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Approaches to solve the vehicle routing problem in the valuables delivery domain

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Abstract

The various extensions of the vehicle routing problem with time windows (VRPTW) are considered. In addition to the VRPTW, the authors present a method to solve the SDVRPTW – the variation of the task allowing separate goods supply to the customers. The two developed metaheuristic algorithms (genetic and hybrid) are described that use the unique task-oriented operators and approaches, such as the limited route inversion, the upgraded heuristic procedure, the initialization of the initial population by ant colonies method, Pareto ranking.

The features of this problem solved are additional route restrictions, such as: the maximum time, the number of customers and cost, as well as the maximum number of vehicles required for delivery. This article is devoted to valuables delivery problems and methods to resolve them.

Keywords: vehicle routing problem, metaheuristic algorithms, VRPTW, SDVRPTW, Pareto ranking.

1 Introduction

Nowadays the logistics has great importance, since the delivery of goods and services covers almost all spheres of human activity. Therefore, optimization of this process is the important issue to explore. This challenge shows itself the most acutely in the valuables delivery. For example, in the banking need to save money spent both on the ATM service and their replenishment is increased. The transportation cost in its turn is calculated based on the distance traveled or time spent.

The main purpose of this article is to show how, using various approaches and algorithms, to reduce the costs of the valuables transportation and delivery by designing the routes in more efficient (close to optimal) way.

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2 Mathematical model

Let us formulate the main goals and restrictions of the vehicle routing problem with time windows.
Objective: Minimize the number of vehicles and the total travel distance.
Restrictions:

- Each vehicle corresponds to one route;
- Each route begins and ends at the depot;
- Overall customer demand for the route cannot exceed the carrying capacity of the vehicle;
- Each customer is served by one and only one vehicle.

We use the following symbols:

Assume N is a number of customers $(1, 2, \dots, n)$ that need to be serviced.

c_{ij} – the transportation cost from the customer i to j.

t_{ij} – the sum of *i*-th customer service time and travel time from *i* to *j*.

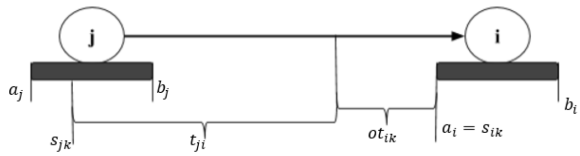

Figure 1. A schematic arrangement of introduced designations

q – the vehicle's maximum capacity. In the sector of the valuables delivery the q is the insurance amount.

d_i – the demand of the customer *i*.

Because of the problem domain (valuables sector) limits the d_i is the cost of requested goods.

$[a_i, b_i]$ – the hard time window within which the *i* -th customer should be serviced.

V – the set of all available vehicles $k, k \in V$.

x_{ijk} – a variable taking a value of *1* if the vehicle *k* is coming from the customer *i* to the customer *j*, and *0* if otherwise.

s_{ik} – the start time to service the customer *i* with the vehicle *k*.

$ot_{ik} = a_i - (s_{jk} + t_{ji}), \forall i \in N, \forall j \in N, \forall k \in V$ – the waiting time to open the time window of the customer with k-th vehicle.

Objective function:

$$Z = \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} c_{ij}\, x_{ijk} \rightarrow min \quad (1)$$

Restrictions:

$$\sum_{k \in V} \sum_{j \in N} x_{ijk} = 1, \forall i \in N \quad (2)$$

$$\sum_{i \in N} \sum_{j \in N} d_i x_{ijk} \le q, \forall k \in V \quad (3)$$

$$\sum_{j \in N} x_{0jk} = 1, \forall k \in V \quad (4)$$

$$\sum_{i \in N} x_{i,0,k} = 1, \forall k \in V \quad (5)$$

$$\sum_{i \in N} x_{ihk} - \sum_{j \in N} x_{hjk} = 0, \forall h \in N, \forall k \in V \quad (6)$$

$$x_{ijk}\left(s_{ik} + t_{ij} - s_{jk}\right) \le 0, \forall i \in N, \forall j \in N, \forall k \in V \quad (7)$$

$$a_i \le s_{ik} \le b_i, \forall i \in N, \forall k \in V \quad (8)$$

$$x_{ijk} \in \{0,1\}, \forall i \in N, \forall j \in N, \forall k \in V \quad (9)$$

A unique feature of this task formulation is the possibility to replace the objective function in order to obtain the best possible solution regarding various criteria.

$$Z_1 = \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} t_{ij}\, x_{ijk} \quad (10)$$

$$Z_3 = \sum_{j \in \{N \setminus 0\}} \sum_{k \in V} x_{0jk} \quad (11)$$

$$Z_2 = \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} t_{ij}\, x_{ijk} + \sum_{k \in V} \sum_{i \in N} (s_{ik} - ot_{ik}) \quad (12)$$

$$Z_4 = \alpha * Z + \beta * Z_1 + \gamma * Z_2 + \delta * Z_3 \quad (13)$$

Where (10) is a function to minimize the time spent; (11) - to minimize the used vehicles; (12) - to minimize the time spent waiting for the time window to open on the route; (13) - to minimize the weighted sum of different criteria, where $\alpha, \beta, \gamma, \delta$ are the problem-oriented factors.

3 Description of the developed algorithms

The algorithms described in this article use an evolutionary approach. First of all, the set of solutions (population) is initialized that is represented schematically in Fig. 2. Further, consistent improvement takes place iteratively on the made populations. At a certain iteration stop condition is met.

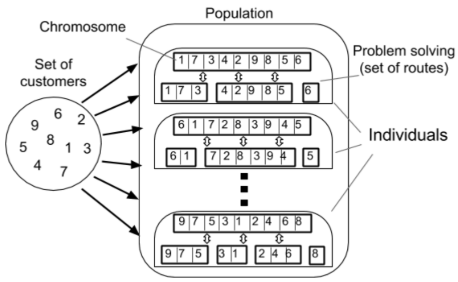

Figure 2. Visual representation of the terms of the genetic al

Two different algorithms described below are genetic and hybrid. First is used to solve the VRPTW problem, and the latter is considered to solve SDVRPTW. Each of these algorithms has its own features, advantages, disadvantages and problem statements under which they are most effective. Fig. 3 shows a general scheme of the genetic and hybrid algorithms**.** The developed methods use different variations of the genetic algorithm operators.

In hybrid algorithm mutation operator is replaced by a heuristic procedure. Which is unique, because eliminates mutation operator from the traditional genetic algorithm (which is part of a hybrid one), because sometimes the latter worsens obtained solutions.

A distinctive feature of the genetic algorithm is the Pareto ranking used to obtain a set of the best solutions regarding the optimization criteria.

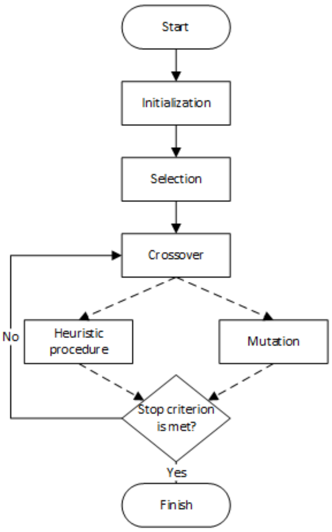

Figure 3. The general scheme of the genetic and hybrid algorithms.

Let us consider each of the operators used in more detail.

Initialization

In the genetic algorithm (R*100)% of individuals, where R is the algorithm's optimization parameter describing the initialization of the population, are created using the greedy procedure described with the following steps:

Step 1. For the set of customers *N* with the cardinality *n* to initialize the empty chromosome *l;*

Step 2. Randomly remove the selected customer $i \in N$;

Step 3. Add the number of the *i* customer to the chromosome *l;*

Step 4. If there are clients within the empirically chosen Euclidean radius of the customer *i*, select the nearest *j*, where $j \notin l$; If there are no customers, return to step 2.

Step 5. Add *j* in the end and remove *j* from *N*;

Step 6. Select the customer j as the center of the Euclidean circle and go to step 4. The remaining portion of the generation is randomly generated.

In the hybrid algorithm, the initial population is produced by means of the ant colonies algorithm adapted to the SDVRPTW problem [1], which allows obtaining the acceptable solutions already in the first iteration.

Routes improvement

Selection

The genetic algorithm uses the tournament selection strategy with elitism. As a selection criterion in this approach Pareto solutions rank has been used as described in [2], not its total cost. This allows us to consider VRPTW as multiobjective optimization problem with respect to two criteria: the total transportation cost and the number of the vehicles used.

In the hybrid algorithm the elitism strategy in selection was used, which selects the chromosome to generate the next generation [3].

Pareto ranking

Each solution in the population is associated with the vector $\vec{v} = (n, c)$, where n is the number of vehicles, and c is the total cost. Using these two criteria a Pareto set of optimal solutions are defined. These solutions get rank – 1. Thereafter, Pareto set is defined among the unranked solutions. These solutions get rank - 2. This procedure is carried out as long as all solutions will be ranked.

This ranking algorithm ensures that every generation, including the first randomly generated one, will have the set of individuals with rank 1. This set will represent the best individuals in each population.

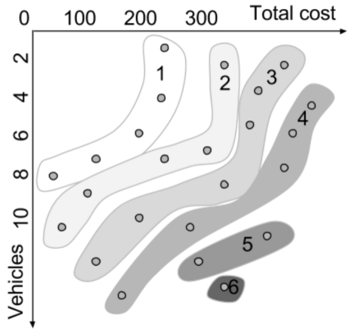

Figure 4. Example of Pareto ranking technic.

Crossover

The genetic algorithm uses the proposed in the [4] a specific Best Cost Route Crossover (BCRC) designed specifically for VRPTW. In addition to the routes cost, this method is aimed to reduce the number of necessary vehicles, and during its work it checks the validity of the solutions obtained. Experimentally found that the cost of this operator performance is more than reasonable.

In the hybrid algorithm the crossover operator is implemented using the following algorithm:

- Select solutions from the population.
- Routes of the chosen solutions are combined in one solution.
- While there are routes in the combined solution following steps are made:
  - a route is selected and inserted into a new solution; random number is chosen between 0 and the number of routes – this is ordinal route number in the combined solution;
  - the selected route is removed from the combined solution;
  - all routes that have customers from the selected solution are removed from combined solution;
  - unserved customers are inserted into the new solution using a heuristic procedure;
  - constructed solution is a child of N selected parents solutions.

The heuristic procedure.

If all customers have been served, proceed to the last point.

- Randomly select the customer k^* among unserved ones.
- If feasible inserts of customer k* in the current route exist, select the one which extra distance (due to a new customer k^* insertion) is less. If there are two feasible inserts with the same extra distance, chose one which has the least total delay (downtime).
- If there are no feasible inserts, new route begins, in which the customer k^* is inserted. This insert is always feasible if the vehicle amount is unlimited.
- Repeat the procedure until all customers are served, the solution is made. Exit

Mutation

The genetic algorithm uses the constrained route reversal mutation, which is the adapted version for this problem of the widely used inversion mutation [5]. Within the individual selected for mutation in the randomly chosen route 2-3 customers are inverted.

In the hybrid algorithm the mutation operator is not used since the population may be deteriorated, and the solutions may exit feasibility area. Heuristic approach described earlier is used to prevent the algorithm from getting stuck in a local minimum.

Stop criterion

For the hybrid algorithm the stop criterion is the attainment of a certain generation (N), the number of which is one of the algorithm parameters. The execution of the genetic algorithm stops when there is no improvement in the optimal solution set throughout Z generations.

4 Results analysis

To estimate the performance of these approaches, the Solomon tests were chosen [6]. These tests are designed for vehicle routing problem with the hard time windows. Table below compares solutions obtained using the considered algorithms. Each problem set includes 100 clients and one depot. The designations in the table below:

V is the number of the vehicles used.

D is total distance of all routes.

Table 1. Comparison of the algorithms performance

Task	Best		Genetic		Hybrid		Task	Best		Genetic		Hybrid	
	V	D	V	D	V	D		V	D	V	D	V	D
R101	19	1646	19	1690	19	1657	R201	4	1252	4	1308	4	1268
R102	17	1486	17	1524	17	1502	R202	3	1192	4	1182	4	1113
R103	13	1293	14	1286	13	1237	R203	3	940	3	996	3	989
R104	9	1007	10	1088	10	1021	R204	2	826	3	806	3	761
C101	10	829	10	832	10	829	C201	3	592	3	597	3	592
C102	10	829	10	844	10	829	C202	3	592	3	608	3	592
C103	10	828	10	851	10	829	C203	3	591	3	603	3	592
C104	10	825	10	845	10	826	C204	3	591	3	599	3	597

Thus, the algorithm using the Pareto ranking in all tasks returns the results which are sufficiently close to the optimum. In some tasks the total routes cost has been less than the best reported results, but an extra vehicle has been used.

In its turn, the hybrid algorithm shows the result as an average of 16% worse than the best registered. This situation is explained by the fact that in the Solomon tests the mean customer’s need is much less than the vehicle capacity, and the problem solution allowing the spilt supply to customers will be close to optimal only if the average demand of customers will be between 50% and 75% of the vehicle capacity [7]. However, in practice fulfilling this condition the hybrid algorithm shows results close to the optimum.

To estimate algorithms applicability to the valuables delivery domain a time performance analysis for these algorithms for different numbers of the customers has been performed. For this test two types of problems with large time windows have been selected: R201 (randomly distributed consumers), C201 (grouped consumers):

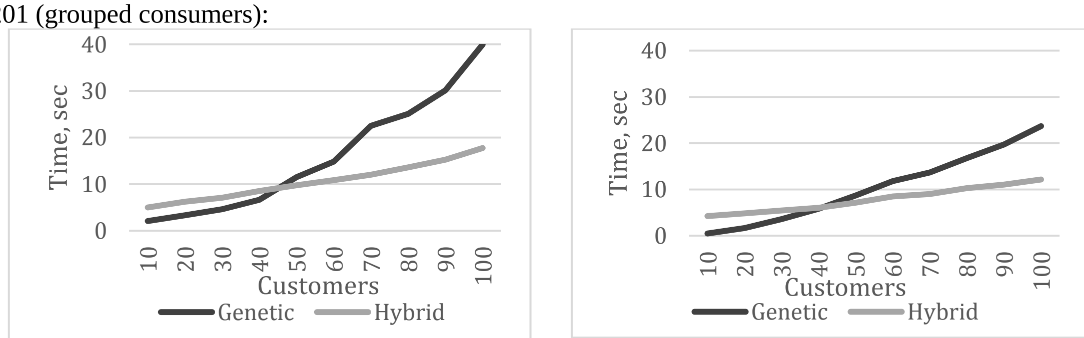

Figure 5. Comparison of the algorithms performance

Based on the results, we can say that the use of genetic algorithm produces the best results in terms of solution quality and acceptable performance up to 100 customers. The use of the hybrid algorithm is more preferable in terms of the performance for more than 50 customers but the quality of the solution is going to be acceptable only in high-demand problems, which requires further researches.

5 Conclusions

This article describes the algorithms for solving 2 versions of the VRP problem: VRPTW and SDVRPTW. Two classes of the metaheuristic algorithms were used: genetic and ant. Special attention was paid to complex route optimization in terms of cost and number of vehicles; the various types of objective functions have been presented. Distinctive unique features of the algorithms developed are: the use of Pareto ranking for the possibility to use multi-criteria optimization; the BCRC operator guaranteeing children improvement while saving the solution feasibility; constrained route reversal mutation enabling to prevent the algorithm from getting stuck in a local minimum without violating the customer’s time windows restrictions; upgraded heuristic procedure that avoids the use of mutation operator in the classic version, which can degrade the solution. The great advantage of developed algorithms is their parameters adaptability for the problem.

The analysis of the experimental results has showed that the developed genetic algorithm provides the best solution in cases where the average customer’s demand is less than 50% of the maximum vehicle load. Otherwise, it is assumed that the hybrid algorithm would be more efficient in terms of both performance and optimal solutions. However, further research is required in this domain. Also, in future studies procedure for calculation of such parameters as size and number of generations depending on the amount and the customers grouping is expected to be developed.

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