Delft University of Technology

Route Set Generation for Quick Scan Applications of Dynamic Traffic Assignment

Taale, Henk; Pel, Adam

DOI
10.1109/MTITS.2019.8883324

Publication date
2019

Document Version
Accepted author manuscript

Published in
MT-ITS 2019 - 6th International Conference on Models and Technologies for Intelligent Transportation Systems

Citation (APA)
Taale, H., & Pel, A. (2019). Route Set Generation for Quick Scan Applications of Dynamic Traffic Assignment. In *MT-ITS 2019 - 6th International Conference on Models and Technologies for Intelligent Transportation Systems* Article 8883324 IEEE. https://doi.org/10.1109/MTITS.2019.8883324

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

Route Set Generation for Quick Scan Applications of Dynamic Traffic Assignment

1st Henk Taale
Department of Transport & Planning
Delft University of Technology
Delft, The Netherlands
h.taale@tudelft.nl

2nd Adam J. Pel
Department of Transport & Planning
Delft University of Technology
Delft, The Netherlands
a.j.pel@tudelft.nl

***Abstract*—Recent years have shown an interest in developing and using quick-scan analysis tools for the evaluation of policy options, such as planning issues, investments in infrastructure or public transport or other measures to cope with the increasing mobility problem. These tools can give a quick and easy insight into the impacts of all kinds of measures, without the large amount of work associated with the use of transport models. The assignment procedure of these tools can be improved and made more consistent with transport models. Therefore, it is needed that the calculation time of standard assignment algorithms is decreased. One possibility is to decrease the size of the route sets used. In this paper, this possibility was investigated for a number of small and medium-sized networks, using a dynamic traffic assignment framework. It was found that a route set in which each OD-pair has a maximum of 4-6 routes is sufficient to get comparable results with the situation with larger route sets. This rule of thumb for the maximum number of routes seems stable if demand increases and is not influenced by the overlap factor, which is an important parameter in the generation of route sets. Further research should focus on the scale factor in the route set generation algorithm and also larger networks need to be studied to be able to come a better founded conclusion about the size of the route set, which can be used in quick-scan tools.**

***Index Terms*—route sets, quick-scan tool, dynamic traffic assignment, DTA**

I. Introduction

Recent years have shown an interest in developing and using quick-scan tools for the evaluation of policy options, such as planning issues, investments in infrastructure or public transport or other measures to cope with the increasing mobility problem. Policymakers have come to realize that transport models can help in making choices, but that their application relies on an extensive data collection and input preparation process. Also, the output of these types of models is not easy to interpret. Therefore, there is a need for quick-scan analysis tools that can give a quick and easy insight into the impacts of planning, infrastructural, design, mobility and traffic management measures, without the large amount of work associated with the use of transport models.

Quick-scan tools can be used to make a first selection of alternatives that have been proposed as a solution to deal with infrastructural, design or mobility problems. Subsequently more advanced transport modeling tools can be used to evaluate the remaining alternatives on their merits related to accessibility, safety or sustainability. Quick-scan tools can also be used to generate alternatives using ”what-if” scenarios. In both cases, it is recommended to deviate only slightly from traditional transport models, because if both type of tools are used in the policy process, consistency questions will arise. Therefore, these tools normally import and use data that come from models, typically the network, the demand (origin-destination matrix) and the flows and speeds (network loads). The data can be visualized to get a picture of the situation, but also enriched to new information with calculation rules. For example using elasticities to determine the effect of a modal shift measure or reassigning the traffic because of an increase in speeds due to traffic management. To maintain a certain consistency these calculation rules should not deviate too much from normal transport and traffic models.

The definition of ’quick’ is a subjective one and can be specified in many different ways. In this research, it is assumed that a quick-scan tool is used in a workshop setting and that results for a certain scenario should be available within a short time period, typically 5-10 minutes. To meet this requirement a reference scenario is derived from OD matrix and the network of the transport model used. The model can contain the information of a large region, for example the whole of the Netherlands. To make it manageable a study area is defined, which contains a smaller area, for example a city or a region around a city. For the OD matrix, aggregations are made to keep the number of zones for the study area at an acceptable level, e.g. on average 250 zones. The network is kept as detailed as it was imported from the transport model. From the reference scenario, scenarios with one or more different measures are developed. The number of these alternative scenarios can differ from one to a large number, dependent on the goal of the study or the workshop. For every alternative scenario the results should be calculated, using the calculation rules mentioned before. In this paper, the focus is traffic assignment, as one of the calculation rules.

In quick-scan tools, traffic assignment can be used to determine the effect of certain measures on route choice behavior, for example the building of new infrastructure or the increase of speed on routes due to traffic management measures. A full-fledged user equilibrium model is not suitable, because that would infringe the ’scan’ character. But traffic assignment should also not be too simple, because then the results will

978-1-5386-9484-8/19/$31.00 ©2019 IEEE

be too inconsistent with the results of other traffic assignment models (whether they are static or dynamic) will produce. So, to assign all traffic to the shortest route is not the best option. Then the question arises what the best method is for traffic assignment in quick-scan tools, which is not too complicated, fast enough to be used in a workshop setting and consistent with traditional traffic assignment models.

To find good and approximate algorithms, the traffic assignment process is decomposed into a number of steps. In general, it is an iterative process. First, demand is assigned to the available routes, based on initial travel times, e.g. the free flow travel times. This distribution of traffic is used to calculate route travel times or costs. On their turn these travel times or costs are used to reassign the demand, which gives new route flows and with these again travel times are calculated. This process is repeated until convergence is reached. Input for the traffic assignment are a transportation network, a travel demand matrix and a set of routes, that connects each origin with the relevant destinations. The structure of this assignment approach and its separate parts shown in figure 1.

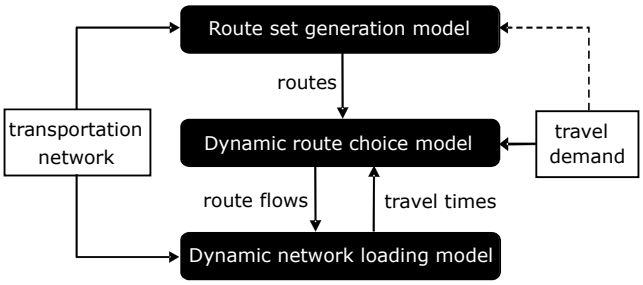

Fig. 1. Structure of a dynamic traffic assignment model

In this research the set of routes for every origin-destination (OD) pair is fixed and is generated a priori, thereby avoiding time-consuming (dynamic) fastest paths computations while running the traffic assignment model, especially for large networks [1]. Although the method was not compared with other link-based and route-based assignment methods (as in [2] and [3]), it is obvious that this assignment type is advantageous for a quick-scan tool.

In this paper, the focus is on the route set generation model and specifically on the question how many routes per OD-pair are needed for reasonable results and what is 'reasonable' has to be defined. But first the available literature on this topic and some methods to generate a set of routes is described. After these methods are tested on several cases, the results are analyzed and some conclusions are drawn.

II. Literature review

As already mentioned in the introduction, transport models are an important tool in the development and evaluation of policy and planning measures. A central component within these models is the traffic assignment that describes the route flows, which are a result of travel demand and network supply interactions. Traffic assignment typically consists of choice set generation and route choice modeling. Distinguishing the processes of route choice set formation on the one hand and modeling the choice between these routes on the other, is advantageous from a theoretical, computational and behavioral point of view [4]. However, for large congested networks the problem of choice set generation is particularly tough, given that there is a clear trade-off between including all relevant alternative routes for behavioral realism and limiting the overall number of routes for computational efficiency (or even feasibility). For example, the planning model for the Western part of the Randstad (The Netherlands) contains ~3.4k centroids and ~1.2M routes, while other important regional models in The Netherlands and Belgium contain up to ~4M routes [5].

Compared to the relatively vast bodies of literature on route set generation, route choice modelling and solving the traffic assignment problem, much limited research has been done on what the effects are of choice set size and composition. At the same time, this research tends to focus on dependencies between the choice set generation and the route choice model estimation, such as in [6], [7], [8], [9] and [10]. Another topic is how choice set generation algorithms are able to yield choice sets that coincide with chosen routes as observed in real-life, as in [11], [12] and [13]. Here, and in other studies like [14], [15], [16] and [17], typical sizes of choice sets that are tested range from 20 to 50 routes, whereas in regional transport models used in practice route choice sets tend to contain fewer than 10 routes per origin-destination pair [5]. For example, in the planning model for the region of The Hague (The Netherlands) the average number of routes per origin-destination (OD) pair exceeds 3 [18], whilst the observed number of unique GPS routes averages 2.1, with a minimum of 1 and maximum of 6 routes [13]. Another example is the study by [19] analyzing the Chicago area, where an average of 2.7 routes per OD-pair were observed, and for which 56% of the OD-pairs were connected by only 1 route, while 95% of the OD-pairs were connected by fewer than 10 routes.

In light of the fact that calculation time and memory usage of these transport models strongly depend on the number of routes in the choice sets, the question remains as to how the choice set size and composition may affect the overall results of the traffic assignment model component, particularly in terms of route flows and travel times as prominent output in policy and planning studies, but also as input for quick-scan tools. This has been analyzed for the case of static traffic assignment by [8], using the Sioux Falls network and the denser Winnipeg network as test cases. Here they find that choice sets of maximum 6-8 routes per OD-pair for Sioux Falls, respectively 10-15 for Winnipeg, lead to (stochastic) equilibrium route flows with only 3-5% higher delays than in case of maximum choice sets (while saving more than 70% CPU time). The question is whether these results can be generalized (1) to other networks, (2) to other traffic conditions, and (3) to the more realistic setting of dynamic traffic assignment. This paper contributes to the third issue.

III. Route Set Generation

To study how the cardinality of the route sets and traffic conditions affect the traffic assignment in a dynamic setting, we first consider methods for constructing the route sets. Below, the notation and definitions are given first. Then, methods for generating routes are presented.

A. Definitions

We consider a network to be a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ is the set of nodes and $\mathcal{A}$ is the set of directed links. Some nodes o are origins and some nodes d are destinations. An origin o and destination d are connected with one or more sets of links, which is called a route $r \in \Re^{od}$, where $\Re^{od}$ is the set of feasible routes or paths between o and d that has no cycle. This is only relevant for OD-pairs with a demand larger than zero and because a dynamic framework is used, the demand should be larger than zero for one or more time periods k. Those OD-pairs (o, d) belong to the set $\mathcal{Q}$, which is a subset of all OD-pairs.

B. Simple Methods

A simple and obvious choice would be that $\Re^{od}$ contains exactly one route for every $(o, d) \in \mathcal{Q}$. This can be the shortest route in distance or time (or some other criterion). This leads to the so-called all-or-nothing (AON) assignment, because all demand for an OD-pair is assigned to this one route. In a quick-scan tool used in the Netherlands, another simple method is implemented. It has two routes: one based on the free-flow speeds and the other on peak-period speeds. These speeds can be imported from the transport model, or from available floating car data, which means that then these are measured speeds. The traffic demand is simply assigned in half. To see how this works out in practice both methods are applied to a small network as shown in figure 2. The network contains both motorways and urban roads and consists of 63 nodes (from which 8 are origins and 8 are destinations) and 141 links. It has 56 OD-pairs with a demand larger than zero for at least one time period. The methods are run for a scenario with 100% demand and one with 125% to see what the effects are.

The results of both methods are shown in table I. For comparison reasons another, more advanced, method is added, which is described later. For now, it is chosen that this method generates a maximum of 5 routes, just for the example. Network coverage is defined as the percentage of lane kilometers that is used by the set of routes. Note that lane kilometers are used instead of link kilometers, to account for the difference between urban links and motorway links. The delay presented is relative to the maximum speed of links.

From the table it is clear that both simple methods give very different results than the advanced method, which is used as the baseline for this example. First, it can noticed that the method with 2 routes generates on average 1.3 routes per OD-pair. That means that a lot of OD-pairs still have only 1 route available. This goes up to 1.4 route per OD-pair if the demand increases, because then there is more congestion and more links have speeds lower than the free-flow speeds, which gives more opportunities to generate different routes. This is also clear from the network coverage which increases with higher demand for this scenario.

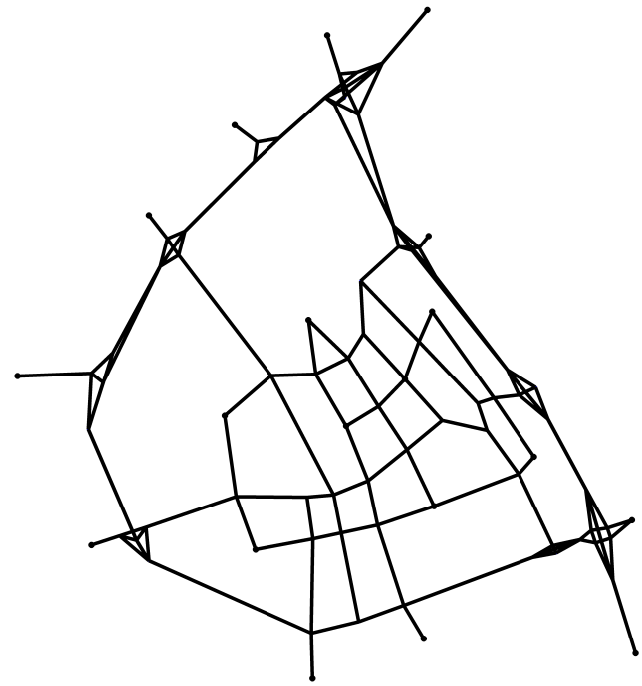

Fig. 2. Example network

TABLE I
Results for the Example Network

Scenario	Routes total	Routes per OD	Coverage (lane km.)	TDT (veh.km)	Delay (veh.hrs)
100% - 1	56	1.0	85.8%	106.9	1159.1
100% - 2	73	1.3	91.1%	108.9	801.0
100% - 5	167	3.0	96.3%	112.1	530.0
125% - 1	56	1.0	85.8%	118.1	2903.6
125% - 2	80	1.4	91.6%	133.8	1714.3
125% - 5	167	3.0	96.3%	137.8	1427.8

Also, the final result in terms of total delay is very different. For the scenario with 1 route the total delay is more than twice the delay in the baseline scenario for both demand levels. If the distance traveled for the higher demand is considered, it is much lower for this scenario than the other two. This has to do with traffic which is stuck in the origin and cannot enter the network due to queues, but is accounted for in the total delay. For the scenario with 2 routes the total delay is about 50% higher for the normal demand level and this decreases to a 20% higher delay with 25% more demand. This could be the effect of more routes available.

The results show that the number of routes has a large influence on the final result. For larger networks also the calculation time comes into play and then it becomes a balance

between enough routes to get good results, but not too much routes resulting in long calculation times.

C. Advanced Method

As stated before for a quick-scan tool an a-priori set of routes would be beneficial in terms of calculation time. The advantage is that the routes can be computed in advance and don't change during other calculations. Also, starting with a set of routes instead of with a single route enables the distribution of the OD flows over multiple routes already from the first iteration. This can speed up the convergence. But a fixed set of routes can also be a disadvantage, because it is possible that used routes are not included in the set. Therefore, it is important that the generated set of routes is sufficiently large, such that for each OD-pair at least all used routes are included.

Sets of routes can be generated in several advanced ways, e.g. all acyclic routes, the k-shortest routes, the essentially least cost routes, the most probable routes and the efficient routes [20]. Normally, travel times are used for this, which can be based on the maximum speed or can be estimated with travel time functions. For this research, a combination of the second and third alternative is used, which means that the number of routes for each OD-pair is limited and the routes are bounded in length. Furthermore, the set is generated with a stochastic process, using a Monte Carlo simulation in which the link costs are varied randomly, but within a certain bandwidth. To adhere to the bandwith, a scaling factor ω is used, which is defined as:

$$\mathbf{C}^{*} = \mathbf{C}(1 + \omega\,|\Lambda|) \tag{1}$$

where $\mathbf{C}$ is the original link cost matrix, which represents the costs to travel each link from one node (row) to the other (column). Normally these costs are defined as the travel time, but this could be extended with other costs also. In equation (1) $\mathbf{C}^{*}$ is the adjusted link cost matrix, ω a scaling factor and Λ a matrix with elements following the standardized normal distribution $N(0,1)$. So, for every link a separate, extra cost term is added. If $\omega = \frac{2}{3}$ is chosen, the length of the adjusted routes can never be longer than three times the original length. That is, with 99.7% certainty, because with that probability the elements of Λ lie between -3 and 3. This is sufficient for the purpose of this study. The algorithm for the generation of routes is given in table II.

In Step 2 and Step 3 shortest paths are calculated. and this is done with Dijkstra's algorithm [21]. For this research, the fast and reliable heap implementation by Bindel [22] is used. Note that Dijkstra is used for a singe origin to all destinations in one execution. In Step 4 there is a check on overlap of routes. This check is introduced to prevent routes that look much the same are included in the route set. For example a route using an off-ramp and on-ramp (compared to a route using the motorway) is unwanted. Before a route r is added to the set of routes or OD-pair (o,d), it is checked with every existing route $s \in \Re^{od}$ if the number of overlapping links divided by the minimum number of links in s or r should be smaller than a threshold.

TABLE II
ALGORITHM FOR THE ROUTE SET GENERATION

Step 1:	Choose number of wanted routes p and number of random drawings m^{*}.
Step 2:	For every (o,d), find the shortest route for the original cost matrix $\mathbf{C}$ and add this route to the set of routes $\Re^{od}$. For $m = 1 : m^{*}$
Step 3:	Draw the error matrix $\Lambda^{(m)}$. Calculate the adjusted link costs with equation (1). For every (o,d) and cost matrix $\mathbf{C}^{(m)}$, find the shortest route r^{odm}.
Step 4:	For every (o,d) and route r^{odm}: Check if r^{odm} is shorter than the p-th longest route in the set $\Re^{od}$. Check if there is not too much overlap with the other routes in the set.
Step 5:	If these condition are fulfilled, add route r^{odm} to route set $\Re^{od}$. If $m < m^{*}$ go back to Step 3.

In [1] it was shown that the algorithm from table II can be applied to large-scale networks in an acceptable amount of time. For that case (and using the computer power of that time) 'acceptable' meant 15-45 minutes for 10-25 routes. The question is if these calculation times will also be acceptable in a quick-scan tool. Before that point is explored, the rest of the modeling framework that is used, is described first.

IV. MODELING FRAMEWORK

To be able to evaluate the results of the route set generation algorithm on the final outcome, for example in terms of total delay, it is necessary to use the complete DTA framework as shown in figure 1. In this section the assignment algorithm, the network loading model and convergence aspects are described briefly.

A. Dynamic Traffic Assignment

To distribute the traffic demand over the available routes for all modeled periods, a dynamic traffic assignment model is needed. For this work the stochastic assignment approach is used [23] and for this approach it is assumed that the travel costs have an error term that is independently and identically distributed and with a certain distribution it leads to the multinomial logit (MNL) model [24]. In this model the probability P_k^{rod} to choose route r for OD-pair (o,d) and time period k is given by

$$P_k^{rod} = \frac{e^{-\theta c_k^{rod}}}{\sum\limits_{s \in \Re^{od}} e^{-\theta c_k^{sod}}}, \qquad \forall o,d,r \in \Re^{od}, k, \tag{2}$$

where $\theta > 0$ is a parameter that reflects the degree of uncertainty in the travel time knowledge of the road users. The MNL-model has a problem with overlapping routes and several solutions have been proposed to overcome this. In [17] an overview of this discussion is given, but it has not been concluded yet, although a preference for the path-size logit approach is expressed. Because of implementation issues, the C-logit model [25] is prefered and used in the stochastic dynamic traffic assignment assignment procedure.

This approach takes overlap of routes into account with the commonality factor CF, which for route r of OD-pair od and time period k, is defined by

$$CF_k^{rod} = \beta \ln \sum_{s \in \Re^{od}} \left[\frac{L_{rs}}{\sqrt{L_r L_s}} \right]^{\gamma}, \quad \forall o, d, r \in \Re^{od}, k, \quad (3)$$

where L_r and L_s are the 'lengths' of routes r and s belonging to OD-pair (o, d), L_{rs} is the 'length' of the common links shared by routes r and s and β and γ are positive parameters, which in our case are $\beta = 1$ and $\gamma = 2$. For the 'length' of the route, the free flow travel time is used. With this commonality factor and the realized travel time c_k^{rod}, the probability to choose route r, for OD-pair od and time period k, is given by

$$P_k^{rod} = \frac{e^{-\theta c_k^{rod} - CF_k^{rod}}}{\sum_{s \in \Re^{od}} e^{-\theta c_k^{sod} - CF_k^{sod}}}, \quad \forall o, d, r \in \Re^{od}, k. \quad (4)$$

and the accompanying route flows f_k^{rod} are then given by

$$f_k^{rod} = P_k^{rod} q_k^{od}, \quad \forall o, d, r \in \Re^{od}, k, \quad (5)$$

where q_k^{od} is the demand for OD-pair (o, d) and time period k. These route flows are used to calculate the route travel times again using a dynamic network loading model.

B. Dynamic Network Loading Model

In the dynamic network loading (DNL) model traffic demand is put on the network at the origins using a demand profile, which can be step-wise or more fluent. Traffic is propagated through the network using travel time functions. These functions are standard functions derived from literature [26], [27] and they are different for different link types (normal link, controlled link, roundabout link, etc.). For normal links the travel time τ_a (s) for link a is calculated as follows:

$$\tau_a = \widetilde{\tau}_a + 0.9 l_a \Delta_h \left(z_a + \sqrt{z_a^2 + \frac{8 k_a \varphi_a}{Q_a \Delta_h}} \right), \quad (6)$$

where $\widetilde{\tau}_a$ is the free flow travel time (s), l_a is the length of the link (m), Δ_h is the length of the analysis time period (h), φ_a is the degree of saturation, $z_a = \varphi_a - 1$, Q_a is the capacity of the link and k_a is a link dependent parameter, which is related to other parameters through

$$k_a = \frac{2 Q_a (\frac{\vartheta_a^f}{\vartheta_a^c} - 1)^2}{\Delta_h (\vartheta_a^f)^2}, \quad (7)$$

where ϑ_a^f is the free flow speed (km/h) for link a and ϑ_a^c is the speed (km/h) at which free flow turns into congestion. The speed at congestion ϑ_a^c is an input parameter and can be different for different free flow speeds. From the free flow speed, the free flow travel time $\widetilde{\tau}$ can be calculated with

$$\widetilde{\tau}_a = \frac{3.6 l_a}{\vartheta_a^f} \quad (8)$$

At decision nodes the traffic is distributed among the outgoing links according to the splitting rates determined by the route flows f_k^{rod}, taking into account the travel time needed to reach this node. Before traffic enters a link, it is checked if this link has enough space. If this is not the case traffic is held back on the upstream link, so blocking back is modeled. If there are more than one upstream links, the queue is divided over these links according to the number of lanes.

The link travel times are used to calculate the route travel times c_k^{rod}, which on their turn are input for the dynamic assignment model. More details on the model and the steps taken, can be found in [28].

C. Convergence

Every traffic assignment model assumes that traffic is in some sort of equilibrium and that can be a deterministic or a stochastic one. Both types of equilibria are found using an iterative solution procedure for the process shown in figure 1. For a stochastic assignment to come to an equilibrium, the solution for a certain iteration $\mathbf{f}^{(calc)}$ is combined with the solution from the previous iteration $\mathbf{f}^{(j-1)}$ to obtain the input $\mathbf{f}^{(j)}$ for the next one:

$$\mathbf{f}^{(j)} = \mathbf{f}^{(j-1)} + \zeta^{(j)} (\mathbf{f}^{(calc)} - \mathbf{f}^{(j-1)}), \quad (9)$$

where $\zeta^{(j)}$ is the smoothing factor. For a stochastic assignment a dynamic adjusted smoothing factor gives the best convergence properties and this smoothing factor is also used in this research [29].

To determine if equilibrium is reached a convergence criterion is used. For this study, the maximum difference (over OD-pairs and time periods) between the route flows of two iterations is used, calculated as a percentage of the demand of that OD-pair during that time period:

$$\varepsilon = 100\% \cdot \max_k \max_{od} \max_r \frac{\left| f_k^{rod(j)} - f_k^{rod(j-1)} \right|}{q_k^{od}}. \quad (10)$$

This error can be considered as the maximum shift in flow from one route to another, for a certain OD-pair and time period. For now $\varepsilon < 1\%$, to keep a balance between comparable results for the networks and calculation time. An option is to keep the absolute shift of flow below a certain threshold. This would give more weight to OD pairs with higher demand, but also could lead to slower convergence.

V. Case Studies

In this section, some results, obtained with the algorithms described, are presented. First, the influence of the overlap factor is investigated and after that the influence of the maximum number of routes.

A. Case 1: Influence of Overlap Factor

For the first case a somewhat larger network than the example network is used. This network has 431 nodes, of which 25 are origins and 25 are destinations. It has 841 links, both urban and motorway and the OD-matrix has 600 OD-pairs with a dynamic demand profile, for 48 5-minute time periods, spanning a simulation period of 4 hours. The network is shown in figure 3 and it is clear that the structure of

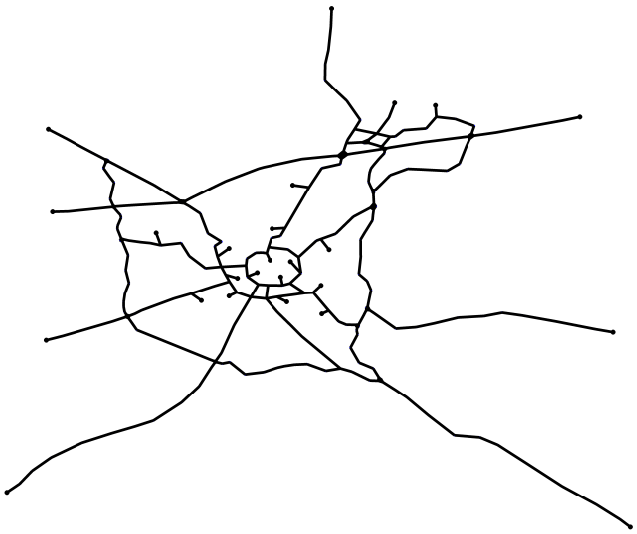

Fig. 3. Network for Case 1

this network is different from the example network: it has a structure with ring roads, which makes the number of route choices possibly larger.

For this network the overlap factor, which determines how much overlap between routes in the route set is allowed, is varied. A large overlap factor means a lot of overlap is permitted. It was varied between 0.75 and 0.99 in steps of 0.05. For every overlap factor, the route set was generated according to the algorithm described in Tabel II, for which p (maximum number of routes) was set to 15 and m^* (number of random draws) to 50. For this network and these settings, figure 4 shows the average number of routes per OD-pair and figure 5 shows the frequency distribution.

The results show that even for a high value of the overlap factor the average number of routes per OD-pair does not exceed 5. This is confirmed in the frequency graph which shows that 5 routes are enough to cover 95% of the route set for the overlap factors 0.75, 0.80, 0.85 and 0.90. Even for an overlap factor of 0.99 5 routes are enough to cover about three quarters of the route set.

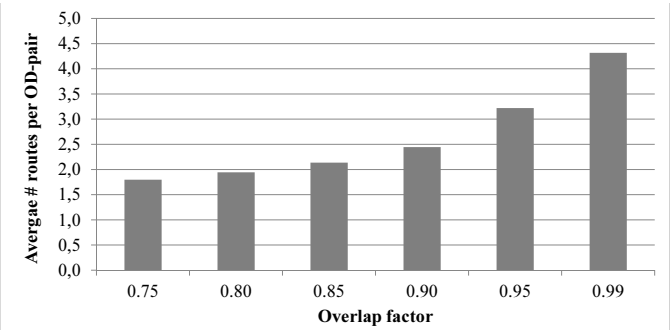

Fig. 4. Average Number of Routes for Case 1

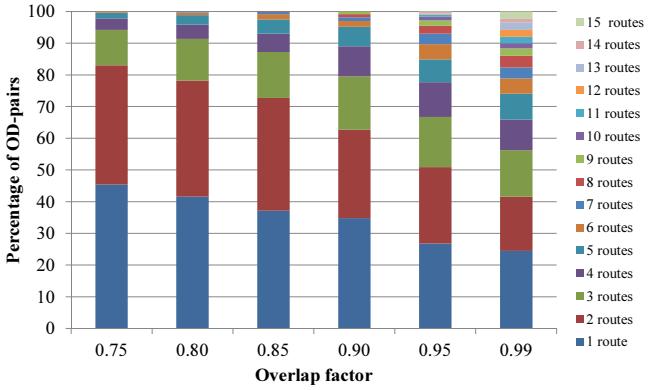

Fig. 5. Frequency of Routes for Case 1

B. Case 1: Number of Maximum Routes

If the overlap factor is set to a fixed value of 0.90 and the number of maximum routes in the route generation process is varied, the final results, in terms of the total delay of the equilibrium solution, can be analyzed. The results are shown in figure 6. For this network and this settings, above a maximum of 9 routes there are no changes any more. In that case the average number of routes per OD-pair is 2.4 and the network coverage is 99.76%, which is already obtained with 3 routes. With a maximum of 4 routes the total delay of the calculated equilibrium is within 1% of the total delay of the equilibrium with 9-15 routes. If the demand is increased with 25% the results stays the same. The total delay triples, but still 4 routes are enough to stay within 1% of the total delay of the runs with 9-15 routes.

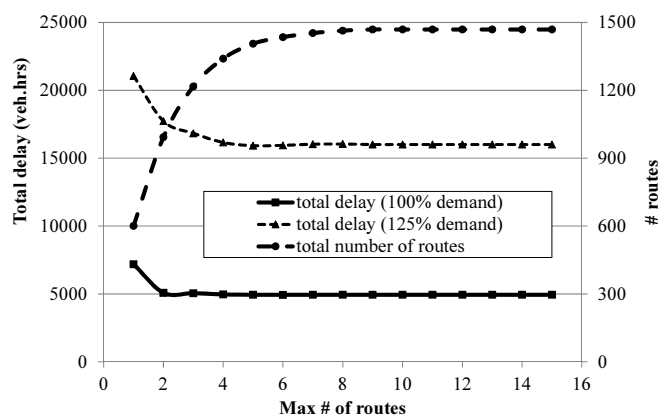

Fig. 6. Total Delay and Number of Routes for Case 1

C. Case 2: Number of Maximum Routes

A second, somewhat larger case involves a part of the Amsterdam road network: the western part of the ring road and the surrounding urban network. It consists of 1438 links, 787 nodes (of which are 100 origins and 99 destinations) and 4618 OD-pairs. All OD-pairs have a dynamic demand profile

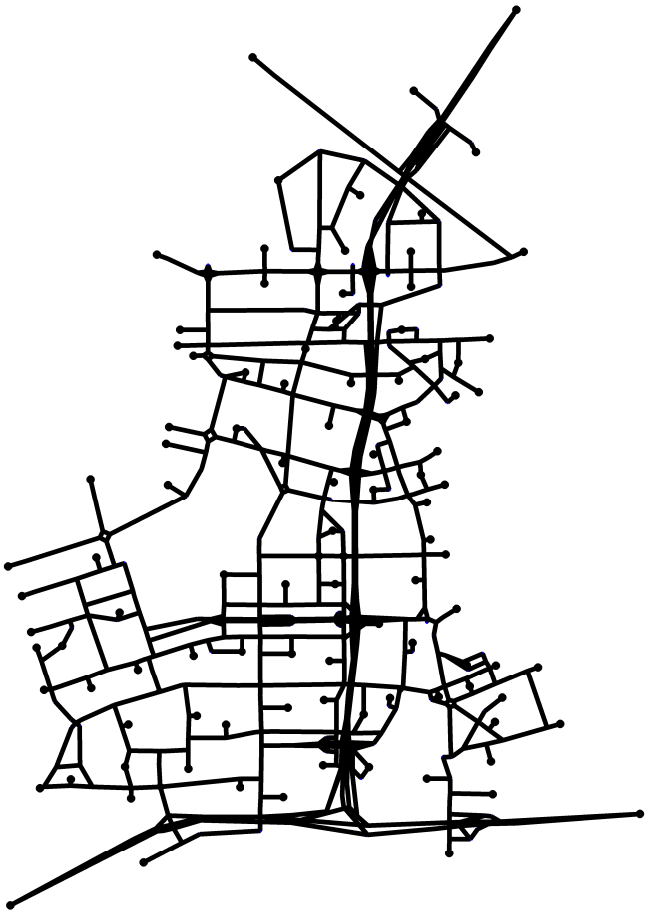

Fig. 7. Network for Case 2

for 10 periods of 15 minutes (2.5 hrs in total). The network is shown in figure 7.

For this network the overlap factor is set to a fixed value of 0.85, because the on- and off-ramps of the motorway are closely spaced and the route generation should not benefit too much from that possibility. Again the route generation algorithm and DTA framework are used to calculate the total delay in the equilibrium situation if the maximum number of routes is varied from 1 to 15. The results are shown in figure 8.

From the figure it can be seen that the number of routes increases until the end, although with a minimal quantity for 15 routes (+18). Also for higher number of maximum routes the route set still increases a little bit with 3-10 routes. The average number of routes per OD-pair in the case of 15 routes is 3.4. This is considerable higher than the previous case, which has to do with the network structure: on the urban many route options are available. The total delay already reaches a more or less stable value for 3 routes. The network coverage has then already reached its maximum value of 98.24% (minimum is 96.02%). This is probably due to the fact that most of the delay is suffered on the motorway and due to the structure of the network long distance traffic has

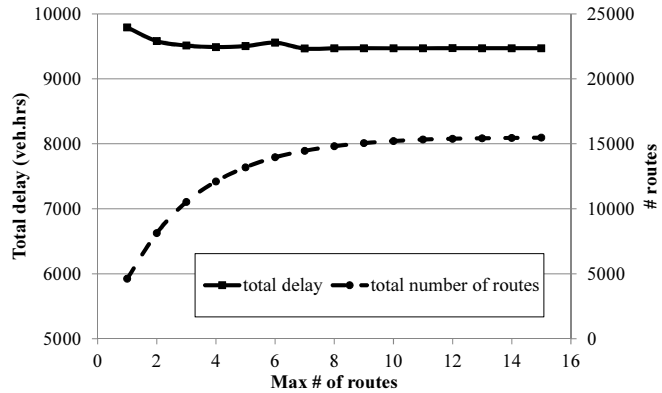

Fig. 8. Total Delay and Number of Routes for Case 2

not much choice than to use the motorway. For more than 3 routes the total delay is within 1% of the equilibrium value of the situation with a maximum number of 15 routes. Although for 6 routes a small deviation can be seen, the values of the total delay for the situations with 7 routes and more are even within 0.1% of this final solution.

VI. Conclusions

In this research, the size of route sets for different networks is investigated. The purpose was to see whether a certain maximum value for the number of routes per OD-pair could be determined. If this could be smaller than normally is used in transport models, quick-scan tools could use the same route set generation and assignment methods, because calculation times can be limited and the consistency with transport models is better.

This was done using an existing dynamic traffic assignment framework together with a route set generation algorithm. The algorithm has a number of variables of which some were varied in this research. The frameworks was tested on an example network which showed that the assumption in current quick-scan tools that 2 routes is enough, is not valid.

From the small and medium-sized networks studied, it can be concluded that a route set in which each OD-pair has a maximum of 4-6 routes is sufficient to get comparable results with the situation with larger route sets. Therefore, a number of 2 routes, which is now sometimes used, is not enough. It was also concluded that the overlap factor, used in the route set generation algorithm to filter comparable routes, influences the size of the route set, but not the point at which the maximum number of routes gives comparable results. Also, this rule of thumb for the maximum number of routes seems stable if demand increases.

Only a limited number of networks was investigated, although the networks were realistic ones. Also, not all possible variables of the route set generation algorithm were investigated. Especially, the scale factor ω (see equation (1)) is worth a closer look. Also, alternatives for the used route-set generation algorithm (k-shortest paths) could be useful to study, especially the use of the overlap factor. Furthermore,

larger networks need to be studied to be able to come a better founded conclusion about the size of the route set, which can be used in practical applications of a quick-scan tool with assignment properties.

REFERENCES

[1] M. C. J. Bliemer and H. Taale, "Route Generation and Dynamic Traffic Assignment for Large Networks," in *Proceedings of the First International Symposium on Dynamic Traffic Assignment*, Leeds, U.K., 2006.

[2] D.-H. Lee, Y. Nie, A. Chen, and Y. C. Leow, "Link- and Path-Based Traffic Assignment Algorithms: Computational and Statistical Study," *Transportation Research Record*, vol. 2076, pp. 10–19, 2002.

[3] O. Perederieieva, M. Ehrgott, J. Y. T. Wang, and A. Raith, "A Computational Study of Traffic Assignment Algorithms," in *Australasian Transport Research Forum 2013 Proceedings*, Brisbane, Australia, Oct. 2013.

[4] P. H. L. Bovy, "On Modelling Route Choice Sets in Transportation Networks: A Synthesis," *Transport Reviews*, vol. 29, no. 1, pp. 43–68, 2009. [Online]. Available: https://doi.org/10.1080/01441640802078673

[5] L. Brederode, A. Pel, L. Wismans, E. de Romph, and S. Hoogendoorn, "Static Traffic Assignment with Queuing: Model Properties and Applications," *Transportmetrica A: Transport Science*, pp. 1–36, 2018. [Online]. Available: https://doi.org/10.1080/23249935.2018.1453561

[6] M. Bliemer and P. Bovy, "Impact of Route Choice Set on Route Choice Probabilities," *Transportation Research Record*, vol. 2076, pp. 10–19, 2008.

[7] C. G. Prato and S. Bekhor, "Modeling Route Choice Behavior: How Relevant is the Choice Set Composition?" *Transportation Research Record*, vol. 2003, pp. 64–73, 2007.

[8] S. Bekhor, T. Toledo, and J. N. Prashker, "Effects of Choice Set Size and Route Choice Models on Path-Based Traffic Assignment," *Transportmetrica*, vol. 4, no. 2, pp. 117–133, 2008. [Online]. Available: https://doi.org/10.1080/18128600808685682

[9] S. Bekhor and C. G. Prato, "Effects of Choice Set Composition in Route Choice Modelling," in *Proceedings of the 11thInternational Conference on Travel Behaviour Research (IATBR)*, 2006.

[10] E. Freijinger, "Random Sampling of Alternatives in a Route Choice Context," in *Proceedings of the European Transport Conference 2007*, Leiden, The Netherlands, Oct. 2007.

[11] P. H. L. Bovy and S. Fiorenzo-Catalano, "Stochastic Route Choice Set Generation: Behavioral and Probabilistic Foundations," *Transportmetrica*, vol. 3, no. 3, pp. 173–189, 2007. [Online]. Available: https://doi.org/10.1080/18128600708685672

[12] S. Bekhor, M. Ben-Akiva, and M. Ramming, "Evaluation of Choice Set Generation Algorithms for Route Choice Models," *Annals of Operations Research*, vol. 144, no. 1, pp. 235–247, April 2006. [Online]. Available: https://ideas.repec.org/a/spr/annopr/v144y2006i1p235-24710.1007-s10479-006-0009-8.html

[13] J. Zantema and D. H. van Amelsfort, "Route Set Generation within a Dynamic Modeling Framework: A Comparison of Methods and GPS Route Choice Data," in *Proceedings of the European Transport Conference 2007*, Leiden, The Netherlands, Oct. 2007.

[14] M. Bierlaire and E. Frejinger, "Route Choice Models with Subpath Components," in *Proceedings of the 5th Swiss Transport Research Conference*, Ascona, Switzerland, Mar. 2005.

[15] C. G. Prato and S. Bekhor, "Applying Branch-and-Bound Technique to Route Choice Set Generation," *Transporation Research Record*, vol. 1985, pp. 19–28, 2006.

[16] M. S. Ramming, "Network Knowledge and Route Choice," Ph.D. dissertation, Massachusetts Institute of Technology, 2002.

[17] C. G. Prato, "Route Choice Modeling: Past, Present and Future Research Directions," *Journal of Choice Modelling*, vol. 2, no. 1, pp. 65–100, 2009.

[18] J. Knockaert, M. Bliemer, D. Ettema, D. Joksimovic, A. Mulder, J. Rouwendal, and D. van Amelsfoort, "Experimental Design and Modelling - Spitsmijden," Consortium Spitsmijden, Tech. Rep., May 2007.

[19] H. Bar-Gera and D. Boyce, "User-Equilibrium Route Set Analysis of a Large Road Network," in *Transportation and Traffic Theory: Flow, Dynamics and Human Interaction (Proceedings of the 16th International Symposium on Transportation and Traffic Theory)*, H. S. Mahmassani, Ed., Jul. 2005, pp. 673–692.

[20] M. C. J. Bliemer, "Analytical Dynamic Traffic Assignment with Interacting User-Classes," Ph.D. dissertation, Delft University of Technology, Delft, The Netherlands, 2001.

[21] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische Mathematik*, vol. 1, pp. 269–271, 1959.

[22] D. Bindel, "Implementation of Dijkstra's Method Using a Matlab Sparse Matrix as an Adjacency Matrix," C-source file, found at www.cs.berkeley.edu/~dbindel, accessed on December 20th, 2004.

[23] C. F. Daganzo and Y. Sheffi, "On stochastic models of traffic assignment," *Transportation Science*, vol. 11, no. 3, pp. 253–274, 1977.

[24] Y. Sheffi, *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods*. Englewood Cliffs, N.J., U.S.A.: Prentice-Hall, 1985.

[25] E. Cascetta, A. Nuzzolo, F. Russo, and A. Vitetta, "A Modified Logit Route Choice Model Overcoming Path Overlapping Problems: Specification and some Calibration Results for Interurban Networks," in *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, 1996, pp. 697–711.

[26] R. Akçelik, "Travel time functions for transport planning purposes: Davidson's function, its time-dependent form and an alternative travel time function," *Australian Road Research*, vol. 21, no. 3, pp. 49–59, 1991, minor revisions: December 2000.

[27] ——, "Speed-flow models for uninterrupted traffic facilities," Akcelik and Associates Pty Ltd, Melbourne, Australia, Tech. Rep. Technical Report, 2003.

[28] H. Taale, "Integrated Anticipatory Control of Road Networks: A Game Theoretical Approach," PhD thesis, Delft University of Technology, Delft, The Netherlands, 2008. [Online]. Available: http://repository.tudelft.nl/view/ir/uuid%3Ae1e257d8-d5e9-465e-9428-5934969d411c/

[29] H. Taale and A. Pel, "Better Convergence for Dynamic Traffic Assignment Methods," *Transportation Research Procedia*, vol. 10, pp. 197–206, 2015.