Genetic and Ant Colony Optimization Based Communal Waste Collection Vehicle Routing

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Abstract— In this paper, the problem of routing vehicles for the collection of municipal waste is considered, which has been increasingly explored in recent years. A logistic model for municipal waste management has been presented, which was used to select the optimal routes of collecting and transporting municipal waste for a realistic example of the city of Niš in Serbia. Two metaheuristic methods - genetic algorithm (GA) and ant colony optimization (ACO) – have been used to solve the problem of waste collection vehicles routing. An analysis of the performance of applied metaheuristic algorithms and comparison of the obtained optimal solutions has been performed. As a basic measure, the total length of the route was considered when evaluating the solution. The aim of this paper is to evaluate the applicability of GA and ACO metaheuristic optimization algorithms for the problem under consideration.

I. Introduction

Waste management is a complex technological activity with numerous variable parameters and properties. The complexity of this system is reflected in several factors that affect the functioning of its three basic subsystems: economic, environmental and managerial. The variability of the factors is especially influenced by the change in the quantities and characteristics of the communal waste, and by the characteristics of the traffic network in which communal vehicles are moving.

The costs of collecting and transporting municipal waste make up the bulk of the costs of the entire waste management system, which is why the optimization of the waste collection and transportation system, besides the ecological, has important economic importance and as such is the main research and development task of waste management.

The main motivation for the research in this paper was the improvement of the municipal waste collection system through the optimization of the collection and transport of municipal waste. The problem has been considered for the territory of the City of Niš, Serbia and the solution has been considered using genetic algorithms (GA) and ant colony optimization (ACO). By choosing the optimal route for the collection of communal waste, direct savings are achieved by reducing the travel route, time and fuel, reducing the number of vehicles, the number of employees and others. This kind of research is supported by numerous works and case studies. Teixeira and associates [1] showed in their work that optimizing the movement of vehicles with the collection of waste can reduce the travel time by around 29%. Similarly, Tavares and associates in their work showed that the optimization can be reduced by about 12% of spent fuel in waste collection [2, 3].

Optimizing the movement of vehicles for the collection of municipal waste belongs to the group of vehicle routing problems (VRP) and is considered as a combinatorial problem of optimization [3]. The problem of vehicle routing for the collection of municipal waste is specific and significantly different from the classic problem of vehicle routing where vehicles leave the central warehouse (depot), visit all users and return to the central warehouse (depot). This path is called the route, and in some cases, the vehicle makes several routes to meet all user requirements.

In the case of vehicle routing for the collection of municipal waste, the vehicle starts from the depot, but after the vehicle is eventually filled with waste, it goes to the landfill where it deposits waste. If it does not collect the total predicted amount of waste, the same vehicle starts from the landfill and makes a new route.

When defining a real problem, it is necessary to have data on the amount of municipal waste, geographic and traffic characteristics of the space, fleet of vehicles, etc. After that, it is necessary to define a mathematical model that solves the defined problem within a reasonable time interval. The development of VRP optimization models in the municipal waste collection system considers several realistic constraints. This leads to complex models that are difficult to be applied effectively.

II. Methodology

Exact and heuristic methods are used to solve the VRP for the collection of municipal waste. The application of exact methods is limited only to simple problems, while for complex real systems, heuristic and more frequently meta-heuristic methods are used. The term meta-heuristics was first proposed by Fred Glover back in 1986, while the same author defined meta-heuristics many years later as a set of algorithmic concepts that are used to define heuristic methods applicable to a wide range of problems [4].

Meta-heuristics is designed to solve complex optimization problems where other optimization methods fail to solve the optimization problem efficiently. These methods are nowadays recognized as one of the most practical approaches to solving many complex problems, and this is particularly relevant to solving many real problems of combinatorial optimization, hence the application to VRP problem. In general, meta-heuristics can be said to be a higher level of heuristics.

Below we present two meta-heuristic methods that have been applied to solve the problem of steering the vehicles for the collection of municipal waste, when the capacity of the vehicle is limited.

A. Genetic algorithm

A Genetic Algorithm (GA) is an optimization technique used to solve nonlinear or non-differentiable optimization problems that is inspired by Charles Darwin's theory of natural evolution [5]. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.

In genetic structure changes are possible by mutation of genetic material whose essence is the extension of the search field and overcoming local extreme values. Crossing in the case of a genetic algorithm represents the process of combining existing units in order to obtain completely new units, like the parents and their offspring. New individuals inherit the characteristics of their parents. In order to maintain population size (for practical reasons), the most effective way is that two parents receive two offspring which replace them. Mutation, as a phase of the genetic algorithm, is very important and an inevitable process for successful convergence. Most often, this phase performs completely independent of selection and crossover [8].

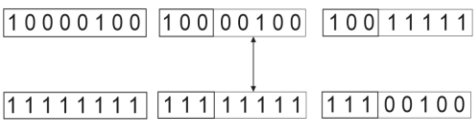

Figure 1. Representation of the process of crossover

Mutation leads to uncontrolled change in genetic material. The main objective is to get the unit, which cannot be obtained in other stages. This random value initiates a search all over the allowed domain, and solutions cannot be prematurely converged [11].

Representation of the mutation must be small number from 0,001% to 0,01%, that the search would not be reduced to random, stochastic and uncontrolled procedure.

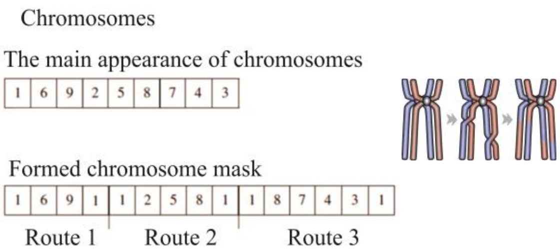

Figure 2. Possible appearance of chromosomes

When new major chromosomes are formed by crossover and mutation, masks are redefined for them again. Processes of determining similarities, selection, crossings and mutations are performed until a predetermined number of generations i.e. iterations is reached [7]. Pseudo code of used genetic algorithm is shown in Table 1.

TABLE I.
PSEUDO CODE OF GENETIC ALGORITHM

Pseudo code of genetic algorithm
Objective function $f(_x)$, $x= (x_1,\ldots,x_n)^T$
Encode the solution into chromosomes (binary strings)
Define fitnees F (eg, $F \propto f(x)$ for maximization)
Generate the initial population
Initial probabilities of crossover (p_c) and mutation (p_m)
While (t < Max number of generations)
Generate new solution by crossover and mutation
If p_c > rand, Crossover; **end if**
If p_m > rand, Mutate; **end if**
Accept the new solutions if their fitness increase
Select the current best for new genereation
end while
Decode the results and visualization

B. Ant Colony Optimization

The Ant Colony Optimization (ACO) algorithm is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs [5]. Artificial ants stand for multi-agent methods inspired by the behavior of real ants.

Method of the ant colony optimization was first proposed by Dorigo Meniezzo and Colorno in 1991. and later by Dorigo and Stutz in 2004. Optimization using ant colony metaheuristics is based on a population that can be used for finding approximate solutions for difficult optimization problems and is a good candidate for the case of routing of vehicles with limited capacity. The algorithm is inspired by the behavior of ants in the nature [10]. The main characteristic of the collective behavior of ants is that all members of the colony directly or indirectly exchange information about their environment, i.e. there is a phenomenon of collective intelligence. In nature, each ant leaves a trail, dropping a certain amount of chemicals called pheromones. The more ants go down one path the more pheromones are left, and it is for each subsequent ant "positive information" about the validity of those paths. In this way, the ants indirectly through pheromones, communicate with each other. By applying this principle ant colony finds the shortest path to the food [9].

The ACO optimization algorithm can be represented by a pseudo code outlined in Table 2 [7].

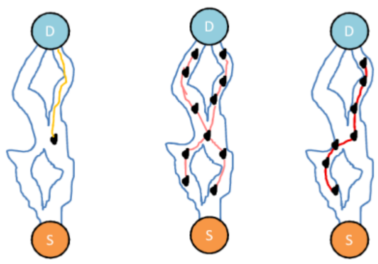

Figure 3. Principle of searching for the shortest path of the ant colony [10]

TABLE II.

PSEUDO CODE OF ANT COLONY OPTIMIZATION

Pseudo code of Ant Colony Optimization
Objective function f (x), $x = (x_1,\dots x_n)^T$
[or f (xij) for roting problem where (i, j) € {1, 2, ….. n}]
Define pheromone evaporation rate γ
while (criterion)
for loop over all n dimensions (or nodes)
Generate new solutions
Evalute the new solutions
Mark better locations/rutes with pheromone $\delta\varphi_{ij}$
Update pheromone : $\varphi ij - (1-\gamma)\ \varphi ij + \delta\varphi ij$
end for
Daemon actions such as finding the current best
end while
Output the best results and pheromone distributions

III. MODEL AND ITS MATHEMATICAL FORMULATION

This model is defined by a transport network consisting of depots and 20 knots. Transport network nodes represent the locations of containers for the disposal of municipal waste located in the territory of the Municipality of Mediana of the city of Niš. This transport network represents the “district” 103 according to the division of the territory of the city of Niš by the Public Utility Company "Mediana-Niš" in 2017 [3]. The nodes are defined by coordinates or latitudes and longitudes. Except coordinates, the number of containers is shown per each node for the observed transport network. At the locations where there are two or more containers, their position is defined by one node or to one coordinate. Containers for the collection of waste have volumes of 1,1m^3.

The transport network start node and end node is depot. Other nodes on the transport network numbered from 2 to 21 (Figure 4). The vehicle for the collection of communal waste starts from the depot, visits the nodes of the transport network so that each node may be visited only once. After a visit to the first node the capacity of the vehicle is checked. If the capacity is not met another node is visited, and if it is filled, vehicle returns to the discharge depot.

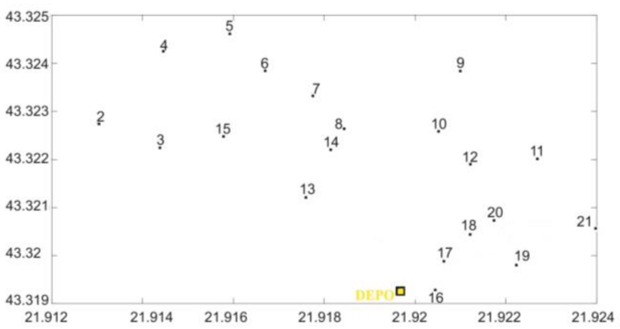

Figure 4. Transport network

This procedure is repeated until all nodes for the observed transport network are visited. Partial service is not possible when servicing, which means that only part of the demand is satisfied in the node. Such a vehicle routing problem is known as a closed system routing vehicles problem, i.e. the vehicle starts from the one node and ends the route in the same node. Waste collection for a given transport network is provided with a vehicle with a capacity of 60m^3.

The vehicle has an elevator for the waste collection from the rear side. Waste collection is carried out using a pressure plate system. The degree of compression of waste is 4. This means that the vehicle can collect a maximum of 60m^3 of municipal waste which is about 55 containers [3].

The vehicle routing problem with limited capacity for collecting municipal waste with a predefined amount of waste for each node of the transport network can mathematically be presented in the following way.

The following notation was used to define the mathematical model formulation:

m - the maximum number of vehicles used, for the model

n - number of knots from which waste is disposed,

V - a set of nodes, $V=\{1,2,\dots,n\}$,

V_0 - depot, the place from where the vehicle starts

Q - maximum vehicle capacity,

q_i - the amount of waste in the node *i* ($i \in V$); the amount of waste in the depot is zero,

d_{ij} - the shortest possible distance between the nodes i and nodes *j* ($i, j \in V$),

c_{ij} - transport costs between the nodes i and nodes j,($i,j \in V$) it is assumed that it is $c_{ij}= d_{ij}$

Variables decision:

$$x_{ijk}\begin{cases}1, if\ the\ vehicle\ is\ after\ the\ node\ i\ visits\ the\ node\ j\\ 0, otherwise\end{cases}\ \forall i,j$$

$$z_{ijk}\begin{cases}1, if\ the\ vehicle\ has\ visited\ the\ node\ i\\ 0, otherwise\end{cases}\ i \in V$$

Minimize function [3]:

$$minF=\sum_{i=0}^{n}\sum_{j=0}^{n}c_{ij}x_{ij} \qquad (1)$$

with limitations:

$$\sum_{i=0}^{n}x_{i0}-\sum_{j=0}^{n}x_{0j}=0 \quad i=0,1,\dots,n \qquad (2)$$

$$\sum_{i=0}^{n}x_{ij}=1, \quad j=1,2,\dots,n \qquad (3)$$

$$\sum_{i=1}^{n}q_i z_i \le Q \qquad i=1,2,\dots,n \qquad (4)$$

$$\sum_{i=1}^{n}x_{ij}=\sum_{i=1}^{n}x_{ji}=z_i \quad j=1,2,\dots,n \qquad (5)$$

$$\sum_{i,j\in S}x_{ij}\le |S|-1 \qquad \forall S\subseteq\{2,\dots,n\} \qquad (6)$$

$$z_i=\{0,1\} \qquad i=1,2,\dots,n \qquad (7)$$

$$x_{ij}=\{0,1\} \qquad i,j=1,2,\dots,n \qquad (8)$$

With (1) the function target of the model is marked. The limitation (2) implies that when the vehicle leaves the depot, it returns to that same depot. Limit shown by equation (3) shows that each node in the transport network must be visited only once by vehicle [3]. Limit (4) implies that the total amount of waste in the node must not exceed the maximum capacity of the vehicle. The limitation (5) is the preservation of the flow of the vehicle, respectively vehicle after serving node j must leave the node j. The limitation (6) prevents the occurrence of cycles that do not represent a complete route. The restriction (7) defines the state of the node's servicing i and can have a value of 0 or 1. Restriction (8) defines passing through the arc between nodes i and nodes j and can have a value of 0 or 1.

IV. RESEARCH RESULTS

Within research performed in this paper, parameters of the considered GA and ACO optimization algorithms have been carefully selected in order to obtain desired results by optimizing the presented model of municipal waste collection. Parameters of the optimization algorithms and obtained results are summarized in Table 3 and routes are visualized in Figure 5.

TABLE III
PARAMETERS OF GA AND ACO ALGORITHMS AND OPTIMAL RESULTS

GA parameters					
MaxIt	nPop	Mu			
500	250	0.02			
GA results					
Num. of routes	Dist (km)	Cap (m^3)	Routes		
1	1.350	51.700	D -16-18-19-20-21-17-D		
2	2.960	59.400	D-6-4-3-15-D		
3	2.320	56.100	D-13-11-12-10-9-14-D		
4	2.850	56.100	D-8-7-5-2-D		
ACO parameters					
MaxIt	alpha	beta	ro	max_cycl	speed
500	1.0	4.0	0.1	1	5
ACO results					
Num. of ro.	Dist (km)	Cap (m^3)	Routes		
1	1.990	56.100	D-16-17-18-20-19-21-11-D		
2	2.450	56.100	D-12-10-9-8-14-13-D		
3	2.600	51.700	D-15-3-2-D		
4	2.830	59.400	D-7-6-5-4-D		

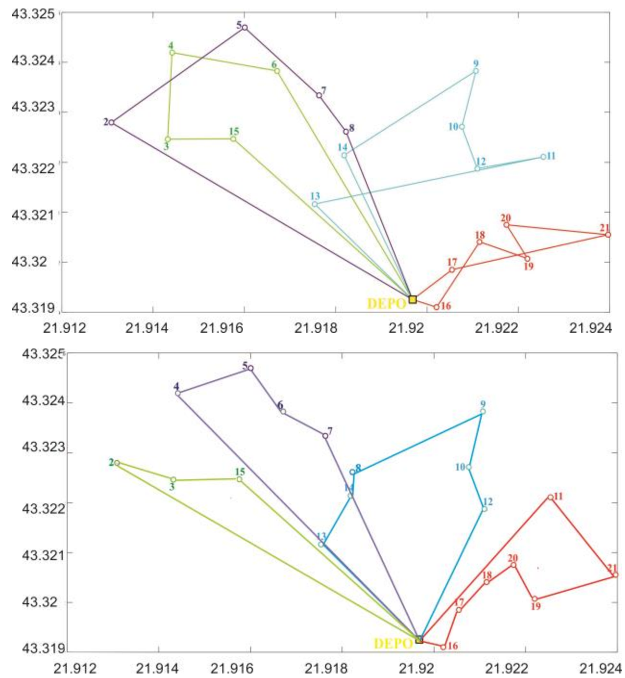

Figure 5. Graphical representation of obtained routes

Obtained results indicate that considered metaheuristic optimization methods, genetic algorithm and the ant colony optimization algorithm, can both be efficiently applied to VRP in communal waste collection task in large urban communities. None of the algorithms demonstrated significant superiority for the given task.

V. CONCLUSIONS

The main finding of this study is formulation of a mathematical model for considered problem of communal waste collection in the urban community of the City of Niš, Serbia and use of metaheuristic optimization to optimize communal waste vehicles routing using defined model.

This model is defined by a transport network consisting of depots and 20 knots. This transport network represents the district 103 according to the division of the territory of the city of Niš by the Public Utility Company "Mediana-Niš" [4]. Using the GA and ACO algorithms optimal routing of the vehicles has been efficiently achieved for the capacity of vehicles of 60 m^3. Optimized routes are with minimized length and provide for the optimal number of vehicles required for serving all nodes.

Regarding further research, it is foreseen that it is possible to propose additional new parameters and limitations to the defined model in order to improve the model itself and to get results under more realistic constraints. Also, it is possible to consider dynamic routing while vehicles operate, to provide for situations while conditions change during task of waste collection execution.

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