Improving a-priori demand estimates transport models using mobile phone data. Rotterdam region case.

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Abstract
Mobile phone data are a rich source to infer all kinds of mobility related information. In this research we present an approach where mobile phone data is used and analysed for enriching the transport model of the region of Rotterdam. In our research we used Call Detail Records (CDR) from one of the 3 mobile phone providers in the Netherlands, facilitating between 30-40% of the Dutch mobile phone usage. This means, by accessing these data we have travel information of about one third of the total Dutch population. No other data source is known that gives travel information at a national scale at this high level. The raw data of one month is processed into basic information which is subsequently translated into OD-information (Origin-Destination) based on several decision rules. This OD information is compared with the traditionally estimated a-priori OD matrix of an operational transport model in the Netherlands and the Dutch yearly national household travel survey. Based on the analysis and assignment results an approach is developed to combine the mobile phone OD-information and a-priori OD matrix using the best of both worlds. Results show a better match of the assignment results of this matrix with the counts indicating a better quality of the matrix.

1. Introduction

Detailed data of individual activities and interactions are currently being collected at an unprecedented spatial and temporal granularity level ranging from the data collection by mobile phones to social media services. These big datasets have a high potential value for monitoring, planning and management of transport systems, however, they are still little used in the transport field in practice thus far. Today, transport planners and engineers rely heavily on transport demand models for their understanding of travel behaviour and effectiveness of infrastructure investments. These models provide quantitative information on current and future travel patterns (e.g., destination and mode choice) and traffic conditions in peak hours [Bliemer et al., 2014, Van Eck et al., 2014]. These models use the same type of data and in the same way as we were able decades ago [Benbow et al., 2008, Joksimovic and Hofman, 2014]. The main basis for these models are travel surveys describing one weekday for each respondent in 'representative' periods when traffic flows are maximal [Ortuzar et al., 2011] and loop detector data used to calibrate the entire model.

There is a big potential in using mobile phone data to improve transport models. Earlier research (Nanni et al., 2013) showed that it is possible to create an origin-destination matrix with mobile phone data in a country with hardly reliable statistics (i.e. Ivory Coast) showing mobility patterns, both nationally and within the capital Abijan. In a similar research for Senegal network optimizations are proposed based on mobility patterns derived from mobile phone data (De Romph, 2015). However, because of the lack of data, the accuracy of the resulting patterns was not or limited evaluated in both cases. Huntsinger and Ward (2015) developed an external trip model using mobile phone data showing promising results compared with household travel survey. Colak et al. (2015) presented a data treatment pipeline that uses mobile phone data and population density to generate trip matrices in two metropolitan areas (i.e. Boston and Rio de Janeiro) showing comparable results with existing information reported in local travel surveys in Boston and existing origin destination matrices in Rio de Janeiro. However, this comparison focused on a highly aggregate comparison and did not compare trip length distribution or possible biases in OD information derived from mobile phone data.

In this research we will investigate the possibilities to enrich an operational transport model in the Netherlands using mobile phone data, combining the strengths of both methods. For this purpose call detail records are used to derive an a-priori OD trip matrix and compared with travel survey data as well as comparing the quality of this a-priori matrix with the operational (and traditional) a-priori matrix using count data. The results are used to determine a promising combination of traditional methods and mobile phone data. In the Section 2 we will provide background information on transport modelling and introduce the operational transport model used of the Rotterdam Region. Section 3 we will describe the mobile phone data used in this research. The analysis of the mobile phone data, including a comparison with household travel surveys is provided in the Section 4. Section 5 will show the enrichment procedure using mobile phone data in combination with the operational transport model and Section 6 the obtained results. This paper will end with conclusions and the next steps for further research in Section 7.

2. Transport modelling

General

Accurate information is a premise for good decision making, as is the case in transportation. Policy makers often rely on information from a transport planning model, because they provide an average picture of the current state (average working day of a current year describing mainly number of trips between zones, used modes and routes, link flows, travel times and congestion problems), prediction of future state and expected effects of policy measures [Mackie, 2010, Mouter, 2014 and Benbow et al. 2008]. Estimations from transport planning models for current as well as predicted state are also input for impact models providing for example information on air quality and noise [Wismans, 2011].

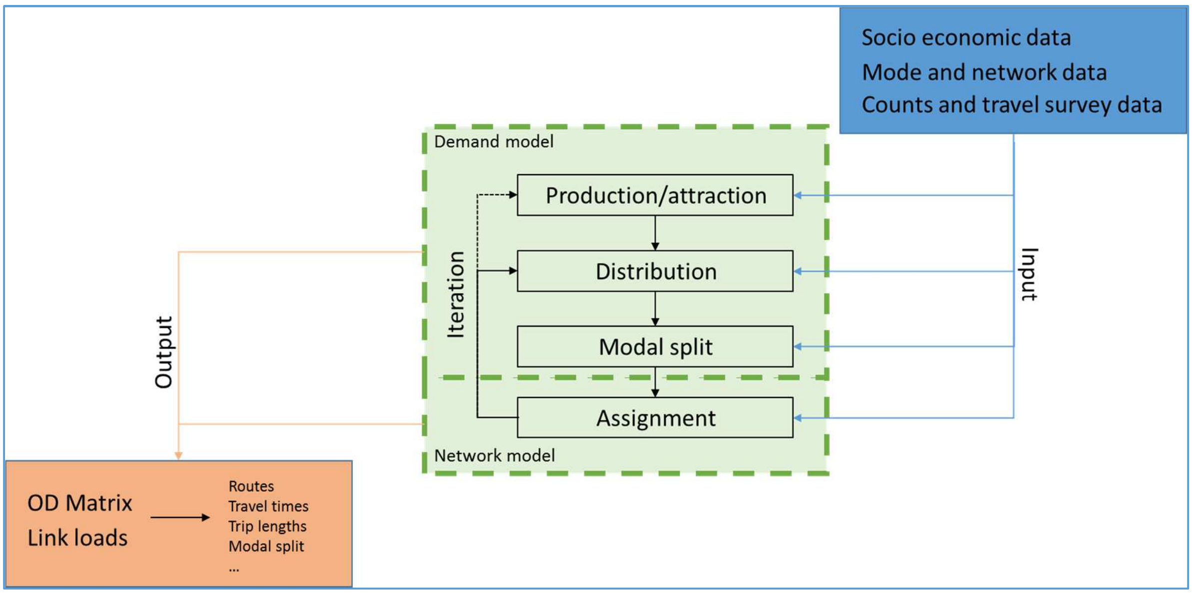


Figure 1. 4-step model

Transport planning models typically estimate demand and assigns this demand on supply of infrastructure estimating route choice and flows on every network link in 4 steps (production/attraction, distribution, modal split and assignment) [Benbow et al. 2008, Bliemer et al. 2014 and Van Eck, 2014]. In the production/attraction step the number of leaving and entering trips per zone are determined. Figure 1 shows an overview of the traditional 4-step model. The distribution step connects the productions and attractions to determine the number of trips between zones, resulting in a total OD matrix. The modes used for these trips is determined in the modal split step resulting in OD matrices per mode. These first three steps are often called the demand model. In the last step these matrices (per mode) are assigned to the network (of the corresponding mode) to determine routes and linkloads using a network model. Because the demand model often uses travel times and equilibrium is assumed, iterations are needed feeding the demand model with assignment results. In practice several steps in the demand model can be combined (e.g. simultaneous distribution modal split step) or extended with additional steps (e.g. departure time choice).

Although transport models need input in the form of measured data, the state of the art models and definitely the state of practice models still focus on an average traffic state and heavily rely on modelling assumptions using the same type of data and in the same way as we were able decades ago. These are mainly stated and revealed preference surveys among a sample of (potential) travellers to estimate and calibrate behavioural models and loop detector counts or incidental field investigations to calibrate the entire model [Joksimovic and Hofman, 2014].

Transport model of Rotterdam Region

In this research we used the transport model of the Rotterdam Region. It is a multi-modal model (Car, trucks, public transport and active modes) distinguishing nearly 6,000 TAZ (Traffic Analysis Zones) using a highly detailed network of the region. The a priori transport model of the Rotterdam region is built using demand patterns and travel characteristics that are determined based on the household travel survey database (OViN). The model is built for the modes vehicles (car and freight), public transport and bike. The model represents an average working day including 2 hour peak periods. Calibration of the synthetic a priori OD-matrices on counts results in the a posteriori OD-matrices. This model is one of the largest operational transport models in the Netherlands and used for many policy decisions. Figure 2 illustrates the modelled loads per mode on part of the network (blue = car, red = truck, green = bicycle and yellow PT).

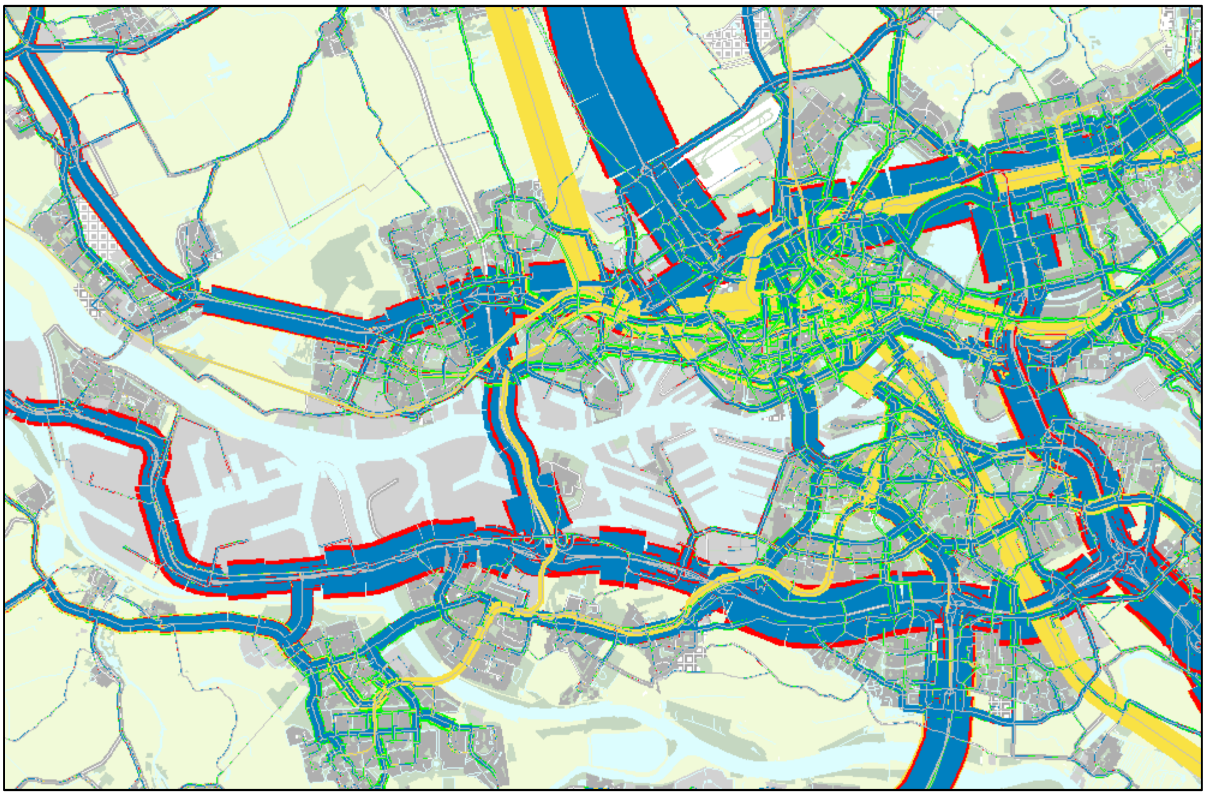


Figure 2. Illustration of transport model Rotterdam Region

Although this model is state of practice, the model is mainly based on the use of traditional data sources to validate and calibrate the model. In addition, the use of a gravity model to connect productions and attractions neglects historically grown strong relations between zones which cannot be properly estimated based on the number of productions and attractions per zone and the skims (i.e. impedance between zones reflected by the generalized costs between these zones). This is also shown in De Romph et al., 2015, in the Senegal case but is also true for the Netherlands. With mobile phone data it is possible to actually measure demand or at least a large sample reflecting this demand which potentially do incorporate these earlier mentioned strong relations between zones. The use of this measured data could result in a transition in demand modelling to a data driven model in which the measured OD matrix forms the basis of the a-priori OD matrix. Furthermore, it introduces the possibility to incorporate day-to-day dynamics instead of focusing on the average work day. However, these measurement are possibly biased introducing new challenges, which need to be addressed (Meppelink et al., to be published). Furthermore, there is a possible mismatch in the level of detail in zone definition needed in the transport model versus possible using mobile phone data. Therefore, we investigate the mobile phone data and the potential to use the derived OD information to enrich the traditional transport model with this information.

3. Mobile phone data set

The mobile phone data used are call detail records (CDR). These are records describing when a mobile phone connected to the network by sending or receiving voice, text, or other data via a provider's network. The records consists of a time stamp, a cell code relating to a cell tower in the network and a one-way hashed id created from a mobile phone number. The privacy of the raw mobile phone data is assured by a rigorous protocol. Firstly the identifying information (phone number) is encrypted. The encrypted information may be saved for one month. In the next month a new encryption is done. In this way the movements of a single device can no longer be recognized than one month. Secondly, there is the 'minimal 16 rule', which means there are no values less than 16 in the data set we use. In case the number of measurements at OD-relation level (Origin-Destination) is less than 16 this value is skipped in the data set. In this way it is impossible to relate information to a single device in small OD-pairs.

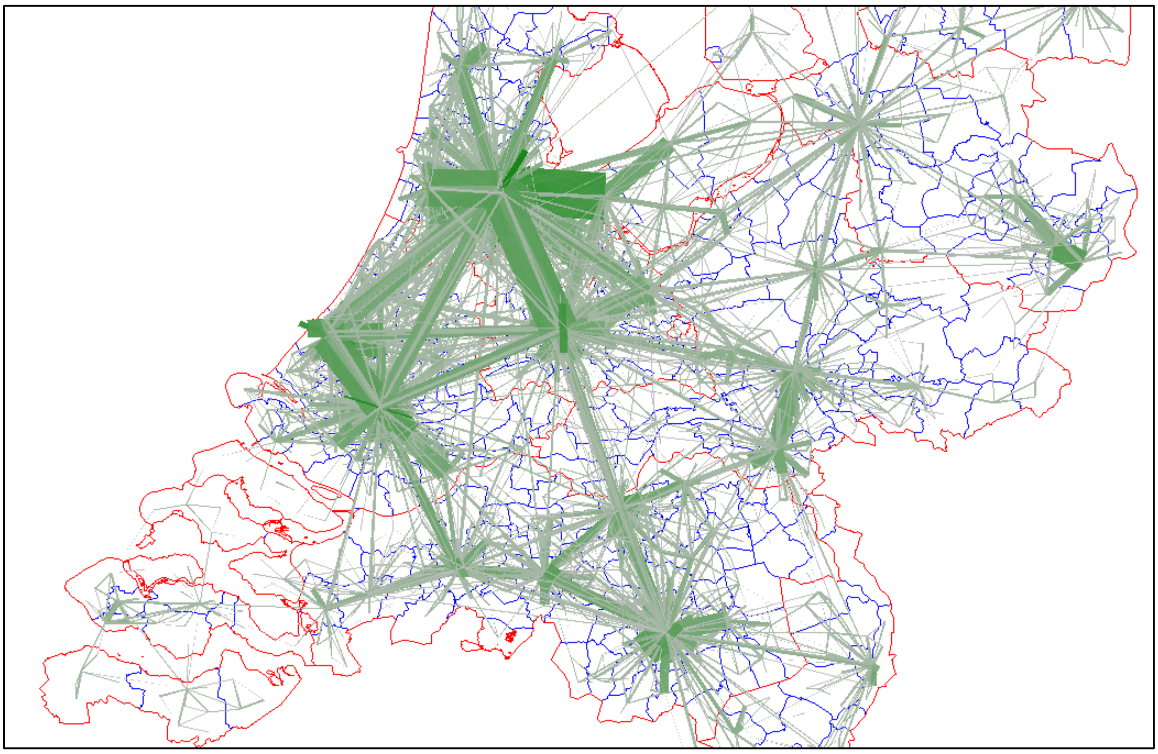


Figure 3. Spatial distribution of trips from mobile phones (data of one single day)

The raw data is processed into basic location information removing noisy data which is subsequently translated into OD-information based on the time ordered stay sequence. A stay is defined when a mobile device is longer than 30 minutes at a certain location. In the query, performed at the data provider behind the firewall, firstly the requested data is selected out of the raw data. Based on the selected period and if needed the time of day the OD-information is gathered and the 'minimal 16 rule' is applied at the end of the query.

In this way we are equipped with OD-information of mobile phone devices (total number of trips) for the Netherlands at the level of cities and village's level for the months of July and November 2014. The data was provided by the data-processing company Mezuro. We started by analysing the first dataset (July 2014) to determine characteristics of the data and in what way we can incorporate this OD-information in transport models. The data of November 2014 is used in the enriching procedure. We used OD-information on working days for a 24 hour period. To minimize the effect of the 'minimal 16 rule' the OD-data of the sum of the working days in this month was provided (instead of a data set for each working day separately). This data set contains more than 1.000.000 of OD-trips.

The Netherlands is split in 1.259 areas for which OD-information of mobile phones is available, where each city or village is a separate zone. This zone definition is the result of the dataset provided. The largest cities in the Netherlands are split in city districts. For example: the city of Rotterdam is divided in 8 districts. In the data no intra-zonal information is available. Therefore, there is a mismatch in zone detail as indicated earlier, which means that we can use the data in the enriching procedure for external trips only similar to Huntsinger and Ward, 2015. In Figure 3 the OD-data of mobile phone data for a single day is presented showing a plausible spatial distribution. The figure shows that most trips are made in the Randstad area (Amsterdam, The Hague, Rotterdam and Utrecht).

4. Data analysis

Figure 4 shows the number of departures per city for 2 weeks in July. The distinction between working days and weekend days (July 12 & 13 et cetera) is clearly present in this figure. Another interesting phenomena that can be detected is the International Four Day Marches in Nijmegen, a huge event with nearly 40.000 participants (and many visitors) that was held on July 15-18.

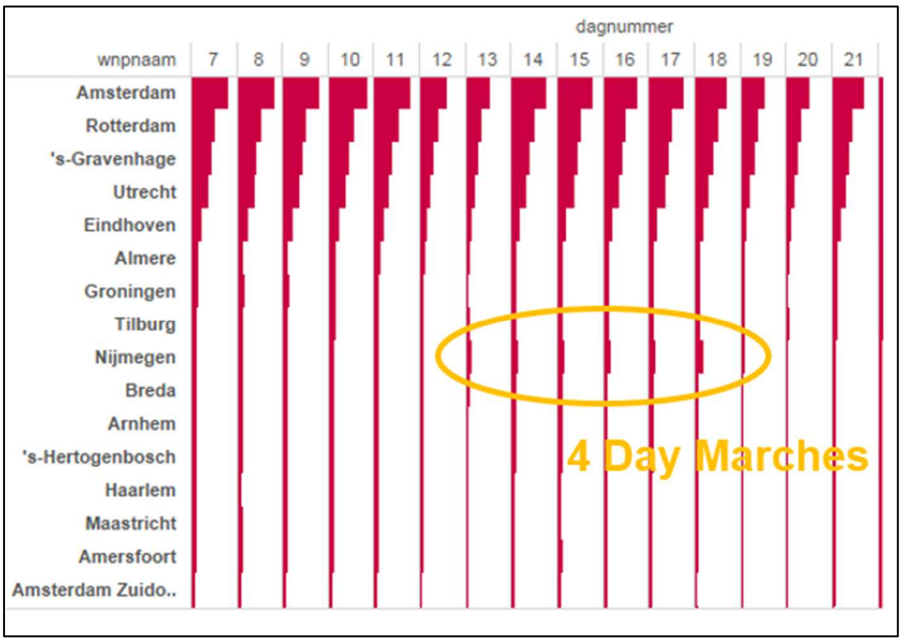


Figure 4. Number of departures per city per day (7-21 July 2014)

Figure 3 shows that the observed trips based on mobile phone data are concentrated between and near cities. Visual analysis of the trips shows that the spatial distribution is generally plausible. Figure 5 shows for example the number of trips originated in the city of Utrecht. As a city in the centre of the Netherlands it shows as expected trips in all directions with plausible stronger relations between other large cities (especially Amsterdam, but also Amersfoort, The Hague and Rotterdam).

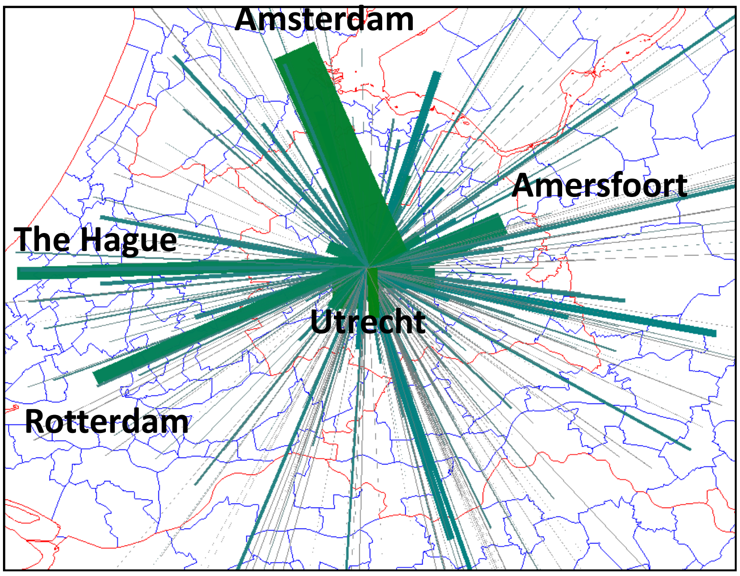


Figure 5. Distribution of trips with origin in the city of Utrecht

Typical relations are also clearly present in the mobile phone data set. For example, Figure 5 shows the distribution of trips with origin in Almere. Once originated as an Amsterdam suburb, nowadays it is the 7th largest city of the Netherlands with about 200.000 inhabitants. Many of them are still very much related to Amsterdam in terms of commuting and family visits. This phenomena is very clear visible in the figure..

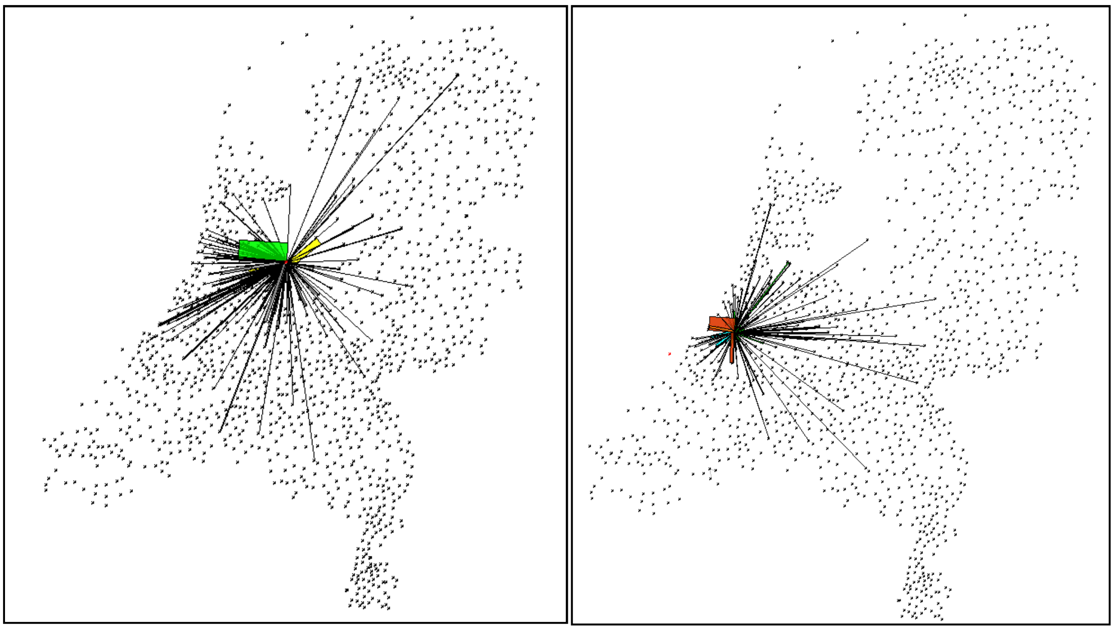
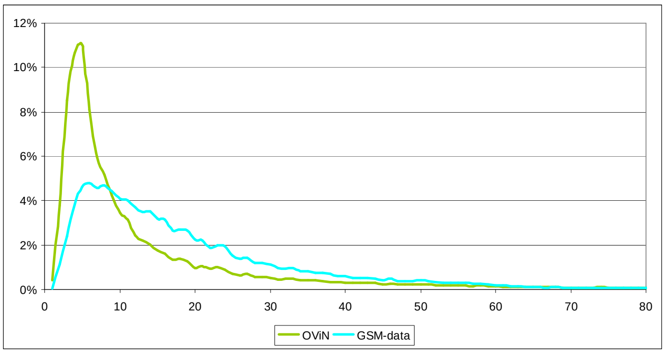


Figure 6. Distribution of trips with origin in the city of Almere (left) and Zoetermeer (right)

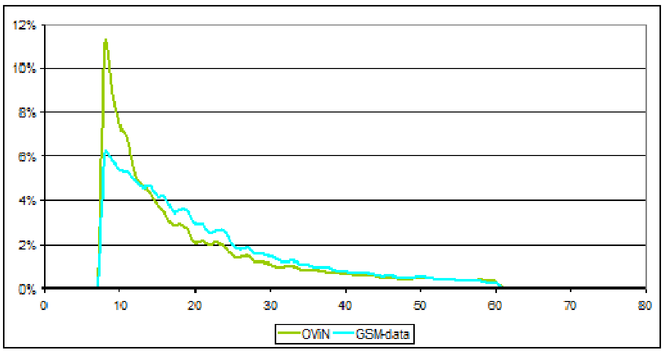
The same phenomena is visible here as Zoetermeer is originated as suburb of The Hague. From historic perspective a lot of commuters living in Zoetermeer work in The Hague, which is clearly present in the mobile phone data. In a traditional transport model it is hard to model these kind of historic relations, which clearly shows the added value of incorporating the mobile phone data in transport modelling. For example, the city of Leiden is also about 15 kilometres (north) of Zoetermeer and in principle a transport would allocate as many trips from Zoetermeer to The Hague as well as to Leiden.

However, the data also shows little long distance trips generated in the Harbour area of Rotterdam, which would be expected given the high number of trucks departing in reality. Although we cannot investigate the raw CDR data it is expected that this can be explained because of the 30 minute criterion and privacy filter of at least 15 trips. The number of truck-trips between a specific origin and destination are likely to be less than 15 in a lot of cases. Taking into account that many trucks will also travel to other countries and the loading and unloading of trucks takes less than 30 minutes on some occasions, it is also possible that some destinations are not identified as a destination. As a result it can be expected that truck trips are underrepresented in the mobile phone data set.

The mobile phone data set contains a large set of approximately one third of the total Dutch population, but is not complete and possibly biased. For this purpose suitable methods are needed to increase the measured trips to absolute values (Meppelink et al., to be published). In this research only the distribution of trips is used, which of course can still be biased. To investigate this we performed a comparison analysis between characteristics of the mobile phone data and the Dutch household travel survey OViN (Onderzoek Verplaatsingen in Nederland) [OViN, 2016]. This survey selects every year an unbiased sample of Dutch households asked to fill in a travel diary for 2 or 3 days. In this diary they report which trips were made in their household, by what mode and what kind of purpose, resulting in approximately 35,000 filled in questionnaires. The OViN is a database of big importance in current transport modelling in the Netherlands using the demand patterns and travel characteristics. However, it is of importance to know that there are differences in trips investigated by both sources. On main difference is that trips made by trucks are not part of OViN. But one should also take in mind that the sample size of OViN (35,000 annually) is way smaller than the mobile phone data set (> 1 million monthly), so that the variance in the mobile phone data is to be expected smaller.



Complete set



Range 8 – 60 km

Figure 7. Comparison trip length (crow flies) distribution of mobile phone data and OViN

In the comparison (see Figure 7) it can be seen that mainly the number of short distance trips (shorter than 8 km) are underrepresented in the mobile phone data set. Above 8 km the mobile phone data set is overrepresented, which slowly decreases and is almost dissolved at 60 km. In Figure 7 the trip length distribution frequencies sum to 100%, which means that underrepresentation in one part of the graph automatically leads to over-representation in another part. Analysis of the distribution focusing on the range between 8 and 60 km shows that the trip length distributions from about 40 kilometres correspond reasonably well. The range of 8 to 15 kilometres is still significantly underestimated, while the range between 15 and 40 kilometres is slightly overestimated.

The underrepresentation of short distance trips can be the result of less mobile phone usage on short distances or that people did not take their mobile phone with them. Another explanation is also that the possibility to measure a trip based on the raw mobile phone data depends on the spatial resolution of masts and the activity duration at the destination.

The number of long distance trips is smaller by increasing distance and therefore the chance increases that the trips will be filtered because of the privacy definition ('minimal 16 rule'). This means that the chance that more than 15 trips are made between a specific origin and destination zone is smaller on larger distances. This is the base principle of the gravity model where the number of trips is inversely proportional to the travel cost between zones

5. Enrichment a-priori demand estimates

Taking into account that the mobile phone data does not contain intra zonal trips and has less detail than the transport planning model of the Rotterdam regions as well as the fact that we only have a sample of the total number of trips, results in the following procedure of the enrichment of the a-priori demand estimates using mobile phone OD information. In this procedure the distribution of the synthetically determined OD-information (a priori model) is replaced by the distribution of the measured OD-information from mobile phone data, while maintaining the absolute demand estimated in the a priori matrix. As a result the following steps are used:

1. Determine the average working day OD-matrix from the mobile phone data.
2. Conversion of the model zoning system (about 4.000 zones) to the zoning system of the mobile phone data.
3. Aggregation of the a priori OD-matrices per mode (car, PT, active) and purposes to a working day personal transport OD-matrix
4. Scaling of the synthetic a priori OD-relations to the measured OD-relations from the mobile phone data
5. Expanding the enriched OD-matrix to the zoning system of the Rotterdam model using the splitting rates according to the a priori model resulting in enriched a priori OD-matrices per mode.

In both cases the diagonal of the a priori OD-matrix is not taken into account in the enrichment procedure, because there are is no intra-zonal information available in the mobile phone data. Next to that the truck matrix has not been altered in both cases based on mobile phone data, because of the identified underrepresentation of these trips.
In the second step 'Conversion of the model zoning system' it has been taken into account that in the study area of Rotterdam the model zones are geographically smaller than the mobile phone zones. Therefore in this part the model zones are aggregated. While in the so-called influence and outer area of Rotterdam the zoning system of the mobile phone data is more detailed than the model zoning system. Therefore, in this part of the Netherlands the data of the mobile phone zones are aggregated.

We performed this procedure two times:

1. Scaling based on the distribution of the mobile phone data for all distances

2. Scaling based on a corrected distribution taking into account the found bias in trip length distribution. The correction is based on the comparison between OViN data and mobile phone data presented earlier. As a result trips shorter than 8 kilometres and longer than 60 kilometres were not enriched using mobile phone data (i.e. the a-priori estimated trips in the transport model are maintained). Furthermore the trip distribution for trips between 8 and 60 kilometres are corrected based on the differences found in the total trip length distribution between OViN data and mobile phone data. As a result the number of trips between 8-13 km are increased, between 14-40 km decreased and larger than 40 km unchanged. Note, that on individual relations this does not result in the same distribution.

6. Results

The enrichment procedure is tested on the operational transport planning model of the Rotterdam region. Because the ground truth of demand is not known, the assessment is based on comparing the assignment results using the original a priori OD matrix estimated in the model with the assignment results of the enriched a priori OD matrix using mobile phone data. In both cases a comparison is made to what extent the assignment of the matrix results in accurate results compared to count data. First analysis consisted out of local experts of the municipality assessing the results using their expert knowledge of the mobility patterns in the region. Next the model fit is assessed based on the T-value which compares the modelled value with measured value.

The first approach in which the bias in trip length distribution was neglected, resulted, as expected, in an overestimation of long trips in the model and large changes in the original a priori matrix. This is due to the underrepresentation of short trips when applying the distribution based on mobile phone data. Overestimation of long trips results after the assignment step to large overestimations of link loads especially on higher order roads. The enriched a priori OD matrix is therefore a deterioration of the original matrix which indicates that you cannot neglect the bias possibly present in mobile phone data when analysing OD information.

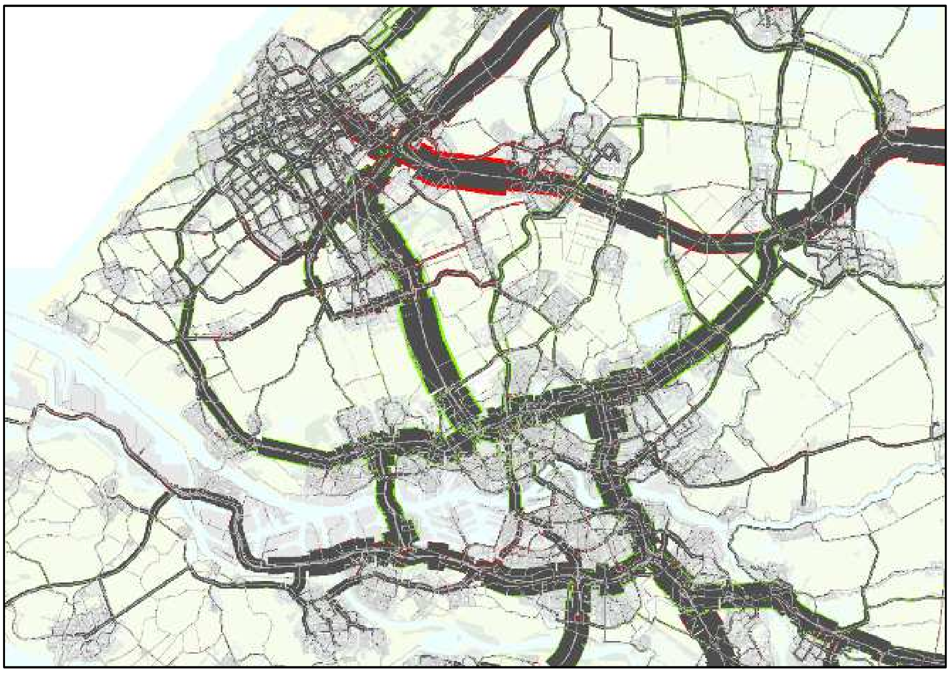


Figure 8. Comparison of assignment of car OD matrix (enriched a-priori versus original a priori)

The second approach, taking into account the bias found, did provide promising results, which have been analysed further. Visual analysis shows that most of the link loads are near the measured counts. A comparison of both assignments (i.e. original a priori versus enriched a priori OD matrix) is shown in Figure 8, showing the region between The Hague (in the north-west) and Rotterdam (in the south). In this figure the bandwidths show the traffic flows, where red parts mean a higher traffic flow in the assignment of the enriched OD-matrix and green parts mean a higher traffic flow of the a priori model.

The figure also shows the earlier presented historically grown strong relation between Zoetermeer and The Hague, which is difficult to model using the traditional approach (see also Figure 6). Further analysis has been performed on the city of Hellevoetsluis, south-west of the city of Rotterdam. It is known that the distribution of trips related to this city always have been hard to model in the Rotterdam transport model, because of the isolated geographical position of the city and the nearby harbour. The gravity model expects a much stronger relation between Hellevoetssluis and the Harbour than present in reality. From Figure 8 it can be seen that the traffic flows near Hellevoetsluis hardly have changed, but in Figure 9 (showing the selected area assignment of Hellevoetsluis) it becomes clear that the distribution has changed. These changes are consistent with the experience of regional traffic engineer experts.

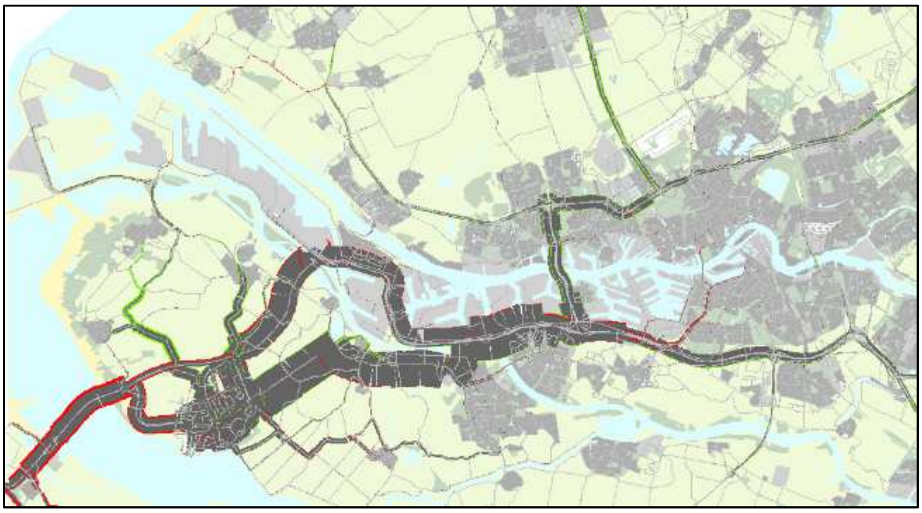


Figure 9. Comparison of selected area assignment of car in the city of Hellevoetsluis

Other interesting observation is that the enriched model shows improved results on the heavily congested A13. The original model has difficulties in accurately modelling the consequences of the congestion problems on mobility patterns, while the enriched model shows improvements when comparing counts and assigned trips (see Figure 10). The enriched model also shows little differences between the original model and enriched model on the A20. Which is desired because earlier evaluation of the model using a licence plate survey showed that the original model accurately modelled this part.

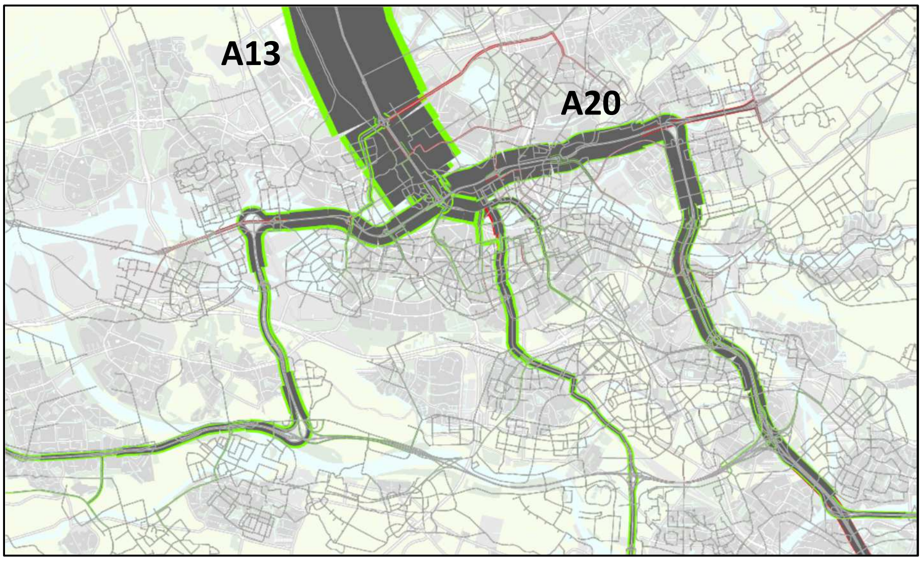


Figure 10. Comparison of distribution A13

The model fit is defined by determining the so-called T-value at each count location. The T-value at location c is defined as follows:

$$T_c = \ln\left(\frac{(X_c - X_{m,c})^2}{X_c}\right) \qquad (1)$$

where X_c is the count value and $X_{m,c}$ the modelled traffic flow at location c. The T-value not only takes the absolute difference into account, but also the absolute count value. Using this measure locations with a high count value (like motorways) can be rated in the same way of locations with a low count value (like a local road). If T_c <= 3,5 this is rated as no relevant deviation; if 3,5 < T_c <= 4,5 this is rated as a border case and a value > 4,5 as a relevant deviation. Table 1 shows the performance of the original a priori matrix versus the two approaches. The earlier mentioned finding that neglecting the bias in approach 1 is clearly shown. Approach 2 however shows an improvement of approximately 5% in T values below 3.5. This improvement means that 1,6 % more of the counts are rated as no relevant deviation (in comparison with the a priori model fit).

Range T-value	**Original a priori**		**A priori enriched approach 1**		**A priori enriched approach 2**	
T_c<3.5	437	37%	392	33.2%	456	38.6%
3.5<T_c<4.5	235	19.9%	171	14.5%	228	19.3%
T_c>4.5	508	43.1%	617	52.3%	496	42.0%
Total	1180		1180		1180	

Table 1. T value classes

This means that calibration effects will be reduced by calibrating the enriched model. Because in building a model for a forecast year the calibration effects are used, this implies that the quality of the forecast also will improve.

7. Conclusions and future research

Mobile phone data has a great potential to improve current transport modelling. Further development of methods and combining different data sources will lead to more data driven modelling approaches used in practice. In this research we present an approach where mobile phone data is used and analysed for enriching the transport model of the region of Rotterdam. Although mobile phone data provides a very large sample of trips, the analysis showed that it is necessary to address the potential bias in this data which needs additional data sources. The OD information derived from the mobile phone data showed an underrepresentation of short trips, which is partly due to the level detail and accuracy of the available location data for this research. Combining the strength of the traditional demand models with measured OD information resulted in an improvement in the a-priori OD matrix indicating by the improved match with traffic counts after assigning the matrix to the network.

Other research already showed that it is possible to derive trip purposes. Although work has been done on addressing the bias of the mobile phone data sample, further improvements are possible. Next to that further research is needed in proper estimation of mode choice as well as detail in zones and identification of trips. Combining mobile phone data with other sources for this purpose can be a solution. The data shows great potential to include day-to-day dynamics in transport modelling, improving the assessment of measures in practice.

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