# Metaheuristic Method for Transport Modelling and Optimization 

Stefka Fidanova ${ }^{1}$<br>Institute of Information and Communication Technologies, Bulgarian Academy of Sciences, Acad. G. Bonchev str. bl25A, 1113 Sofia, Bulgaria<br>stefka@parallel.bas.bg

## 1 Introduction

Now dais the people use different way for transportation from one place to another one. It is important to can model the use of public transport and thus to can optimize it. Normally the railway transport (excluding the super fast trains with velocity more than $200 \mathrm{~km} / \mathrm{h}$ ) is cheaper, but slower. The fast trains and buses are faster, but more expensive. Therefore preparing a transportation model we need to take in to account all this. Thus we define the problem for modelling the public transport as multiobjective optimization problem with two objective functions, total price of all tickets and total travelling time of all passengers. Our aim is to minimize the both objective functions. These objectives are controversial, when one of them decreases the other increases. In the case the optimization problem is multiobjective we receive a set of non-dominated solutions. We can analyze them and according to the preferences of the potential passengers we can see how many of them will use tram and how many of them will use will a bus (or fast tram if it exist).

## 2 Ant Colony Optimization

The proposed problem is very hard of computational point of view. Therefore we apply ant colony optimization algorithm to solve it.

The idea for ant algorithm comes from the real ant behavior. They 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 stronger 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. With the help of the pheromone they try to construct better solutions and to find the optimal ones. The problem is represented by a graph and the solution is represented by a path in the graph or by tree in the graph. For the successes of the algorithm, it is very important how the graph will be constructed. Ants start from random nodes of the graph and 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 $p_{i j}$, to chose the node $j$ when the current node is $i$, is based on the heuristic information $\eta_{i j}$ and on the pheromone level $\tau_{i j}$ of the move, where $i, j=1, \ldots, n . \alpha$ and $\beta$ shows the importance of the pheromone and the heuristic information respectively.

$$
\begin{equation*}
p_{i j}=\frac{\tau_{i j}^{\alpha} \eta_{i j}^{\beta}}{\sum_{k \in\{\text { allowed }\}} \tau_{i k}^{\alpha} \eta_{i k}^{\beta}} \tag{1}
\end{equation*}
$$

The heuristic information is problem dependent. It is appropriate combination of problem parameter and is very important for ants management. The ant selects the move with highest probability. The initial pheromone is set to a small positive value $\tau_{0}$ and then ants update this value after completing the construction stage [1-3]. The search stops when $p_{i j}=0$ for all values of $i$ and $j$.

The pheromone trail update rule is given by:

$$
\begin{equation*}
\tau_{i j} \leftarrow \rho \tau_{i j}+\Delta \tau_{i j} \tag{2}
\end{equation*}
$$

where $\Delta \tau_{i j}$ ia 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, we add the new pheromone, which is proportional to the quality of the solution (value of the fitness function). There are several variants of ACO algorithm. The main difference is the pheromone updating.

In our implementation the time is divided to time slots (for example 48 time slot, which corresponds to 30 minutes). We solve the problem for one line. A set of 48 nodes corresponds to every station showing the time slots. Thus our graph of the problem shows if there is any vehicle on a station in fixed time moment. We will put the pheromone on the nodes of the graph.

## 3 Experimental Results

We have prepared a software, which realizes our algorithm. The input data are: arriving time of every one of the trains and buses on every one of the stations; number of passengers which want to travel in every time moment from station $i$ to station $j$; the price to travel from station $i$ to station $j$ with every one of the vehicles; the capacity of the vehicles. As a result the software gives us the values of the objective functions and the number of the passengers in every of the time moments in every of the vehicles.

We prepare a small example with one train and one bus and 4 stations. We can see in different cases how many passengers will use the train and how many of them will use a bus, according their preference to pay less or to arrive faster.

Table 1. Experimental results

|  |  |  |  |
| :---: | :---: | :---: | :---: |
| No | Price | Time | Train |
| 1 | 265 | 451 | 86 |
| 2 | 270 | 450 | 79 |
| 3 | 272 | 448 | 86 |
| 4 | 274 | 446 | 79 |
| 5 | 277 | 443 | 76 |
| 6 | 282 | 438 | 66 |
| 7 | 289 | 431 | 78 |
| 8 | 291 | 429 | 69 |
| 9 | 292 | 428 | 64 |
| 10 | 295 | 425 | 66 |
| 11 | 301 | 419 | 65 |
| 12 | 302 | 418 | 60 |
| 13 | 307 | 413 | 62 |
| 14 | 309 | 411 | 64 |
| 15 | 313 | 407 | 67 |
| 16 | 321 | 399 | 60 |
| 17 | 324 | 396 | 63 |
| 18 | 331 | 389 | 61 |

On this example we use 5 ants and 5 iterations. The algorithm achieves 18 nondominated solutions. The table refT1 shows achieved solutions ordered by increasing order of the price and decreasing order of the time. The forth column shows the number of passengers, used tram. We observe that when the price increases, the number of passengers used tram decreases. There is several exceptions. In solution No 6 , the price is lower than in solution No 7 and 8, but the number of passengers used train is less. When we checked the details we sow that in this case more passengers prefer to use train for long destination. In solution 16 the passengers used train is less than the passengers in solutions 17 and 18, because the passengers used train prefer short destinations. The algorithm can be applied first on long (national) lines and after fixing them the algorithm can be applied on local lines and to optimize them too.

## 4 Conclusion

With this model we can analyze existing public transport. We can predict how the passenger flow will change if the timetable of the vehicles will be changed or if new vehicle will be included/excluded.

## Acknowledgements

This work was partially supported by EC project AcomIn and by National Scientific fund by the grand $02 / 20$.

## References

1. E. Bonabeau, M. Dorigo, G. Theraulaz, Swarm Intelligence: From Natural to Artificial Systems, Oxford University Press, 1999.
2. M. Dorigo, T. Stutzle. Ant Colony Optimization, MIT Press, 2004.
3. S. Fidanova, K. Atanasov Generalized Net Model for the Process of Hibride Ant Colony Optimization Comptes Randus de l'Academie Bulgare des Sciences, 62(3), 2009, 315-322.
