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TESTING OF A DEMAND MATRIX ESTIMATION METHOD INCORPORATING OBSERVED SPEEDS AND CONGESTION PATTERNS ON THE DUTCH STRATEGIC MODEL SYSTEM USING AN ASSIGNMENT MODEL WITH HARD CAPACITY CONSTRAINTS

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1. INTRODUCTION

To prepare the Dutch regional and national strategic transport models (LMS/NRM) for policy questions of the future, its owner (Rijkswaterstaat – WVL) wants to improve the correspondence between modelled and observed link speeds and route travel times; in particular for motorized traffic in the base year in congested situations. This paper describes a project in which the NRM-West (the regional model of the Randstad) is used as a test case for modelling improvements to the LMS/NRM to better fit with floating car data describing speed and route travel times.

With some 7 million inhabitants, the models study area (Randstad) is the largest urban region in the Netherlands containing its four largest cities Amsterdam, Rotterdam, The Hague and Utrecht, and is one of the most important urban regions in North-west Europe. The region experiences heavy congestion on a structural basis, which means that congestion patterns (location and severity of queues) are highly interrelated and travel times are sensitive and volatile.

1.1. Context

The LMS/NRM was developed as a strategic transport model system to be applied on study areas such as the Randstad, and as such must be able to reach a stable equilibrium between destination, mode, departure time and route choice in a heavily congested context. In order to do so, the current assignment model QBLOK (Significance, 2017) aims to reach (route choice) user equilibrium while accounting for flow metering and spillback. Furthermore, the overall system incorporates a feedback loop between the assignment and the demand models to account for the influence of delays on the equilibrium between the travelers mode, destination and departure time choices.

To better match observed travel times, the main focus of this research project is to improve outcomes from the assignment model whilst maintaining (or improving) the ability to reach equilibrium. The current assignment procedure QBLOK has proven to be hard to calibrate and/or improve and is known to suffer from convergence and stability issues.

In this research the current assignment method is replaced by STAQ (Brederode et al., 2010) which is not based on heuristics but solves an optimization problem and is consistent with traffic flow theory allowing for calibration on observed values for speed and flow. This should result in more realistic travel times.

2. METHODOLOGY

In order to replace the assignment model, fundamental diagrams need to be defined for all links in the network. Furthermore, because the assignment model defines the relationship between the demand in OD matrix and link flows, the OD matrices must be recalibrated for use with the new assignment model.

2.1. Assignment model: STAQ

STAQ is a quasi-dynamic traffic assignment model that has been developed to support transport policy development and planning in situations where both static and dynamic assignment models may fail: strategic applications on large-scale congested networks. It does so by combining favorable properties from static traffic assignment (STA) and dynamic traffic assignment (DTA) models whilst maintaining the theoretical foundation of traffic flow theory.

The model strictly obeys link capacity constraints, and therefore explicitly captures flow metering and queue formation due to congestion (just like DTA models do), but assumes stationary demand during a single time period (e.g. a whole peak hour, just like STA models do) and is therefore much more scalable and mathematically tractable. Furthermore, the model has proven to converge to the required level and does not need any more input data than a STA model does. STAQ is implemented as a propagation model within the StreamLine framework in OmniTRANS transport planning software where it is intended to be used for large scale urban transport models containing both freeways as well as urban road sections.

The model uses any concave, two regime fundamental diagram for the relation between speed, flow and density on the link level, but in this study we use the quadratic linear diagram (QL) from Bliemer et al., 2014 (Figure 1). To describe interaction of flows on nodes the explicit node model from Tampère et al., 2011 is used, because it complies to a set of seven requirements for first order macroscopic node models described in the same paper. One of these requirements is that the node model should comply with local supply constraints, which is the very reason that STAQ obeys strict link capacity constraints. The node model can be extended with an additional junction modelling component, taking into account capacity and delay effects on the level of turning movement as a result of traffic rules, geometry and/or signal schemes on the junction. In this study, junction modelling is applied on all 408 intersections adjoined to on- and off-ramps to the motorways.

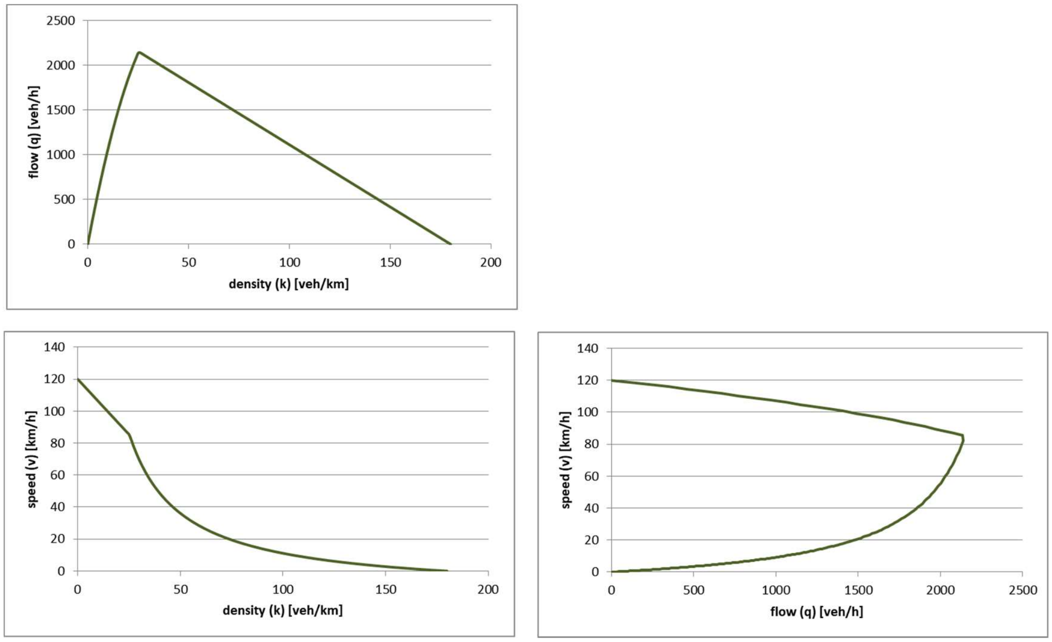


Figure 1: Quadratic – Linear fundamental diagram for a link with capacity: 2150 veh/h, free flow speed: 120 km/h, critical speed: 90 km/h, jam density: 180 veh/km.

The assignment model can be used with different route choice models, but in this study the multinomial logit (MNL) model is used with scale parameters set to one over 14% of the minimal route cost of the considered OD pair. This normalization to the minimal route cost makes the route choice model scale-invariant, meaning that it is only sensitive to the ratio of different route costs, not their absolute values. STAQ is a multi-user class assignment, where each class has its own route choice parameters, free flow speed and set of network restrictions. Note that the model algorithm is not described here; the interested reader is referred to section 4 of Bliemer et al (2013).

2.2. Network preparation

To define the fundamental diagram for each link, its free flow speed, critical speed, capacity and jam density need to be set. Prior values for free flow speed and capacity where taken from the old assignment model, whereas critical speed was set by expert judgement to values shown in Table 1. Jam density was set to 180 veh/km for all links.

free flow speed	critical speed
>=100	85
>=80	75
<80	93.75% of freeflow speed

Table 1: expert judgement settings for critical speed

For the junction modelling component, the geometry of 408 intersections (Figure 2) was defined using 360 degree camera footage. Intersections originally digitized as an ‘expanded node’ (a combination of several links and nodes representing one junction) where merged back into a single node to prevent the formation of unrealistic gridlock due to blocking back within the expanded node. Furthermore prohibitions on 420 turning movements where defined (mainly on adjacent off and onramps).

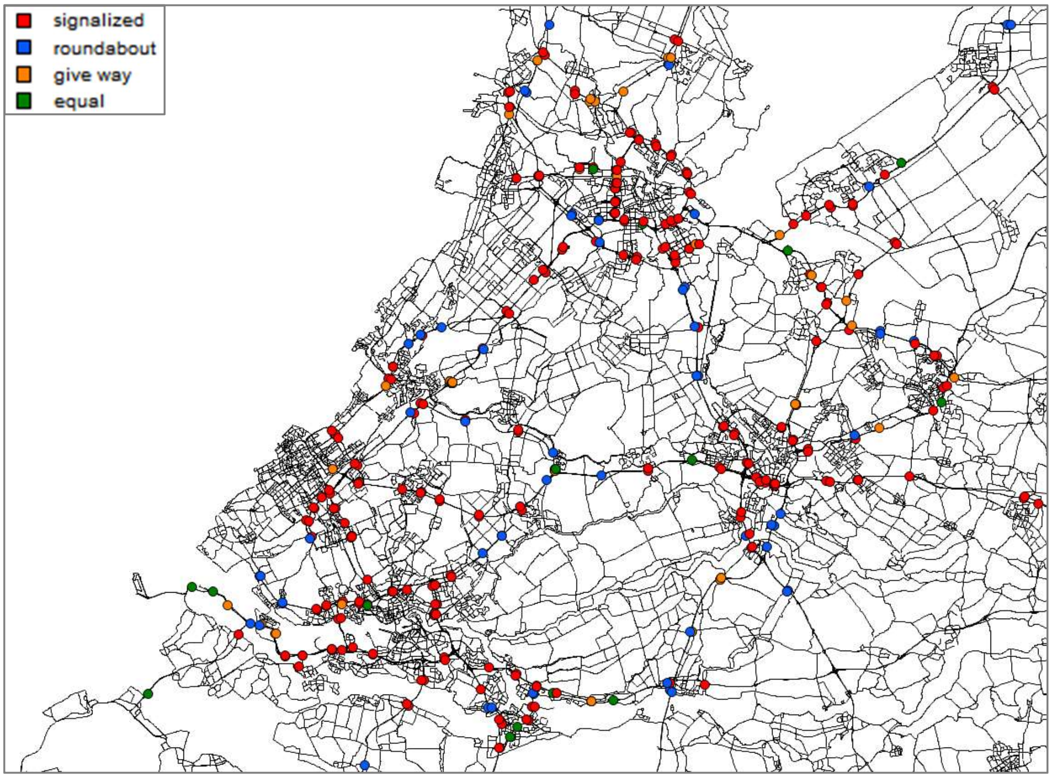


Figure 2: network with locations of defined intersections

On some motorway sections, capacity refinements are needed when in reality the effective capacity is structurally lower than the theoretical link capacity. This mostly occurs on merges, weaving sections, highway intersections and slip lanes. In this study on the NRM-west network, the capacity was decreased on 324 weaving sections using the Dutch equivalent of the highway capacity manual (Rijkswaterstaat, 2015) to calculate the capacity reduction as a function of the length and configuration of the weaving section and the percentage weaving traffic (Figure 3).

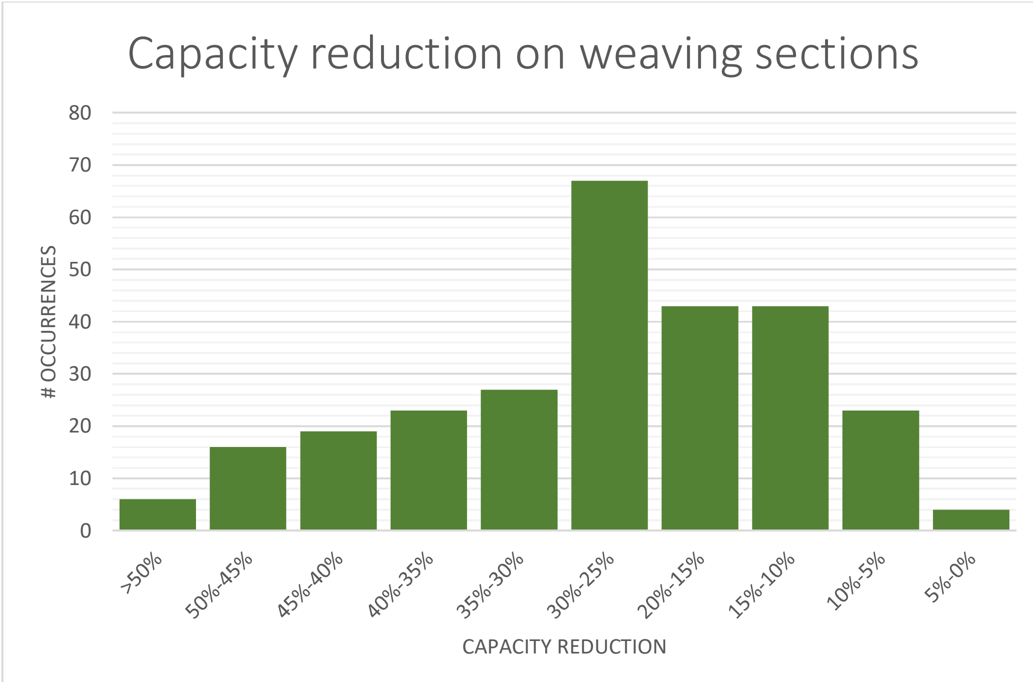


Figure 3: capacity reduction on weaving sections

2.3. Matrix estimation: concept

The (travel demand) matrix estimation problem is a bi-level optimization problem where in the upper level differences between observed and modelled link flows, and differences between the trip length distribution, trip productions and trip attractions between prior and estimated OD matrices are minimized, while in the lower level the traffic assignment problem is solved using a traffic assignment model (Figure 4). Although a bi-level problem corresponds to a Stackelberg game, most matrix estimation software threat it as a Cournot-Nash game and try to solve it by alternatingly solving the lower and upper level problem.

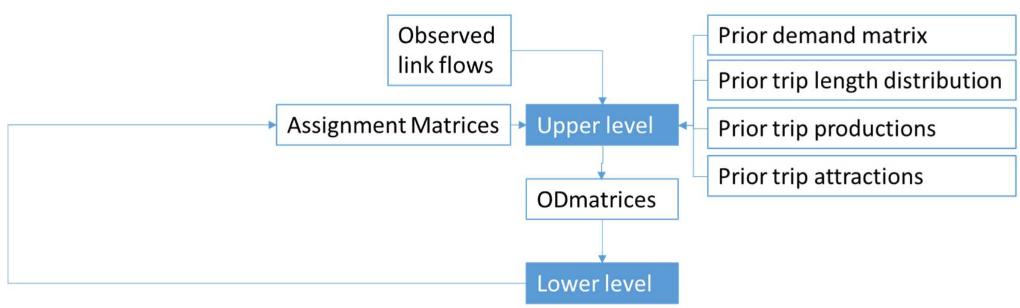


Figure 4: general matrix estimation framework

The lower level uses the OD demand matrix from the upper level and the assignment model to determine the relationship between travel demand on OD-level and modelled flows on link level. For each observed link, the lower level outputs an assignment matrix which, for each OD-pair, contains the proportion of its demand that contributes to the modelled flow on the considered link. Note that when multiplied by the ODmatrix, this matrix contains all traffic that uses the considered link. We shall therefore refer to values in assignment matrices as proportion factors.

The upper level is merely a solver that is applied to minimize differences between observed and modelled link flows by changing the demand of relevant OD pairs in the demand matrix. It uses the assignment matrices to determine the set of relevant OD pairs for each of the observed links. The upper level outputs an updated OD-matrix. In most solvers objective function components and/or constraints can be added to the optimization problem. Mostly these are used to incorporate information on trip distribution and/or trip ends into the estimation.

2.4. Upper level implementation: AVVMAT solver

Since the implementation of a different assignment model in the LMS/NRM methodology implies a lot of (potential) side effects to the model system as a whole, we choose to not also change the matrix estimation software. Instead, we use the current matrix estimation software AVVMAT and preprocess its inputs in such a way that it is compatible with the strict capacity constraints of the assignment method. AVVMAT is based on the Combined Calibration matrix calibration program develop by Hague Consulting Group in the 1990's. AVVMAT assumes a multiplicative model in which each matrix cell is a function of its initial value and a set of parameters (count, trip ends, trip length class, etc.). Furthermore AVVMAT assumes that the parameters are statistical of nature and therefor have a level of reliability. AVVMAT assumes a Poison distribution. Lindveld, 2006 describes the derivation and implementation of the AVVMAT OD matrix estimator in more detail.

2.5. Lower level implementation: STAQ based assignment matrices

In STA models, travel demand is described by a single OD matrix per class containing its stationary (average, peak, n^{th} percentile) travel demand between all origins-destination pairs in the network during the study period. In STA models, all travel demand in the OD matrix will arrive at its destination by definition. This means that in the STA context, any proportion factors in the assignment matrices below 1.0 are due to spatial distribution of demand over different routes and are to be interpreted as route choice probabilities.

In STAQ, the strict link capacity constraints and resulting congestion effects demand a more concise definition of travel demand regarding the time dimension. We define it as the demand that chooses to *depart* in the study period, no matter whether it reaches its destination within the study period. This means that, in the STAQ context, assignment matrices may contain proportion factors below 1.0 not only as a result of spatial distribution (route choice), but also as a result of temporal distribution of demand (flow metering by upstream bottlenecks and/or spillback of a downstream bottleneck).

The values in an assignment matrix generated with STAQ can be calculated by multiplying the spatial (route) proportion factor of the OD pair with any temporal (bottleneck) proportion factors that are encountered when traversing the route from origin to the considered link and then summing these proportion factors over any routes on the OD-pair that use the considered link. Both types of proportion factors are explicitly calculated within any STAQ assignment and can be stored on route and turning movement level respectively to be used for construction of assignment matrices.

2.6. Matrix estimation with STAQ and AVVMAT

For matrix estimation, the difference between route and bottleneck proportion factors is important, because whenever a bottleneck proportion factor is encountered, the capacity of the bottleneck causing it will dictate the amount of flow that can pass. This means that for all observed links downstream of an active bottleneck, the flow from that OD pair is insensitive to changes in the demand on the OD pair. Instead, as long as the bottleneck remains active, any change in OD demand will only result in a change of the corresponding bottleneck proportion factor.

This is something that is *not* accounted for in AVVMAT or any other matrix estimation procedures for static traffic assignment models. These procedures do not distinguish between bottleneck and route proportion factors and treat all values in the assignment matrix as route proportion factors. This means that such software is not able to correctly calibrate to flows observed on links downstream from active bottleneck(s) because it will use all OD pairs that use the observed link, even when the upstream bottleneck has rendered them insensitive to the observed link.

Therefore, in this study, any insensitive OD-pairs are filtered from the assignment matrices by setting all cells that have an active bottleneck proportion factor associated to it to zero. Recall that each observed link has its own assignment matrix, such that OD pairs can be sensitive to one observed link but insensitive to another observed link (further downstream) at the same time.

Finally, by definition, all OD pairs are insensitive to links containing a queue in front of a downstream bottleneck, since flow on these links is dictated by the capacity of the downstream bottleneck as long as the link is in spillback state. In such situations the observed flow cannot be used to calibrate OD-demand. Therefore, in this study we discard any count locations observed in queues from the assignment matrices as these do not contain any information about OD-demand.

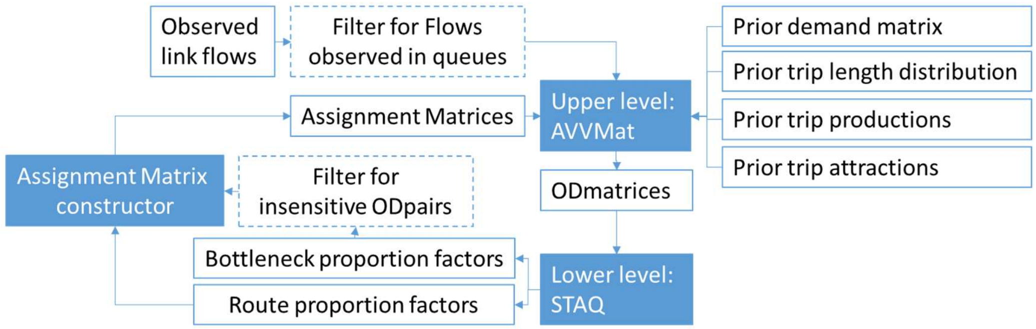


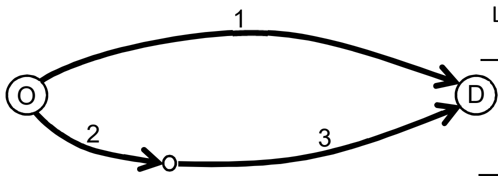
Figure 5: Matrix estimation framework applied in this project

Note that in the current matrix estimation procedure for NRM/LMS calibration no filtering on insensitive OD pairs is taking place. Instead both calibration and evaluation make use of 'desired flow' (in Dutch: 'wensvraag') values for count locations that are suspected to be influenced by upstream bottlenecks. These desired flow values are estimated based on the observed flow values using the 'Tonenmethodiek' (Transpute, 2003) but are hard to validate since the true desired flow cannot be measured. Therefore, the filter for insensitive OD pairs is an important innovation compared to the current matrix estimation procedure for NRM/LMS, because it removes the use of the 'desired flow' concept and replaces it with direct usage of observed count values (even when influenced by upstream bottlenecks) for both calibration and evaluation.

2.7. Handling sensitivities of the route choice and node models in STAQ

Note that the content of assignment matrices is conditional to the level of demand in the OD-matrices that were used by the traffic assignment model to generate them. Any changes to the demand matrices by the solver in the upper level may influence route choice and the state (active / inactive) and severity of potential bottlenecks. This means that (1) the required changes in demand should be kept to a minimum which requires a prior matrix with sufficient quality; and (2) assignment matrices might need updating during the optimization when changes in demand become too large. The combined effect is that the extent to which assignment matrices need updating depends on the required changes in demand and the sensitivities of the route choice model (for the route proportion factors) and the node model (for the bottleneck proportion factors).

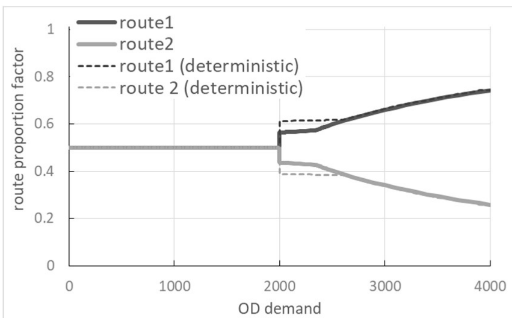
With respect to the sensitivity of the route choice model, recall that we assume a perception error term for route cost yielding a scale parameter of 14% of the max route cost for the considered ODpair. This error term reduces the sensitivity of the route choice model and contributes to the continuity of the relationship between OD demand and route proportion factors. This is demonstrated using STAQ equilibrium assignments on the test network displayed in Figure 6. Both routes in this network have equal route cost in free flow conditions. However, the lower route contains a bottleneck of 1000 veh/h which means that it becomes active when OD demand is greater than 2000 veh/h, diverting demand to the upper route.



Link #	Length (l) [km]	Free speed (v) [km/h]	Capacity (C) [veh/h]
1	10	120	2000
2	4	120	2000
3	6	120	1000

Figure 6: test network with one OD-pair and two routes

The (continuous lines) in the left graph in Figure 7 shows the relationship between OD demand and route proportion factors under equilibrium conditions for this network using the MNL route choice model with a scale parameter of 14% of the minimum route cost. To show to what extent the error term enforces the continuity of the relationship between OD demand and route proportion factors, the results of a (quasi-) deterministic route choice model (i.e. very large scale parameter) is also added (dashed lines). Comparing the results of these route choice models, it becomes clear that the error term greatly improves the continuity of the relationship, but a discontinuity remains.



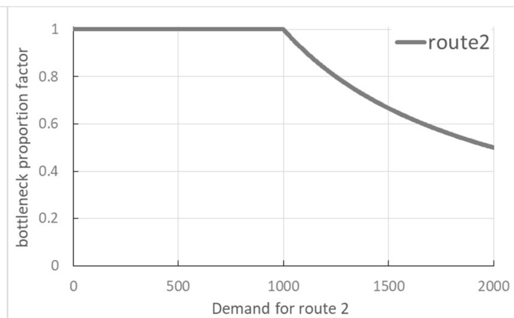


Figure 7: relationship between OD demand and route proportion factors(left); relationship between route demand and bottleneck proportion factors (right).

With respect to the sensitivity of the node model, recall that the model from Tampère et al., 2011 was chosen because, alongside other reasons, it obeys strict link capacity constraints. For this reason, the node model implies a discontinuity in the relationship between OD demand and bottleneck proportion factors whenever a demand change causes a bottleneck to switch from an inactive to an active state or vice versa. This discontinuity is clearly visible when looking at the relation between the demand for route 2 and the bottleneck proportion factor of the node on route 2 between links 2 and 3 (this is the only potential bottleneck in the network). Whenever demand for route 2 exceeds 1000 (this is exactly when OD demand is 2000), the bottleneck becomes active and discontinuity occurs.

In our matrix estimation context, an update of the assignment matrices for all OD pairs with routes using this bottleneck would be necessary, since all downstream count locations should be added or filtered from the assignment matrix as described in 2.6. Furthermore, all (gradient approximation) calculations done so far by the upper level with respect to these OD pairs are now useless, since they are no longer valid after the state-change of the (potential) bottleneck. Doing so would practically mean starting over the matrix estimation process with an altered prior matrix, causing unnecessary bias from the original prior matrix, wasted calculation time and probably non-convergence of the bi-level optimization problem as a whole.

The issue described in this section is present in all matrix estimation methods using an assignment model with strict capacity constraints. It has been described before in the context of matrix estimation using DTA models by Frederix, 2012 who referred to it as "*Non-convexity* [of the upper level objective function] *due to congestion dynamics"*. Frederix suggests that transitions between traffic regimes during matrix estimation should be avoided at all times, meaning that assignment of the prior demand matrix should yield the correct state for all potential bottlenecks and this state should be maintained during matrix estimation. These suggestions are operationalized within in this project using methods that will be described in sections 0 and 3.5.

3. PRELIMINARY RESULTS

This section describes results of matrix estimation for the PM peak period using STAQ and AVVMAT on the NRM-West with base year 2014. The NRM-west is a strategic transport model system containing 3.392 centroids, some 130.000 links and around 95.000 nodes. In this project, geometry of 408 nodes was added to apply junction modelling on them (section 2.2).
Because at the time of writing, the project is still ongoing, these are preliminary results. Final results are expected to be better, since improvements to the matrix estimation methodology and its input are still being made. Furthermore, estimation results for the AM peak and off-peak periods are omitted as these have not been run with the latest methodology and input values yet.

3.1. Evaluation framework

To assess the quality of the proposed methodology, the LMS/NRM evaluation framework that was also applied to the last regular matrix estimation project (Joksimovic and van Grol, 2016) is used. Some changes to the framework where made to reflect the goals and nature of this project (a test case for modelling improvements to the LMS/NRM). The most important changes to the framework are:

- The total number of vehicle loss hours in comparison with observed vehicle loss hours from van Veluwen and de Vries, 2015 is added to emphasize the importance of accurate modelled travel times.
- Observed count values (instead of estimated values for desired flow) are compared to modelled values (instead of a modelled equivalence of desired flow); this is a direct result of the chosen matrix estimation method described in 2.6 and 2.7)
- The level of convergence of the assignment is now added as a criterion (the duality gap should be lower than 5E-04; the stop criterion used to be a fixed number of iterations). This is expected to greatly improve stability of model outcomes.

In the remainder of this section, for the sake of brevity, only a summary of the evaluation framework will be analyzed. The following indicators are included in the summary:

- With respect to the OD matrices, the relative differences between the number of trips, average trip length and sum over absolute differences per trip length bin in the evaluated OD matrix and observed data from OViN 2014 (CBS, 2014).
- With respect to the assignment results, the percentage of primary congestion locations modelled, the number of iteration to converge to a duality gap value below 5E-04, the percentage of observed routes with a difference in travel time less than 20% and the percentages of count locations with normalized T-values[1] below 2.5 split up by mode and link type (motorway vs other roads).

3.2. Evaluation of assignment results using the prior demand matrices

The prior demand matrices where estimated using the demand model of LMS/NRM (Significance, 2017) which uses choice models estimated on data from the Dutch national travel diary (MON) surveys 2007-2009 (SCP, 2009). Because data from its predecessor survey (OViN) of 2014 (CBS, 2014) is used for evaluation of the OD matrices, the matrices estimated by the LMS/NRM are corrected to better match OViN 2014. Following Joksimovic and van Grol, 2016, these corrected matrices are used as prior demand matrices for matrix estimation.

	difference in:	prior
demand matrices	number of trips	-1%
	average trip length	0%
	absolute sum over bin differences	0%
assignment results	%primary congestion locations	9%
	number of iterations to convergence	8
	route travel time differences <20%	82%
	T-values flow <2.5 car, motorways	22%
	T-values flow <2.5 freight, motorways	17%
	T-values flow <2.5 car, other roads	38%
	T-values flow <2.5 freight, other roads	33%

Table 2: evaluation of results using the prior demand matrices (summarized)

Table 2 displays the summarized evaluation results using these prior demand matrices. The first three rows in the table show that the demand matrices fit almost perfectly to the OViN 2014, which is to be expected as they are corrected using this very dataset. Only 9% of the observed bottleneck locations is modelled, indicating that the demand is too low for the majority of bottleneck locations. The low number of iterations needed for convergence (8), indicates that there is relative little congestion in the network. This is confirmed when the assignment results are graphically compared with the observed congestion locations (Figure 8): the relative speeds in this figure are mostly high (green)

[1] The T-value used here is not to be confused with the statistical student-t test. The T-value used here is defined as $T = \ln((c-v)^2/\min(c,v))$, where c: observed link flow and v: modelled link flow

throughout the entire network, whereas they should be low (orange or red) upstream from bottleneck locations.

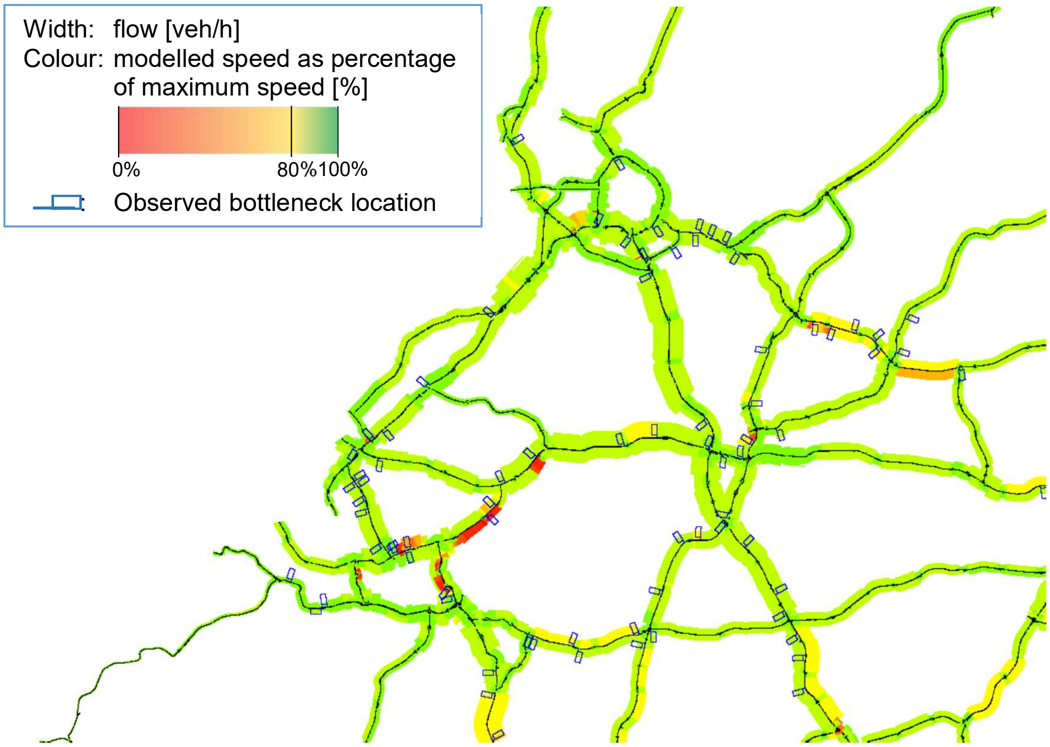


Figure 8: assignment results prior demand matrices and observed bottleneck locations

Based on these observations, we conclude that the majority of the modelled link flows, number of active bottlenecks and route travel times are much lower than the observed values. In other words, according to the observed data, the prior demand matrices substantially underestimate the true demand in peak periods and thus number of active bottlenecks. Note that the indicator for route travel time differences<20% seems to show a good fit, but further investigation shows that this is caused an over representation of uncongested routes in the dataset.

3.3. Enrichment of demand matrices using congestion patterns

Because assignment of the prior demand matrices yields almost no active bottlenecks (section 3.2), and because no state changes of (potential) bottlenecks should occur during matrix estimation (section 2.7), within the present project, a method was developed to enrich the prior demand matrix to minimize the number of under- or over-estimated active bottlenecks by the assignment. Because assignment of the prior demand matrices only showed underestimations, the emphasis in this paper lays almost solely on how to add demand, but the same principles could be used to remove demand in case of prior demand matrices that over-estimate the number of active bottlenecks.

The enrichment method described in this section is applied to the prior demand matrices beforehand the actual matrix estimation (described in 2.6). The method starts by identification of congestion patterns from observed data. In this project, data gathered for the annual congestion-location rankings from VID (2014) is used as a basis. For each observed active bottleneck location, this dataset describes the location of the head of the queue and the gravity of the congestion caused by the bottleneck. This gravity (in Dutch: 'filezwaarte') is expressed as the number of minutes that congestion occurred multiplied by the length of the queue for each respective minute, summed over the year. This data was derived from observed speeds from loop detectors data and by direct observations from the police, road authorities and road guards.

To maintain consistency with the definition of the study period of NRM-west model used (the annual average business day in 2014) congestion during weekends and holidays and congestion purely caused by long-term roadworks was removed from the dataset. Because the enrichment is to be applied only to the peak periods, the dataset was split into separate datasets for the AM and PM periods of an average business day in 2014 and then ranked by gravity separately. This resulted in 79 active bottleneck locations in the PM peak (results from AM peak are pending). Using a rule of thumb, the annual gravities where translated into gravities per peak period.

The enrichment process follows the approach depicted in Figure 5, but its input has been altered using the two steps displayed in Figure 9 to allow for estimation on congestion patterns instead of observed link flows.

In the first step, for each bottleneck location, its gravity is converted into an excess demand within an average peak period using a simple point queue model. For the assignment model to reproduce the observed congestion patterns, the flow that wants to make use of the road segment causing a bottleneck (the bottleneck link) should be equal to the capacity of that bottleneck link plus the calculated excess demand. Thus, using the point queue model and capacities of the bottleneck links the observed congestion patterns can be translated into link demands that are valid for the link directly upstream from the bottleneck.

In the second step, using the selection of bottleneck links derived from the observed congestion patterns, assignment matrices can be generated using the method described in 2.5. From these assignment matrices, the routes that are constrained by upstream bottlenecks is known. Because these routes cannot be used to influence the flow on the bottleneck link, they will be filtered from the assignment matrices before entering AVVMAT. However, a proportion of the demand for these routes still reaches these links and thus accounts for a part of the link flow. Therefore, the link demands derived from the congestion patterns are reduced by the flow on routes constrained by upstream bottlenecks to attain virtual count values that will be used for the enrichment.

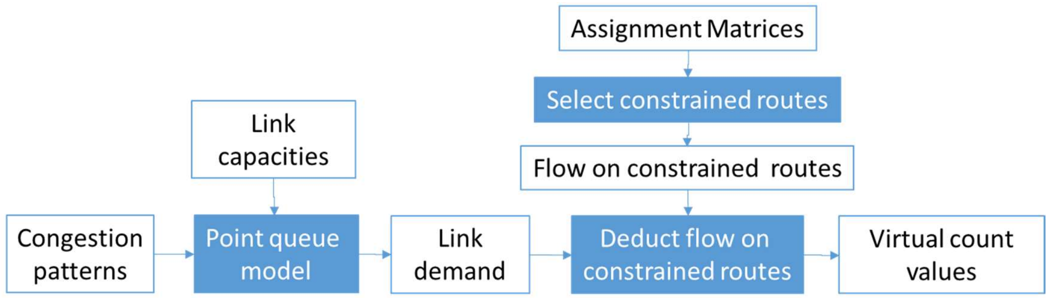


Figure 9: derivation of virtual count values

Using these virtual count values assignment matrices filtered for constrained routes, the solver in AVVMAT (section 2.3) can be used to perform matrix estimation on congestion patterns. Constraints on trip length distribution, trip production and trip attraction from OViN are taken into account during enrichment, in the same way as during normal matrix estimation.

Note that, because in this project the prior demand matrices substantially underestimate the level of congestion, during the process, the assignment matrices need to be updated several times (the feedback loop between lower and upper level in Figure 5) to allow the lower level to update route and bottleneck proportion factors and to filter out OD pairs accordingly. Several tests led to an incremental approach in which the feedback loop was run 5 times. In the first three runs, only a quarter, half and three quarters of the enrichment effect was added to the prior matrix before generating and filtering new assignment matrices; the fourth and fifth run directly use the enriched demand from the previous run. This way, OD-pairs that cause activation of bottlenecks in a later increment can still be used for the enrichment in previous increments. This leads to better a better distribution of enrichment effects over OD-pairs and less unintended upstream bottleneck activations. The main purpose of the fifth run is to allow the route choice model to settle in further.

3.4. Evaluation of assignment results using the enriched demand matrices

Table 3 displays the summarized evaluation results using demand matrices enriched using the method described in 0. Enrichment was done using 79 observed bottleneck locations, all 288 trip length distribution constraints and all 6748 trip end constraints. Relative weights where set at 90% for bottleneck locations, 75% on trip end constraints and 100% on trip length distribution constraints. The first three rows in the table show that the demand matrices still fit well to the OViN 2014, which is caused by inclusion of trip length distribution and trip end constraints, and because demand on only a relatively limited number of OD pairs is changed during the enrichment.

	difference in:	prior	enriched
demand matrices	number of trips	-1%	-1%
	average trip length	0%	1%
	absolute sum over bin differences	0%	1%
assignment results	%primary congestion locations	9%	77%
	number of iterations to convergence	8	15
	route travel time differences <20%	82%	52%
	T-values flow <2.5 car, motorways	22%	15%
	T-values flow <2.5 freight, motorways	17%	12%
	T-values flow <2.5 car, other roads	38%	27%
	T-values flow <2.5 freight, other roads	33%	24%

Table 3: evaluation of results using the bottleneck enriched demand matrices (summarized)

After enrichment, 77% of the observed bottleneck locations is modelled, which is a big improvement over the initial 9%. The number of iterations needed for convergence nearly doubled to 15, reflecting the increase of congestion in the network. The graphical comparison with observed congestion locations (Figure 10) indicates which bottlenecks where activated by the enrichment. From this figure, it becomes clear that mainly the bottleneck locations on the ring road Amsterdam (upper north west part of the figure) are missing. At the time of writing, the cause for these missing bottleneck locations was not analyzed yet, but it must be related to upstream bottlenecks preventing demand to reach the locations on the ring road and/or (trip length distribution and trip end) constraints in AVVMAT.
T-values on count locations have become worse which makes sense considering that these are not included in the enrichment method. The demand matrix estimation process should take care of these differences.

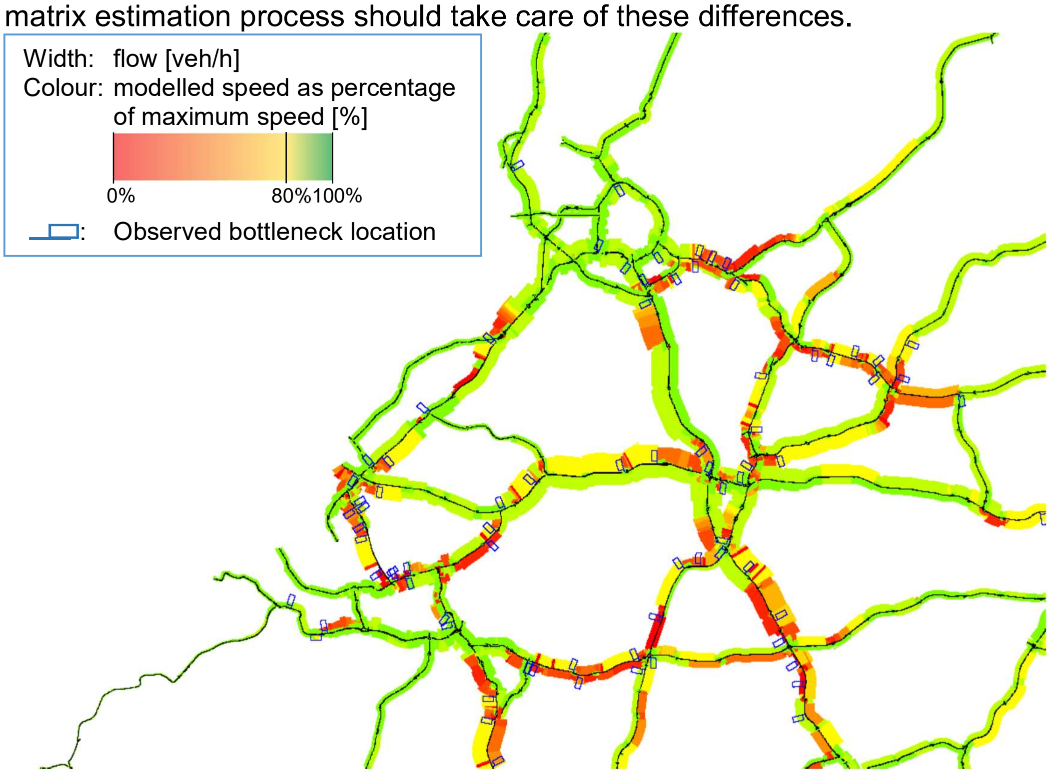


Figure 11: assignment results enriched demand matrices and observed congestion locations

3.5. Evaluation of assignment results using estimated matrices

Because at the time of writing the enrichment results are not yet sufficient satisfactory (it has not yet been explained why 23% of bottleneck locations are still missing and why travel times seem to have worsened) only two first estimation attempts where run based on the enrichment results from section 3.4. More attempts based on a more recent enrichment run where done afterwards but these produced worse results and are, for the sake of brevity, omitted from this paper. Given the above, the results reported in this section are still experimental of nature and further research and test runs (for both the enrichment and estimation) are needed to improve them.

In both considered test runs, matrix estimation was done using 2981 count values across the study and influence area of the model. Earlier estimation attempts led to the exclusion of trip length distribution constraints to increase AVVMATs search space and to the inclusion of bottleneck locations to retain the results from the enrichment. In the first run, all 6784 trip end constraints where used and relative weights where set at 90% for both bottleneck locations and traffic counts, whereas the relative weight on trip end constraints remained 75%. In the second run, trip end constraints were dropped and relative weights on congestion locations and traffic counts were set at 2.5% and 90% respectively in an attempt to better preserve the active bottleneck locations from the enrichment process. Table 4 summarizes the differences between the two runs and compares their settings with the enrichment procedure.

Constraints/inputs (quantities between brackets)	Enrichment	Estimation	
		Attempt #1	Attempt #2
Trip lenght distribution constraints (288)	100%	-	-
Trip end constraints (6784)	75%	75%	-
Congestion locations (79)	90%	90%	100%
Traffic counts (2981)	-	90%	2.5%

Table 4: relative weights used in enrichment run and estimation attempts

Table 5

Table 5: evaluation of results using estimated demand matrices (summarized)

summarizes results of both estimation attempts. For easy comparison the results from the prior and enriched demand matrices shown earlier in Table 3 are also included.

Considering estimation attempt #1, differences in demand matrices increase but are still acceptable. The number of congestion locations decreases to 51%, indicating that there are inconsistencies between congestion locations and count locations and/or trip end constraints. This problem might (partly) be circumvented by decreasing the weights on the latter two. Route travel times have improved compared to the enriched results, but area still below the prior results, this is yet to be explained. T-values have also improved but are still unsatisfactory.

Considering estimation attempt #2, the number of congestion locations is retained, but at the cost of nearly all other indicators. This is a clear indication, that there are inconsistencies in the input. Especially route travel time differences and congestion locations appear to be contradicting, whereas it is hypothesized that a realistic congestion pattern is a requirement for realistic route travel times. A similar pattern seems to exist for count values and congestion locations, albeit less distinct.

	difference in:	prior	enriched	estimated 1	estimated 2
demand matrices	number of trips	-1%	-1%	9%	13%
	average trip length	0%	1%	6%	7%
	absolute sum over bin differences	0%	1%	6%	6%
assignment results	%primary congestion locations	9%	77%	51%	66%
	number of iterations to convergence	8	15	16	15
	route travel time differences <20%	82%	52%	63%	36%
	T-values flow <2.5 car, motorways	22%	15%	43%	42%
	T-values flow <2.5 freight, motorways	17%	12%	64%	60%
	T-values flow <2.5 car, other roads	38%	27%	52%	37%
	T-values flow <2.5 freight, other roads	33%	24%	24%	24%

Table 5: evaluation of results using estimated demand matrices (summarized)

4. CONCLUSIONS AND RECOMMENDATIONS

This paper described the use of an alternative assignment and calibration procedure combined with synthetic matrices of the Netherlands Regional Model to better fit with floating car data on speed and route travel times. The main focus was to improve outcomes from the assignment model whilst maintaining (or improving) its ability to reach equilibrium. To do so, the assignment model was replaced by STAQ, the estimation method and process where altered accordingly and test runs on the NRM-west where executed to analyze the effects.

On the (network) supply side, fundamental diagrams where defined for all links in the network, and junction geometry was added to all 408 intersections adjoined to on- and off-ramps to the motorways within the study area. Furthermore, the theoretical capacity was corrected on 324 weaving sections using percentages of weaving traffic derived from the prior demand matrices.

On the demand side, the OD matrices where recalibrated using the regular LMS/NRM matrix estimation software: AVVMAT, using 2981 count values while taking into account 6784 trip end and 288 trip length distribution constraints. To take the effect of flow metering on downstream links from an active bottleneck into account, any routes that traverse one or more active bottlenecks before reaching a count location where filtered from the corresponding assignment matrix (since the flow rate on a count location is insensitive to changes in demand on such routes).

The filter for insensitive OD pairs is an important innovation compared to the current matrix estimation procedure for NRM/LMS, because it removes the use of the ‘desired flow’ concept and replaces it with direct usage of observed count values (even when influenced by upstream bottlenecks) for both calibration and evaluation.
Sensitivities of the route choice and node models within STAQ were recognized as potential causes for non-convergence of the matrix estimation method. To avoid this problem, no transitions between traffic regimes should occur during matrix estimation, meaning that assignment of the prior demand matrix should yield the correct state for all potential bottlenecks and this state should be maintained during matrix estimation.

Assignment results of the prior demand matrices showed that the majority of the modelled link flows, number of active bottlenecks and route travel times are much lower than the observed values. Therefore, an enrichment method was developed and applied to match observed congestion patterns before the matrix estimation procedure starts. After application of the enrichment procedure, the number of modelled bottlenecks increased from 9% to 77% at the cost of a decreased fit on observed link flows, whereas trip ends and trip distribution differences remained well within the acceptable region.

Two first matrix estimation attempts showed that deviations in trip distribution and trip ends increase but can be retained within acceptable levels. However, serious inconsistencies appear to exist between congestion locations on the one side and route travel times and traffic counts on the other. The cause for these inconsistencies should be researched by looking for inconsistencies in the input data on a level much more detailed than the network-aggregated tables reported in this paper.

In general, this project so far has shown that the methodologies for enrichment and estimation seem to work, but that apparent inconsistencies in the input should be removed. Most important analysis would be:

- to analyze which route travel times are over- and under estimated, to find out what causes the decrease route travel time quality during enrichment on congestion patterns (e.g.: look for low observed travel times on a route that traverses observed congestion locations);
- to look for observed flows that are clearly inconsistent with the gravity and/or location of a bottleneck location situated directly downstream.

Closely related to the first bullet above, with respect to the primary evaluation criterion for route travel times, we recommend to distinguish routes with (substantial) congestion from other routes and/or make use of a lower tolerance for differences on free flow routes (as the travel time differences on these routes are much lower per definition).
Once the inconsistencies are removed sufficiently, probably some tuning of the incremental schema applied, alongside with the weights is needed. Furthermore, inclusion of (a subset of) counts in the refinement and/or inclusion of bottleneck locations in the estimation procedure could be tested to further integrate the refinement and estimation procedures. This would require more

weight-tuning and/or small changes in AVVMAT software to allow for a wider range of weights but could lead to a more consistent and quicker matrix estimation method.

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