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Ant Colony Optimization Algorithm for Fuzzy Transport Modelling

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***Abstract*—Public transport plays an important role in our live. It is very important to have a reliable service. Up to 1000 km, trains and buses play the main role in the public transport. The number of the people and which kind of transport they prefer is important information for transport operators. In this paper is proposed algorithm for transport modeling and passenger flow, based on Ant Colony Optimization method. The problem is described as multi-objective optimization problem. There are two optimization purposes: minimal transportation time and minimal price. Some fuzzy element is included. When the price is in a predefined interval it is considered the same. Similar for the starting traveling time. The aim is to show how many passengers will prefer train and how many will prefer buses according their preferences, the price or the time.**

I. Introduction

COMFORTABLE transportation from one town to another one is very important. It exists different ways of transportation. The cheaper transport is a railway (excluding the super-fast with velocity more than 200 km/h), but the trains are slower. Buses and fast trains are more expensive, but faster. All this need to be taken in to account, when a transportation model is prepared. In this paper the transportation problem is defined as an optimization problem. It is a multi-objective problem with two objective functions: total time and total price of all passengers. The goal is to minimize the both objective functions. The two objective functions are antithetic, the faster transportation is expensive and the cheaper transportation is slower. Thus when one of the objective functions decreases, the other increases. The problem is multi-objective, therefore is received set of nondominated solutions instead of one optimal solution. The set of solutions is analyzed and the final decision, which solution is optimal accordingly with some additional constraints. The solutions of our problem shows how many passenger will use the train and how many will use bus and fast train.

The oldest public transport, among those that are still in use, is the railroads. Nowdays the main concurrencies of the trains are buses, especially in the regions with highways. Thus the models, which can analyze the passenger flow and its preferences, are important for transportation planning. In our model we include some fuzzy element, thus we try to make it more realistic and close to human thinking.

Various transportation models can be found in the literature [2]. The importance of every of the models depends of its functions. One of the models are concentrated on scheduling [1]. Other models are focused on simulation to analyse the level of utilization of different types of transportation [13]. The model in [10] aims to optimize the transportation network design. In [5] is modeled freeway traffic flow. When a network of freeway is is given , their model can predict the traffic flow with high accuracy. Our model is focused on modeling the passenger flow according their preferences. The fuzzification of the model makes it more realistic, more close to the human thinking. When the price or the time is in some predetermined interval we accept it as the same. The problem shows the distribution of the passenger flow and how it changes when the timetable or type of the vehicles are changed.

The problem is difficult in computational point of view and cannot be solved with traditional numerical methods with reasonable computational resources. It is more appropriate to apply some metaheuristic method on this kind of problems. We apply ant colony optimization algorithm. The model is tested on real problem, the passenger flow between Sofia and Varna, one of the longest destinations in Bulgaria.

The rest of the paper is organized as follows. In section 2 is given an ant colony optimization algorithm. In section 3 the transportation problem is formulated and an ACO algorithm which solves it is proposed. Experimental results are shown and analyzed in Section 4. In section 5 are drawn some concluding remarks and possibilities for future work.

II. Ant Colony Optimization Method

The considered optimization problem (see Section III) is NP-hard, and therefore we consider the use of a metaheuristic search for its solution. Therefore is impractical to be applied some traditional numerical method. Hereof we apply Ant Colony Optimization (ACO) algorithm, one of the best metaheuristics.

The behavior of ants in nature has inspired the creation of this method. Ants put on the ground chemical substance called pheromone, which help them to return to their nest when they look for a food. The ants smell the pheromone and follow the path with a highest pheromone concentration. Thus they find shorter path between the nest and the source of the food.

The ACO algorithm uses a colony of artificial ants that behave as cooperating agents, like ants in the nature. With the help of the pheromone they try to construct better solutions and to optimize them. The problem is represented by a graph and the solution is represented by a path in the graph or by tree in the graph. The graph representation is crucial for the good algorithm performance.

Ants start from random nodes of the graph and try to construct feasible solutions. When all ants construct their solution the pheromone values are updated. Ants compute a set of feasible moves and select the best one, according to the transition probability rule. The transition probability p_{ij}, to choose the node j when the current node is i, is based on the heuristic information η_{ij} and on the pheromone level τ_{ij} of the move, where $i, j = 1, \ldots, n$. α and β shows the importance of the pheromone and the heuristic information respectively.

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\,\eta_{ij}^{\beta}}{\sum\limits_{k\in\{allowed\}} \tau_{ik}^{\alpha}\,\eta_{ik}^{\beta}} \tag{1}$$

The construction of the heuristic information function depends highly of the solved problem. It is appropriate combination of problem parameters and is very important for ants' management. An ant selects the move with highest probability. The initial pheromone is set to a small positive value τ_0 and then ants update this value after completing the construction stage [3], [6], [7]. The search stops when $p_{ij} = 0$ for all values of i and j, which means that it is impossible to include new node in the current partial solution.

The pheromone trail update rule is given by:

$$\tau_{ij} \leftarrow \rho\tau_{ij} + \Delta\tau_{ij}, \tag{2}$$

where $\Delta\tau_{ij}$ is a new added pheromone and it depends of the quality of achieved solution.

The pheromone is decreased with a parameter $\rho \in [0, 1]$. This parameter models evaporation in the nature and decreases the influence of old information in the search process. After that, a new pheromone is included. It is proportional to the quality of the solution (value of the fitness function). Several variants of ACO algorithm exist. The main difference is the pheromone updating.

Multi-Objective Optimization (MOP) begins in the nineteenth century in the work of Edgeworth and Pareto in economics [11]. The optimal solution for MOP is not a single solution as for mono-objective optimization problems, but a set of solutions defined as Pareto optimal solutions. A solution is Pareto optimal if it is not possible to improve a given objective without deteriorating at least another one. The main goal of the resolution of a multi-objective problem is to obtain the Pareto optimal set and consequently the Pareto front. One solution dominates another if minimum one of its components is better than the same component of other solutions and other components are not worse. The Pareto front is the set of non dominated solutions related to the solved problem. After that, the users decide which solution from the Pareto front to use according additional constraints, related with their specific application. When metaheuristics are applied, the goal becomes to obtain solutions close to the Pareto front.

III. Problem Formulation

Various problems arise in the area of long-distance passenger transport with a different kind of transport. One of the problem is optimal scheduling [9], others concern the optimal management of the passenger flow [12]. In some developments, it is involved only one type of vehicle [4]. The common is that all they are difficult in computational point of view.

Our problem concerns passengers traveling in a same direction, covered with several different types of vehicles, trains and buses and every one of them can have different price and speed. The problem is how passengers will be allocated to different vehicles Let the first stop be station A and the last stop be station B. There are two kinds of vehicles, trains and buses, which travel between station A and station B. Every vehicle has its set of stations where it stops, only the first station and the terminus are common for all vehicles. Some of the stations can be common for some of the vehicles. Let the set of all stations is $S = \{s_1, \ldots, s_n\}$ and on every station s_i, $i = 1, \ldots, n-1$, n is the number of stations, at every time slot there are number of passengers which want to travel to station s_j, $j = i+1, \ldots, n$. Every vehicle travel with different speed and the price to travel from station s_i to station s_j can be different. We fix a parameters k_1 and k_2. They are used for calculation of the time and price intervals respectively. If a passenger have in mind to start his travel at time t he will chose a vehicle in the interval $(t - k_1, t + k_1)$. If a passenger have in mind to pay for his travel price P he can pay price from the interval $(P, P + P * k_2/100)$. Thus, we include in our model some fuzzy element with an aim it to become more realistic.

The input data of our problem are set of stations S, starting time of every vehicle from the first station, time for every vehicle to go from station s_i to station s_j, the capacity of every vehicle, the price for every vehicle to travel from one station to another one, number of passengers which want to travel from one station to another one at every moment. Our algorithm calculates how many passengers will get on every of the vehicles on station s_i to station s_j at every time slot. There are two objectives, the total price of all tickets, Equation 3, and the total travel time, Equation 4. If some vehicle does not stop on some station, we put the travel time and the price to this destination to be 0.

$$TP = \sum_{i=1}^{M} p_i \tag{3}$$

where TP is the total price, M is the number of passengers, p_i is the price, payed by the passenger i.

$$TT = \sum_{i=1}^{M} T_i \tag{4}$$

where TT is the total time, M is the number of passengers, T_i is the traveling time of passenger i.

TABLE I: Algorithm parameters

ρ	0.5
α	1
β	1
τ_0	0.5
number of ants	10
number of iterations	100

The output is the number of passengers in every vehicle in every station and the values of the two objective functions.

It is NP-hard multi-objective optimization problem, therefore we chose a metaheuristic method to solve it, in particular ACO.

The model is prepared to solve the problem for one direction. It can be applied to model and optimize transportation network direction by direction. One of the important points of the ACO algorithm is representation of the problem by graph. In our case the time is divided to time periods, $N \times 24$ time periods correspond to 60/N minutes, thus $2 \times 24 = 48$ time periods, correspond to 30 minutes. Every station is represented by set of $N \times 24$ nodes, showing different time moments in which a vehicle stops on this station. The pheromone is deposited on the nodes of the graph. The ants start to construct their solutions from the first station. If the number of the passengers from this station is P, the ants chose a random number P_1 from the interval $[0, min\{P, C_1\}]$ and assign this number to the first vehicle as a number of passengers. To the next vehicle the interval is decreased with P_1. C_1 is the capacity of the vehicle. The number of all passengers getting vehicle in some time moment is maximal possible. If there is only one vehicle at this moment the maximal possible number of passengers gets on this vehicle. We model the number of the passengers for the next stations by applying probabilistic rule called transition probability. Our heuristic information is a sum of the reciprocal values of the two objective functions.

IV. Experimental Results

We have programmed our ACO algorithm in C programming language. After several experiments the algorithm parameters are set as it is shown in a Table I

We test our algorithm on one real problem, destination Sofia Varna. The starting station is Sofia, Bulgarian capital and the terminus is Varna the maritime capital of the country. The distance between the first and the last station is about 450 km. There are 5 trains and 23 buses which travel from Sofia to Varna, but they move with different speed, the prices are different and they stop on different stations between Sofia and Varna. There are not data available on passenger numbers therefore we approximate them, taking in to account the population of every one of the towns where some of the vehicles stops. 5 trains and 23 buses, with different speed and price travel between them every day. The stations can differ for different vehicles.

The Table II and Table III shows achieved solutions by two variant of ACO algorithm, deterministic and fuzzy respectively. The results in Table II are from our previous work

TABLE II: Experimental results Sofia Varna, deterministic

No	Price	Time	Train
1	51843	25840	1951
2	51797	25842	1952
3	51579	25862	1978
4	51571	25869	1979
5	51563	25870	1980

TABLE III: Experimental results Sofia Varna, fuzzy

No	Price	Time	Train
1	51821	25856	1961
2	51775	25864	1963
3	51565	25873	1991
4	51560	25880	1995
5	51549	25882	1998

[8] where we apply the deterministic variant of the algorithm. 10 ants are used and the algorithm is run 100 iterations. In a both cases there are 5 nondominated solutions. In every row are shown the travel price of hall passengers, the travel time of hall passengers and the sum of the passengers used train. In the both tables can be seen that the solutions with more passengers in the train have more traveling time and less price. The number of passengers used train or respectively bus is changed if on the same station on the same time there is more than one transportation possibility for deterministic case. In deterministic case the difference in number of passengers in the train comes from long destinations. In fuzzy variant of the algorithm we observe that the number of the passengers in the train is more than in the buss comparing with deterministic case. When the price between the bus and train is similar in a short destination in the fuzzy case it is perceived as the same, it is the same for the time, and the passengers chose bus or train with the same probability. In deterministic case even the small difference is perceived as a different and the vehicle with less price has high probability to be chosen by the passengers which prefer cheaper transportation. Thus we can explain why in the fuzzy case more passengers chose the train than in deterministic one.

V. Conclusion

Transportation is a very important branch of economics and our everyday life. The different kinds of transportation propose different services. Ones are faster, others are cheaper. The passenger decision depends on his preferences. In this paper we propose a model of the flow of passengers taking into account the two main criteria that guide the passengers in their choice, traveling time and traveling price. Thus the problem is defined as multi-objective optimization problem with two objective functions. A fuzzy variant of the model is proposed. When the prices or times are in a predefined interval, they are considered equal. Thus the model becomes closer to human thinking and, from there, more realistic. The proposed model can help for transport analysis of existing transport. It can predict the change of passenger flow when some vehicle is included or excluded and when the timetable is changed.

Thus the transportation can be optimized and to become close to the people's needs. In a future we can include additional elements in the model like other preferences of the passengers.

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