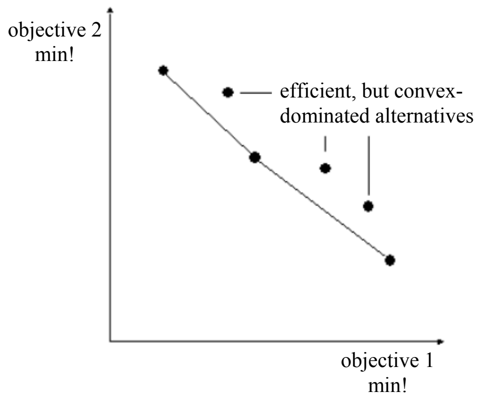

Figure 1. Efficient, convex-dominated solutions

Source: M.J. Geiger.

The genetic algorithm maintains a population of candidate members over many generations. Population members (solutions) are encoded as variable length strings of integers. A selection mechanism chooses parents who go to the reproduction phase, i.e. crossover and mutation, which in turn produces children who replace the parents. We use the tournament selection. Each selection round is proceeded by the evaluation of the current population of solutions. Geiger (2001) points out that, if the objectives considered are integrated with a weighted sum to get a scalar evaluation (as it is the case in our study), efficient but convex-dominated alternatives are difficult to obtain, see Figure 1.

This is a significant drawback of standard selection mechanisms. In the multicriterial case, the decision maker very often (especially if long-term plans are to be implemented) wants to have a possibility of choosing from a set of good alternatives by means of procedures which are external to the optimization algorithm and often involve expert judgement. These alternatives can come from the final population of the algorithm. It is desirable that these alternatives contain efficient, yet convex-dominated solutions. The presence of such solutions is also crucial for sufficient diversity of populations. To overcome this problem, a selection operator which provides a self-adoption technique is implemented. In this approach, we use dominance information of the individuals of the population by calculating for each individual i the number of alternatives n_i by which this individual is dominated. For a population consisting of N alternatives we have: $0 <= n_i <= N-1$. Individuals that are not dominated by others receive a higher fitness value than individuals that are dominated. We calculate fitness values for all individuals using linear normalization. Individuals with the lowest values of n_i ($n_i = 0$) receive the highest corresponding value of $f_i = f_{max}$ and the individual with the highest value $n_{max} = \max\{n_i, i = 1,..., N\}$ receives the lowest value of $f_i = f_{min}$ for $f_{max} > f_{min} > 0$. For all other individuals the following condition is imposed: $f_i = f_{max} - ((f_{max} - f_{min}) / n_{max})n_i$.

An efficient reproduction mechanism, i.e. selection, crossover and mutation, is largely responsible for the performance of the algorithms. Conventional single/double point crossover operations are relevant to orderless strings. They make a cut point (or points) on both of the strings. A crossover is then completed by swapping substrings after the cut point (or between two cut points) in both strings. In VRPs, where routes are crossed over, each integer value appears only once in a string, and such a procedure produces invalid offsprings, for they can have duplicated values in the resulting strings. To prevent such offsprings from being constructed, we use a set of ordered crossover operators, see Tan et al. [16]. The one that turned out to be especially useful is a so called permutation crossover.

Apart from the above part-and-parcel components of genetic algorithms, we used their extensions: breaks for local search (typical for the intensification phase of taboo search algorithms), variable mutation probability and (in some experiments) controlled proportion of feasible and infeasible solutions in evolving populations, as well as initialization of populations by means of deterministic heuristics such as push-forward-insertion heuristic and interchange procedures.

4. Simulations and results

We have run efficiency tests on multiple sets of data simulated from predefined probability distributions. Here are the findings which we believe are most important:

1. The procedure works efficiently for all tested distributions over a wide range of parameter values by which these distributions are parametrized.
2. For the majority of problem classes it is possible to define instances (by a suitable parametrization of probability distributions) which makes the procedure highly time consuming, hence ineffective for practitioners.
3. For implementations which allow populations to contain infeasible solutions, the convergence process is on average longer, but results produced are on average better.
4. For such implementations it may, however, often be the case that convergence to a feasible region is not achieved after a significant number of iterations.
5. Best results are achieved when evolving populations are controlled with respect to the proportion of feasible and infeasible solutions.
6. The employment of selection technique which refers to the concept of dominance relation produces results which are more useful in practice.

The above findings are intuitive and consistent with common knowledge about genetic algorithms. The first of them supports the thesis that such algorithms are powerful tools of optimization, even for very complex problems, such as rich multicriteria VRPs. The second finding constitutes a warning. It refers to something similar to what is called in the literature the deceptive problem – a problem for which a given heuristic method (here a genetic algorithm) tends to fail in finding satisfactory solutions within a reasonable time. Fortunately, parametrisations for which the second case occurs do not happen very often and seem to be implausible in real-life scenarios. Findings 3 and 5 indicate that the inclusion of infeasible solutions in evolving populations does not have to increase the computing time excessively, and, if reasonably modeled, such mixed populations produce superior results. Finally, point 6 is an example of the advisability of developing components of metaheuristics which explicitly take into account the multiobjective structure of problems being solved.

Since, to our best knowledge, there are no reference data sets on rich VRPs (not to mention multicriterial ones), which we could use to compare our implementation with other implementations, we provide results obtained on our simulated data. Table 2 presents runtime needed to conduct 200 iterations of the algorithm for problems varying from 10 to 100 clients*. Evolving populations always consist of 50 solutions. Computations were conducted on a Celeron 1.5 Gh CPU with 512 Mb RAM.

The second column presents average time consumption over simulated data sets with different parametrisations of probability distributions. The third column reports worst-case run times. Averages do not take into account instances for which computations didn't terminate within 3600 seconds. Such instances are indicated in the third column by inf-ties. The results reported are comparable to the benchmark results reported in other studies, e.g. in Tan et al. [16]. Our simulations produce visibly longer, but still practically acceptable runtimes. Longer runtimes are due to our problems' being much richer than the ones considered in the paper referred to.

Table 2

Time efficiency of the algorithm

Problem size	Average run time (seconds)	Worst runtime (seconds)
10	85.16	431.11
50	240.96	inf
100	1863.91	inf

* In reported instances it is assumed that each customer places only one order. These can, however, be considered as instances in which there are less customers than assumed, but some of them place multiple orders.

Concluding Remarks

In the paper we investigated if rich VRPs – computationally greedy problems made even more complex by the introduction of multiple criteria – can still be effectively (ie. within reasonable time) solved by means of standard techniques – genetic algorithms. We implemented an algorithm capable of handling such VRPs. The answer is affirmative. Our results also confirm the thesis that it is useful to adapt components of optimization heuristics (here of a genetic algorithm) so that they explicitly take advantage of the multi objective structure of problems they are designed to solve. Further work will cover the following two topics. First, we will concentrate on the issue of enhancing crossover operators to the multiobjective framework. Second, we will try to experiment with the structure of rich VRPs, so that their complexity is lowered by the use of multiobjective approach in single criteria problems with nested structure of complex restrictions, e.g. in the case of Loading VRPs.

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