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# Applying Meta-heuristic Algorithm with parallel computation framework to simulation-based Dynamic Traffic Assignment

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## 1 Introduction

The Dynamic Traffic Assignment (DTA) refers to the procedure of assigning trips to paths in a given transportation system considering the Origin Destination pair (OD) flow demand and the network dynamic traffic states. The main output of DTA is path flow distribution over all feasible paths for all OD pairs. Travelers in the traffic network usually attempt to minimize their own travel time (cost). The solution of the assignment problem which is based on Wardrop's first principle is called User Equilibrium (UE).

The goal of this study is computing UE solutions in a simulation-based DTA process. There are many researches that have shown this problem can be represented as a fixed-point problem [1]. There are many solution algorithm in the literature that have been proved to be efficient to solve DTA. Nevertheless, in a large-scale and trip-based setting it is not possible to guarantee that fixed point algorithms converge towards the optimal solution because of the step size and because there is no exact method for determining the step size in the literature [2]. There are some criteria such as the total gap [3] to see how far the solution is from the optimal solution. It often happens that the total gap stops improving after some iterations because the step size is small and prevents the solution from being improved further. From a computational point of view, the main drawback of these methods for addressing DTA on large-scale networks is that they are not parallelizable. This is because all algorithms need to know the last iteration results to determine the next best path

flow for the next iteration. Indeed, they need the state of the network before carrying out the next iteration. Therefore all of the existing methods work behave as serial algorithms to find the UE.

The goal of this study is to overcome the drawbacks of serial algorithms. This study proposes a new solution method based on the Simulated Annealing (SA) method and uses parallel simulations to better explore the solution space. The algorithm is developed generally to solve traffic assignment with parallel computation in order to consider more than one path distribution per iteration. It is obvious that with parallel simulation, the algorithm is going to run more simulations in comparison with existing methods but it is expected to carry out a better exploration of the solution space and consequently achieve better solutions in terms of quality and closeness to the optimal solution. Moreover with parallelizing the framework, the algorithm could solve the problem with better computation time in comparison with classic methods.

## 2 Methodology

SA algorithm is a meta-heuristic method, it is inspired by annealing in metallurgy. The basic simulated annealing algorithm is presented in [4]. This study redesigns and adapts the classic SA to simulation-based traffic assignment. Figure 1 presents the solution algorithm of this study:

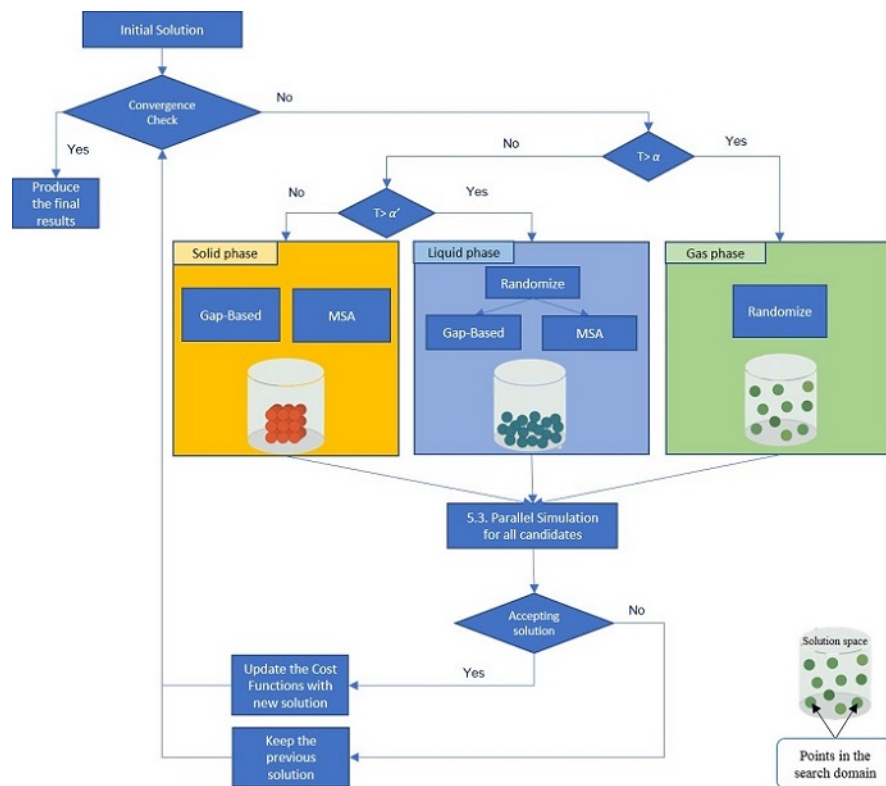


Figure 1: Solution algorithm flowchart

The algorithm starts with an initial solution which is generated randomly. The next solution is generated with respect to the current one based on the temperature ( $T$ ) of the current iteration. The current phase of the iteration depends on the temperature of the process. Inspired by the physics of matter, this study distinguishes three different methods to generate a neighbor solution, gas, liquid and solid; these methods represent the states of matter in nature. When the temperature is high ( $T > \alpha$  where  $\alpha$  denotes the boiling temperature), the *gas method* is applied. During the SA algorithm, by decreasing the temperature the algorithm enters the liquid phase ( $\alpha > T > \alpha'$  where  $\alpha'$  denotes the melting temperature) and then the *liquid method* is applied. When the temperature is quite low ( $T < \alpha'$ ), the *solid method* is applied.

In the gas phase, we explore the solution space without limitation of any step size. Therefore, the candidates for neighbor solution are generated randomly for path flow distribution. The algorithm applies the process on every OD by changing randomly their flow assignment with respect to the constraints applying to the demand (feasible OD-assignment). In the liquid Phase, we target exploring the solutions space randomly and also apply step size methods. First, we apply a randomizing process on the current solution, Then we optimize it by applying the Method of successive Average (MSA) [5] to get the first solution and the Gap-Based method [3] to get the second solution. In the solid phase, we execute the same process as liquid phase but without randomization. It means the two solutions are generated based on the current solution.

Afterward, the algorithm runs parallel simulations to update the network based on new different path distributions that are obtained from the previous step. For a new solution  $s'$ , the total gap  $TGap(s')$  between the users' travel time and the shortest path travel time is calculated and corresponds to the energy of solution ( $E$ ) compared to the current solution  $s$ . The last step consists in making a decision about accepting one of the best new solution based on  $TGap$  compared to the current solution of the algorithm. The acceptance decision is made by the binary test. If  $P_s \geq R_s$ , the new solution will be accepted. Here,  $P_s = e^{-\frac{\nabla E}{T}}$ ,  $\nabla E = TGap(s') - TGap(s)$  and  $R_{tr}$  is the random number ( $0 < R_{tr} < 1$ ). The quality of the solution is evaluated in the convergence check step. At the end of each iteration the temperature is decreased ( $T = \frac{T_0}{\ln(k+1)}$  where  $T_0$  denotes the initial temperature and  $k$  denotes the iteration index) and the algorithm iterates until converging to the optimal solution or the lowest temperature ( $T_{min}$ ) is reached.

### 3 Numerical Experiments

In order to compare the performance of this new method, this study evaluates the algorithm in the static case and compares the method with MSA method and then apply the method to DTA problem for the large-scale test case. In the static case, the method is applied to a  $5 \times 5$  grid network with static cost functions. The primary results for 3 and 6 ODs with the fixed demand

of 50 users per OD are presented in Figure 2. The results shows that the new method dominates the MSA method even in the small-scale and static network. We are currently running simulations on a large-scale network (Lyon 6e + Villeurbanne: 1,883 Nodes, 5,935 Links, 94 Origins, 227 Destinations, 54,190 trips) with dynamic implementation and the results are very promising.

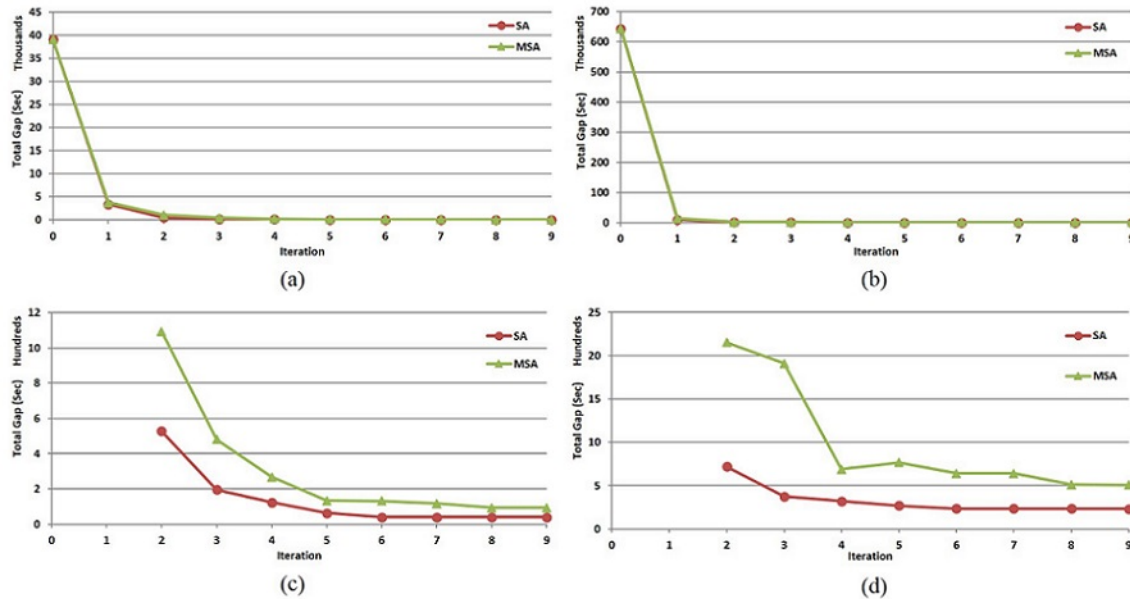


Figure 2: Total gap in  $5 \times 5$  grid network for SA and MSA methods.  
(a), (c): results for 3 ODs. (b), (d): results for 5 ODs.

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