Comparing performance and quality of traffic assignment techniques for microscopic road traffic simulations

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Abstract

Focusing on the tradeoff between accuracy of the assignment and computation time this paper proposes different traffic assignment methods targeting at microscopic traffic simulation. The corresponding network-wide performance indices, the generated route sets and the respective significance tests are analyzed and compared. The results indicate that the saving on computation time is significant with use of macroscopic assignments. However, the deficiency of neglecting turning behaviors in macroscopic assignments results in worse assignment results. Moreover, the used computation time of some microscopic methods (e.g. the one-shot method) is competitive with that of the macroscopic assignments. While the exact parameterization as well as the sensitivity of the methods to the size of the scenarios still need further investigation, it seems favorable to employ microscopic assignment techniques or hybrid methods for producing a good traffic assignment for a microscopic simulation.

Keywords: microscopic simulation, traffic assignment, SUE, DUA, route set similarity

1 Motivation

In the last decade microscopic simulation modeling has been extensively applied in order to accurately describe driving behaviors and vehicular traffic dynamic, which are important for online traffic management. Traffic assignment is one of the essential components in a successive traffic management. With a reliable origin-destination matrix (O-D matrix) an accurate traffic assignment results in precise traffic-state predictions. The traffic assignment problem has been extensively investigated for more than 40 years, by researchers like Dafermos and Sparrow [1], Wardrop [2], Sheffi [3], Ben-Akiva et al. [4], Ran and Boyce [5], Boyce et al. [6], Bovy, and Hoogendoorn [7], Nie et al. [8], and Jin [9]. Generally speaking, the applied models in the traffic assignment can be categorized into simulation models and network equilibrium models. With the innovation and advancement in Information Technology (IT), significant interests in microscopic traffic simulation modeling are generated for describing the driving behaviors and traffic dynamic specifically. Already such modeling technique is also already applied in the traffic analysis of large-scale networks. Examples of such application

have been conducted by Duncan [10], Yang and Koutsopoulos [11], Han [12], Krajzewicz et al. [13, 14, 15] and Behrisch et al. [16].

The Institute of Transportation Systems at the German Aerospace Centre has been involved in many projects where large, city-wide scenarios were simulated. For this purpose, the microscopic traffic simulation package (SUMO − Simulation of Urban MObility) was developed and used. This package applies a Dynamic User Assignment (D.U.A.) algorithm, proposed by Gawron [17], for modeling route choice and traffic assignment. In the past, this approach was found to be reliable and robust, but it is also burdened with very time consuming computations. Currently, the Institute of Transportation Systems is conducting the project DELPHI, aiming at on-line simulation of large and dense road networks in the cities like Cologne and Munich in Germany. With the increasing size of networks, the complexity of the D.U.A. algorithm prevents fast adaptations to the network; hence an efficient assignment algorithm has to be found. Seven assignment techniques are compared in this paper. The structure of this paper will be organized in the following fashion. The compared assignment algorithms are first introduced. Then, the applied evaluation methods and the test networks are described in Section 3 and 4 respectively. The results are presented in Section 5. Finally, the conclusion and the respective future works are made and proposed respectively.

2 Compared Algorithms

Within the described work, four microscopic and three macroscopic traffic assignment algorithms were investigated. The characteristics of each algorithm are described below and a summary is shown in Table 1 at the end of this chapter.

Each of the algorithms produces a set of vehicle "journeys". Each journey represents a vehicle with its departure time, and its route which is a list of edges (streets) the vehicle has to travel in order to reach its destination and which starts with the edge the vehicle starts at.

2.1 Dynamic user assignment

The dynamic user assignment algorithm developed by C. Gawron (DUA-Gawron) is a microscopic approach meaning that the routes through a network to simulate are computed for every vehicle individually. The basic procedure is as follows:

Step 1: Initialize the process by computing the fastest route through the empty network for each simulated vehicle. Set the usage probability for this route to 1.

Step 2: Perform the simulation using the current routes in order to obtain the edges' travel times over simulation time.

Step 3: Compare the mean travel times to the last run (if any) and quit if the algorithm converges, i.e. if the mean travel time reduction falls below a given threshold.

Step 4: Compute new routes for vehicles using the current travel times within the network. Then, continue with step 2.

The crucial point is the computation of the vehicles' new routes in step 4. In order to avoid oscillations, each driver knows a set of routes and chooses one randomly regarding the route's duration using the edge travel times computed in the prior simulation. At first, the driver's estimations of the travel times for the routes he knows are adapted to the travel times obtained from the simulation:

$$\tau'_d(x) = \begin{cases} \tau_s(x) & \text{if } x \text{ was simulated} \\ \beta\tau_r(x) + (1-\beta)\tau_d(x) & \text{otherwise} \end{cases} \tag{1}$$

where $\tau_d(x), \tau_s(x), \tau_r(x)$ travel times of route x, perceived by driver d, retrieved from the simulation, and reconstructed from the edge travel times wrote by the simulation respectively

β remembering factor

Then each route's probability to be chosen is updated. The probability for each unused route known by the driver is recomputed by a function that compares its travel time with the travel time of the route used in the last simulation step. The used route's probability is adapted herein, too:

$$p'_d(r) = \frac{p_d(r)(p_d(r) + p_d(s))\exp(\frac{\alpha\delta_{rs}}{1-\delta_{rs}^2})}{p_d(r)\exp(\frac{\alpha\delta_{rs}}{1-\delta_{rs}^2}) + p_d(s)} \tag{2}$$

and

$$p'_d(s) = p_d(r) + p_d(s) - p'_d(r) \tag{3}$$

where $p_d(x)$ prior probability to use route x;

$p'_d(x)$ new probability to use route x;

r route used in the last simulation run, s another route from the list of known routes;

δ_{rs} relative costs difference between routes r and s, computed as:

$$\delta_{rs} = \frac{\tau_d(s) - \tau_d(r)}{\tau_d(s) + \tau_d(r)} \tag{4}$$

and $\tau_d(x)$ is the travel time for driver d to complete route x.

In fact, the algorithm does not compute the set of routes known by a driver initially, but only the best one in each of the iterations. If this best route is not yet within the driver's list of known routes, it is added to this list and evaluated together with the others.

Within the investigations described herein, edge travel times were collected and aggregated over a time span of 900s. During the computation of a route's duration, the edge weight was used which matched the computed vehicle time the vehicle enters the edge (aggregation begin<=entry time<aggregation end). α was set to 0.5, and β to 0.9.

2.2   Simple Dijkstra assignment

The plain Dijkstra implementation searches for each vehicle the fastest route through the empty network. It uses travel times of the edges which are computed from the maximum ve-

locity allowed on the edge and the edge's length. Changes in the travel times due to previously routed vehicles are not regarded.

2.3 One-shot routing

One-shot algorithms have been proposed as an appropriate method for computing routes for each of the simulated vehicles [18]. The one-shot method implemented for the investigations described herein computes a new route for each vehicle as soon as the vehicle is inserted into the net. The route is computed using the Dijkstra algorithm, where each edge's weight is continuously adapted to the travel time of this edge within the simulation. The used weight is:

$$w(t,e) = \begin{cases} l(e)/v_{max}(e) & t = 0 \\ w(t-1,e)*r + l(e)/v_{curr}(t,e)*(1-r) & otherwise \end{cases} \tag{5}$$

where $w(t,e)$ weight of edge e at the current simulation step t
$l(e)$ length of edge e
$v_{max}(e)$ maximum velocity allowed on edge e
$v_{curr}(t,e)$ mean velocity of vehicles on edge e in time step t
r remembering factor

As one can see, the algorithm only needs to know the vehicle's start and end nodes and the time the vehicle starts in order to compute a route. Within the simulation runs done for this report, r was set to 0.5.

2.4 One-shot routing with rerouting

This method is an extension of the described one-shot routing approach. When the vehicle is inserted into the network, a new route is computed for each vehicle as described in 2.3. Then, for every vehicle, a new, fastest route is computed every n simulation steps using the current edge weights $w(t,e)$ as long as the vehicle has not reached its destination.

When computing a new route for the vehicle, its destination is kept, whereas the edge the vehicle is currently at is used as the edge the new route shall start at. The part of the route after the vehicle's current edge is then directly replaced by the currently fastest continuation.

Within the following evaluations, new routes were searched every 15 (simulation) seconds.

2.5 Incremental assignment

Incremental assignment is a well-known macroscopic assignment method and has been extensively applied due to its simplicity for decades. The main concept is to assign the given O-D matrix proportionally and iteratively. At each iteration link travel times will be updated according to latest link flows and the corresponding link cost functions. The proportion of the assigned O-D matrix at each iteration and the number of the iterations are decided by users. The resultant traffic pattern from this assignment will not correspond to the user-equilibrium state, since the assigned traffic demand cannot be changed, once it is done. Nevertheless, this assignment has been adopted because of the appealing advantage that the required computation time is much lesser than other traffic assignment techniques. A congested traffic state can still be represented by this assignment with more number of iterations.

In order to apply the macroscopic assignment result in the microscopic simulation – SUMO, it is necessary to further generate the vehicular route set and the corresponding vehicular releasing times. The used routes of the O-D pairs at each iteration were recorded and adopted as the routes of the vehicles, assigned in the respective iteration. According to the number of the defined iterations, the analyzed period will be split into the respective time intervals. For example, there are 10 6-minute intervals if the number of the iterations and the analyzed period is 10 and 1 hour respectively. The releasing times of the vehicles, assigned in each time intervals, were then generated randomly.

Furthermore, link capacities in urban areas are primarily determined by intersection capacities, controlled by the corresponding signal timing plans. The given signal plans at intersections were thus considered in order to calculate link capacities accurately.

2.6 Stochastic user equilibrium assignment with k-shortest routes

The stochastic user equilibrium assignment (SUE) is adopted in order to take into consideration the user-equilibrium traffic state and various travel-time perceptions among motorists. The method of successive averages (MSA) is then applied. In addition, the k-shortest routes algorithm is used to get reasonable routes. At the SUE state, no driver can improve/reduce their received travel times. Two models are applied in this study: the c-logit model and the modified logit model proposed by Cascetta [19] and Lohse [20] respectively.

<u>C-logit model</u>
This model is a logit-based model with the assumption that all route alternatives and the random components ε in the drivers' received travel times, i.e. $C = c + \varepsilon$, are identically and independently distributed Gumbel variates [3]. In comparison to the logit model, the similarity of the routes is further considered with the use of the commonality factor (CF) in the c-logit model. The calculated route choice probabilities are therefore more reasonable than those from the logit model. The respective formula is shown below.

$$p(k) = \frac{\exp\left[\theta \cdot (C_k - CF_k)\right]}{\sum_{h \in R_{ij}} \exp\left[\theta \cdot (C_h - CF_h)\right]} \quad \forall \ k \in R_{ij} \ , \forall \ i \in I, \ \forall \ j \in J \tag{6}$$

where $p(k)$ route choice probability for path k
     θ dispersion parameter of the travel time perception among drivers
     C_k travel cost on path k
     R_{ij} route set for O-D pair ij
     CF_k commonality factor of Path k and can be determined with the following equation:

$$CF_k = \beta_0 \ln \sum_{h \in R_{ij}} \left[\frac{L_{hk}}{L_h^{0.5} \cdot L_k^{0.5}} \right]^{\gamma} \tag{7}$$

     L_{hk} identical part between Path h and k. The respective unit can be distance, travel time or other measurements. In this paper, travel time is adopted as the unit.
     L_h and L_k "length" of Path h and k respectively (i.e. travel time in this paper)
     β_0 and γ calibration parameters

Modified Lohse-logit model

The Lohse-logit model is based on the logit model and lots of empirical studies. The travel time of the shortest path of each O-D pair is taken into consideration so that the calculated route choice probabilities are more reasonable than the standard logit-based model with reference to short-distance trips. The modified formula is indicated below.

$$p(k) = \frac{\exp[-(\beta \cdot X_k)^2]}{\sum_{h \in R_{ij}} \exp[[-(\beta \cdot X_h)^2]]} \quad \forall \; k \in R_{ij}, \forall \; i \in I, \; \forall \; j \in J \tag{8}$$

where $X_k = \dfrac{C_k}{C_{min,ij}} - 1$ and $C_{min,ij}$ is the travel cost of the shortest route of O-D pair ij

β dispersion parameter of the perception of the travel time among drivers. An empirical equation is deviated and suggested by Lohse and applied in this study:

$$\beta = 12/(1 + \exp(0.7 - 0.015 \cdot C_{min,ij})) \tag{9}$$

In this paper, the above-mentioned CF factor wasalso adopted in this model for preventing irrational route choice probabilities. Like the incremental assignment the assignment result from the SUE models was disaggregated and the respective vehicular routes and releasing times were will be generated for the microscopic simulation. In addition, the influence of signal timing plans on link capacities were considered as well.

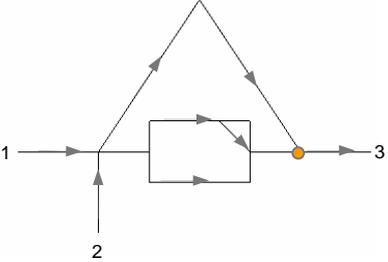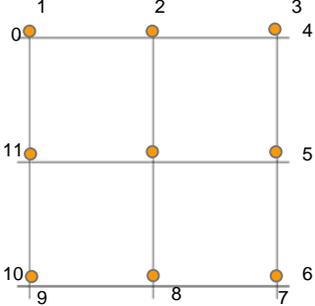*Table 1: Summary of the characteristics of the compared assignment algorithms*

Type	Algorithm		Description
microscopic	DUA-Gawron		• iterative assignment based on network weights obtained from a previous simulation run; • iterative calls to the simulation and the routing application; • ensures the computation of an equilibrated assignment; • requires more computation time due to many simulation/router calls
	Simple Dijkstra		• fastest path searching with use of travel times in an empty network
	one-shot routing	simple	• Vehicles are routed as soon as they enter the network using current edge travel times.
		rerouting	• similar to simple one-shot routing, but with additional reroutes of vehicles every n time-steps • adapted edge travel times used for rerouting
macroscopic	incremental assignment		• According to the specified number of iterations, the analyzed traffic demand is incrementally assigned on the investigated network regarding with capacity constraints. • Vehicular release times are generated randomly within the analyzed time period.
	stochastic user equilibrium assignment (SUE)	c-logit model	• Different perceptions of travel time among drivers and the similarity of routes are taken into consideration in the route choice. • The route choice probability is followed the logit distribution. • Vehicular release times are generated randomly within the analyzed time period.
		modified Lohse-logit model	• Different perceptions of travel time among drivers are taken into account. • Based on the idea in the c-logit model, the similarity of routes is taken into consideration in the route choice. • Vehicular release times are generated randomly within the analyzed time period.

3 Test Networks

In order to analyze the difference in performance with regard to different network sizes, the investigated algorithms were compared using two synthetic networks and a real network based on the road network in Magdeburg, Germany. This network was converted from the macroscopic Magdeburg network, established with the VISUM software. The locations of the respective signals and their timing plans were considered in the analysis as well. All the ma-

trices used are time-dependant and are based on one-hour interval. Table 2 gives an overview of the scenarios.

Table 2: Description of the test networks

Network layout	Network characters
One-way network[*]	• synthetic network with two O-D pairs from Zone 1 to Zone 3 (800 vehicles/hr) and from Zone 2 to Zone 3 (200 vehicles/hr) • one-way/one-lane traffic network with 16 nodes and 18 links • one traffic light installed at the rightmost intersection and with a pre-timed signal plan • road priority rules applied at the intersections without traffic lights
Grid network[*]	• synthetic network with 12 traffic zones and 124 O-D pairs • 33,200 vehicles over the day, following a standardized time series • hourly time-series traffic flow pattern adopted to generate 24 hourly matrices • It is a two-way traffic network with 21 nodes and 48 links. Each road has one lane. • Traffic lights installed at all intersections and with pre-timed signal plans
Magdeburg network	• 263 traffic zones and ca. 7,500 effective O-D pairs per hour[**] • about 630,000 vehicles over 16 hours, from 5a.m. to 9p.m within a weekday • one-way and two-way mixed network with 2,535 nodes and 5,514 links • combination of highways (shown in blue) and inner-city roads (shown in red) • traffic lights installed at 266 intersections • road priority rules applied at the intersections without traffic lights

[*]: Numbers represent the traffic zones; ●: traffic light installed.
[**]: An effective O-D pair means that the respective traffic demand is greater than zero.

4   Evaluation methods

The indices chosen to compare the algorithms come in four categories. Global performance indices such as the average travel time, significance tests on the deviation of the individual parameter distributions (even if the average is the same, the distribution of a parameter could be different among the algorithms), analysis of route set similarities and single car based comparisons. This chapter describes the methods used to calculate these indices.

4.1 Network-wide performance analysis

The primal result of every assignment is a set of routes, which is fed into the traffic simulation SUMO. It simulates the whole time period for which data is available (see test networks). The main output of this simulation is a departure and an arrival time for every vehicle which is used to calculate (together with the route) the travel time, travel speed and travel length. Furthermore SUMO gives the departure delay (occurring if a vehicle could not be inserted because its starting street was full) and the stop time (number of seconds the vehicle was slower than 0.1 m/s) which are amalgamated into the waiting time.

4.2 Significance test

The Kruskal-Wallis test [21] is used for testing equality of the parameter sets. Intuitively, it is identical to a one-way analysis of variance with the data replaced by their ranks. Since it is a non-parametric method, the Kruskal-Wallis test does not assume a normal population, but an identically-shaped distribution for each group, except for any difference in medians.
The test works as follows: after calculating the rank of every parameter in the union of the sets, the rank sum S_i is calculated for every set. Afterwards, the test statistics

$$H = \frac{12}{N(N+1)} \cdot \sum_{i=1}^{g} (\frac{S_i^2}{n_i}) - 3(N+1) \tag{10}$$

with N, the number of total samples, and n_i, the number of the samples in Set i, is compared against a chi-square distribution for examining significance.

4.3 Similarity analysis of routes

In order to estimate the differences in the route sets, the following algorithm was employed. The similarity between any two routes is calculated as the number of the overlapped edges, existing in both routes, divided by the maximum number of edges of both routes. This gives a number between 0 and 1 with 1 denoting identity (assuming that there are no edges occurring twice in the same route, which was the case in the scenarios).
The similarity of two route sets is then calculated by finding a matching of the routes of the first set to the routes of the second which maximizes the sum of the similarities of the matched route pairs. (This is done by calculating a maximum weighted matching in a complete bipartite graph built from the routes (as nodes) and their similarities as edge weights. [22]) This sum is divided by the number of routes to get a similarity index between 0 and 1. As a second index the percentage of identical routes is calculated.

5 Analysis results

Based on the above mentioned evaluation method, the difference in performance among assignment methods is quantitative examined. In addition, a qualitative analysis is conducted for a comprehensive evaluation.

5.1 Required CPU time

The numbers presented in this paragraph are not supported by a large enough sample to give a precise estimation of the needed running time. They serve mainly as an indicator for the order of magnitude which is to be expected when employing one or the other method.

As the results in Table 3 show the main factor affecting the time required to calculate the assignment is the size of the scenario, measured by the total number of vehicles (the grid and the one way net differ only marginally in net size but have considerably different running times) and the net size. Comparing the algorithms the DUA is by far the slowest method while one shot routing (especially without rerouting) is quite comparable to the macroscopic techniques. The simple Dijkstra is of course tremendously fast and serves mainly as a basis for comparison in this context. The reason that the incremental assignment although conceptually simpler than the other macroscopic methods needs a larger running time is due to the fact that its number of iterations is fixed while the other methods have convergence criteria which may be matched earlier.

Table 3: Required CPU times (in seconds) of the analyzed traffic assignments

Test Networks	DUA-Gawron[*]	Simple Dijkstra	One shot routing		Incremental assign-ment[***]	SUE	
			simple	rerouting[**]		c-logit model	modified Lohse-logit model
One-way Network	39	1	1	1	0.2	< 0.1	0.1
Grid Network	489	9	10	14	48	7	12
Magdeburg Network	322,156	343	3,535	46,852	48,580	30,719	56,019

*: the number of iterations is 50; **: the period of the rerouting is 15 sec; ***: the number of iterations is 20

5.2 Network-wide performance

The result in Table 4 indicates that, in the one-way network, the performance measures based on either microscopic or macroscopic assignments are similar, expect the simple Dijkstra. The vehicles with the application of all assignments can be released into the network almost punctually, i.e. the average departure delay is very small (0.98s - 1.41s). The oneshot routing − simple performs slightly better than the DUA-Gawron, the one-shot routing with 15-sec periodical rerouting and the other three macroscopic assignments. The significant poor performance of the simple Dijkstra is mainly since the route search for each O-D pair was executed only once with reference to free-flow traffic state. Furthermore, the three macroscopic assignments perform slightly better than the DUA-Gawron and worse than the two one-shot routing methods. Among the macroscopic assignments, it is further shown that the performance measures of the incremental assignment and the c-logit model are slightly better than the modified Lohse-logit model. In the grid network, the performances of the assignments have changed due to the increase of the network size and the traffic demand. Vehicles based on the both one-shot routing methods have large departure delay, 90 and 146 seconds in tandem the simple and the periodical rerouting method respectively. Such high departure delay results in fewer vehicles in the network during the simulation. Thus these two one-shot routing methods deliver some better performance measures, such as higher average travel speed and lesser average travel time. However, these performance measures are not representative in this situation. Moreover, the macroscopic SUE models deliver quite similar results when comparing to the microscopic DUA-Gawron model with the performance of the latter being slightly better.

The simple Dijkstra and the incremental assignment have similar performances, which are worse than the performances of both SUE and DUA-Gawron models. Stochastic route choice factor is considered in both SUE and DUA-Gawron models and the used routes are more reasonable than those from the simple Dijkstra and the incremental assignments.

Table 4: Network Performance among the investigated traffic assignments

Test networks	Assignment Technique		Performance indices				
			avg. travel length (m/veh)	avg. travel speed (m/s/veh)	avg. travel time (s/veh)	avg. waiting time[****] (s/veh)	avg. departure delay (s/veh)
One-way Network	DUA-Gawron[*]		3760.02	12.07	312.44	17.69	0.98
	Simple Dijkstra		3558.07	6.85	558.79	71.44	0,97
	One-shot routing[**]	Simple	3884.72	12.64	307.68	11.75	0.71
		Rerouting	3898.02	12.64	308.53	12.92	0.94
	Incremental assignment[***]		3813.97	12.33	309.75	15.57	0.98
	SUE	c-logit model	3788.03	12.25	309.70	16.00	1.41
		modified Lohse-logit model	3776.98	12.08	313.65	18.45	1.41
Grid Network	DUA-Gawron[*]		1760.20	6.36	260.40	76.11	0.14
	Simple Dijkstra		1710.16	5.76	367.67	135.60	0.14
	One-shot routing[**]	Simple	1862.73	6.26	281.18	172.00	90.33
		Rerouting	2162.88	6.43	318.60	237.72	146.63
	Incremental assignment[***]		1710.22	5.76	355.27	130.35	0.14
	SUE	c-logit model	1790.50	6.34	264.22	73.47	0.14
		modified Lohse-logit model	1791.20	6.33	264.22	73.36	0.14

*: the number of iterations is 50; **: the period of the rerouting is 15 sec; ***: the number of iterations is 20;
****: waiting time is the sum of the waiting time within the network and the departure delay

In the Magdeburg network, the overflow situation had appeared when executing the macroscopic assignment models. It is due to the reduced link capacities, resulted from the given signal timing plans. With a close observation of traffic movements in the simulation, it indicates that the given signal timing plans at intersections were improper and the respective link capacities were not efficiently used. Moreover, it is observed that spillbacks have arisen at intersections and result in severe congestion in the network. It is since the effect of turning behaviors, especially left-turn behaviors, was not considered in the macroscopic assignment. Due to the above-mentioned severe congestion effect, lots of vehicles were not able to be released into the network during the simulation period. The respective network performance measures, such as average travel speed and average travel time, are therefore not included for comparing the performances among all applied assignment methods. The applied microscopic assignments, i.e. DUA-Gawron and one-shoting methods, delivered significantly better results than the macroscopic assignment methods due to its close coupling to the simulation, i.e. the effects of road geometric shapes, signal timing plans and road priority rules can be microscopically considered with the trade-off of a giant computation time. However, it should be noticed that, with a given network data, the DUA-Gawron and one-shoting methods try to find the optimal solution, which probably does not correspond to the respective traffic situation in the reality.

5.3 Significance test

As mentioned above, the significance test was performed to examine if the distributions of the generated vehicular performance measures among the investigated assignments are statistically identical with 95% confidence interval. The considered performance measures include travel time, travel speed, travel length and waiting time of each vehicle. If the test regarding any of the measures is examined as statistically significant, the difference of the examined assignment results is evaluated as significant. Table 5 shows that almost all vehicular performance distributions, generated by different assignments methods, are significantly different, although the respective mean values, shown in Table 4, are similar. Moreover, it is noticeable that the c-logit model and the modified Lohse-logit model deliver the statistically identical vehicular performance distribution in the grid network. It means that these two models are substitutable for each other in this case study. Such a statistically identical result comes out as well when comparing the performance distributions between the DUA-Gawron method and the modified Lohse-logit model in the one-way network.

Table 5: Result of the significance test among the investigated traffic assignments

Assignment		DUA-Gawron[*]	Simple Dijkstra	One shot routing[**]		Incremental assignment[***]	SUE	
				simple	rerouting		c-logit model	modified Lohse-logit model
DUA-Gawron[*]			S^g	S^g	S^g	S^g	S^g	S^g
Simple Dijkstra		S		S^g	S^g	S^g	S^g	S^g
One shot routing[**]	simple	S	S		S^g	S^g	S^g	S^g
	rerouting	S	S	S		S^g	S^g	S^g
Incremental assignment[***]		S	S	S	S		S^g	S^g
SUE	c-logit model	S	S	S	S	S		NS^g
	modified Lohse-logit model	NS	S	S	S	S	S	

*: the number of iterations is 50; **: the period of the rerouting is 15 sec; ***: the number of iterations is 20;
S: significant NS: not significant; The test results of the one-way network and the grid network are indicated in the shadow area and the area without shadow respectively.

5.4 Route set similarity

The comparison of the route sets as depicted in Table 5 shows that in the small networks the similarity of the route sets is very large (especially for the one way net where it is always above 0.9, except for comparisons to Dijkstra). While one reason for the high similarity is the small number of realistic routes in small networks, this also shows that the differences in the average travel time result to some extent from the correct combination of departure time and route choice rather than from route choice alone.
Additionally the very high similarity between the two SUE models, makes it almost impossible to distinguish these two results.

Table 5: Result of route comparison test among the investigated traffic assignments

Assignment		DUA-Gawron[*]	Simple Dijkstra	One shot routing[**]		Incremental assignment[***]	SUE	
				simple	rerouting		c-logit model	modified Lohse-logit model
DUA-Gawron[*]			0.89 0.81	0.90 0.80	0.78 0.59	0.91 0.84	0.85 0.71	0.85 0.70
Simple Dijkstra		0.71 0.26		0.80 0.63	0.68 0.42	0.94 0.92	0.78 0.59	0.78 0.58
One shot routing[**]	simple	0.93 0.88	0.66 0.25		0.88 0.77	0.83 0.67	0.90 0.80	0.90 0.80
	rerouting	0.91 0.85	0.64 0.21	0.97 0.93		0.71 0.46	0.86 0.74	0.87 0.74
Incremental assignment[***]		0.94 0.79	0.70 0.35	0.92 0.80	0.90 0.73		0.82 0.63	0.81 0.63
SUE	c-logit model	0.98 0.97	0.70 0.25	0.95 0.90	0.93 0.88	0.94 0.80		1.00 0.99
	modified Lohse-logit model	0.99 0.98	0.70 0.25	0.94 0.90	0.92 0.87	0.95 0.80	0.99 0.99	

*: the number of iterations is 50; **: the period of the rerouting is 15 sec; ***: the number of iterations is 20;
The test results of the one-way network and the grid network are indicated in the shadow area and the area without shadow respectively. The first number in each cell denotes the similarity index as described above; the second number the fraction of identical routes.

6   Conclusion and future works

The awareness about sustainable transport and efficient allocation of resources is significantly aroused for years. Microscopic traffic simulation tools have thus been extensively applied for precisely evaluating the effectiveness of proposed strategies and even for online traffic management for road networks. However, the greater the network, the more the execution time is required for the respective traffic assignment and traffic-state updating in the microscopic traffic simulation. The achievement of online traffic management in large traffic networks is thus impeded. To calculate a good traffic assignment for a microscopic simulation efficiently different traffic assignment methods were compared in this paper. The results indicate that, to a certain degree, the macroscopic assignment models can deliver similar network-wide assignment results when compared to the applied microscopic models, although they show to be far more sensitive to congestions resulting from network peculiarities. It also showed that the result from the simple Dijkstra method (without route alternatives) is the worst one, although the used computation time is the least. When dealing with a sophisticated network, such as the Magdeburg network, the deficiency of neglecting turning behaviors in the macroscopic assignment models results in severe spillbacks and congestion in the network. The assignment results based on the DUA-Gawron and one-shot methods do not result in congestion in the simulation. Nevertheless, it should be noticed that these microscopic methods try to find the optimal solution with a given network data by modifying vehicular routes at each simulation iteration.

Furthermore, the saving on computation time is significant, when comparing the macroscopic assignments to the DUA-Gawron method. It is noticeable that the required computation time of the one-shot method with rerouting is quite competitive with that of the macroscopic assignments. Regarding the significant test of the distributions among the vehicular perform-

ance measures, generated by different assignment models, the results show that almost all tests are evaluated as statistically significant with 95% confidence interval. With the insignificant test result of the two SUE models in the grid network, these two models can be substitutable for each other. The examination of the route set similarity indicated that the route set similarity among the applied assignment models decreases with the increase of the network size. The route set similarity among the DUA-Gawron, the one-shot with rerouting and the SUE assignment methods are more than 85% and 70% in the one-way and the grid network respectively.

For future works, it is aimed to refine the calculation of the travel time in the macroscopic assignment models for further investigation among microscopic and macroscopic assignment models. More factors, such as penalty factors for turning movements, should be taken into consideration in order to take into account travel delay in the calculation of travel time. With more accurate estimated travel time, the route choice probability of each vehicle can be determined more rationally. Furthermore, the DUA-Gawron method has the advantage that road geometric shapes, signal timing plans and road priority rules can be microscopically taken into account during the simulation. The proposed one-shot method with rerouting also has such advantages. However, the adequate update interval needs to be further verified for an efficient simulation. Finally, nowadays, network generation tends to be automatically executed, since it is unrealistic to conduct such work for a large sophisticated network manually. In this research, an automatic network converter is also implemented and adopted. Such automatic network conversion and importing may sometimes result in network distortion and inaccurate simulation results. Greater attention should therefore also be paid to the further improvement and development of the implemented network conversion technique.

4. References

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