A Dynamic Traffic Forecasting Application on the Amsterdam Beltway

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Abstract
This paper presents some theoretical developments that have resulted in a dynamic traffic forecasting procedure that is feasible, both from a technical viewpoint (data availability) and from a practical viewpoint (data preparation). The procedure consists of a dynamic Origin-Destination (OD) matrix estimation module and a dynamic traffic assignment module. The OD-estimation module is an extension of traditional (static) OD-estimation methods, i.e. production-attraction models combined with exponential deterrence functions. To make the procedure computationally feasible an efficient parameter estimation method has been provided. To test the combined OD-estimation/dynamic assignment model, data was collected continuously during three weeks at 141 locations on the beltway of Amsterdam. As an alternative to the proposed procedure, historical averages have been compiled from all observed data. Comparisons between true, predicted, and averaged data show that a lot of effort must be invested in specifying OD-demand and network characteristics in order for the new method to be competitive with historic averages as a means to obtain traffic forecasts. Exceptional circumstances such as severe incidents however are reproduced better with the dynamic forecasting procedure.
Keywords: dynamic traffic assignment, OD-estimation, travel demand modelling
1. Introduction:

One of the requirements of dynamic traffic management is to provide predictions of future traffic conditions. Based on these predictions a traffic operator can make decisions concerning rerouting, travel information & advice and ramp metering. For on-line application a prediction system must respond to accidents, weather conditions and road works. To perform this task, the system must be provided with data from various sources.

In practice a traffic prediction system must work within the limitations of data availability. This paper presents a traffic prediction system, designed to operate with data available in the Netherlands. The main components of this system are a module for the estimation of dynamic Origin-Destination (OD) matrices, and a dynamic assignment module. The OD-estimation module was developed especially to cope with the imperfections of the input data, such as missing data, inaccuracies, mis-specifications, etc.

The main part of the paper is devoted to a description of the actions that were taken to arrive at a dynamic OD-matrix. The dynamic assignment module is a result of an on-going research project at Delft university, and a model was used without modification from De Romph (1994). The structure of the paper largely corresponds to figure 1, which gives an overview of the prediction system. This framework consists of seven datasets (rectangles) and five actions (circles). Each dataset and action is described briefly.

Figure 1 contains the following datasets:

- **Network**: A specification of the topology of the network. For each link the maximum speed, the maximum density and the road type is given. The road type of a link determines the speed-density function to be used. The network used for this pilot study is described in section 2.1.
- **Induction loop data**: Each minute the flow and the speed is measured at several locations in the network. The Dutch Motorway Traffic Management (MTM) system is used to collect the data and is described in section 2.2.
- **30 minute OD-matrix**: A dynamic OD-matrix specified with an aggregation level of thirty minutes. The origins and destination are the on- and the off-ramps in the network.
- **Dynamic OD-matrix**: A dynamic OD-matrix specified with a 5 minute interval. This matrix is the result of a ‘dynamizing’ procedure and is used as input for the dynamic assignment model.
- **On-ramp volumes**: Time series of flows with an interval length of five minutes of all the on-ramps in the network.
- **Speed-density functions**: For each road type in the network a different relation between speed and density is used.
- **Prediction**: As a result of the dynamic assignment, an estimation of the flow, the density, the speed and the traveltime for each link in the network and for each period of the total time span is given.

Figure 1 contains the following actions:

- **Predict/Observe on-ramp volumes**: For each on-ramp in the network the volumes entering the network for the future periods are estimated with historical data. Current volumes
are matched to historical patterns using a least square minimization, see *De Romph (1994)*.

- **Estimate 30 minute matrix**: A new time-dependent model of travel demand is used to generate synthetic OD-matrices. The method is described in detail in section 4.
- **Dynamizing**: Based on the 30 minute OD-matrix and the on-ramp volumes, the interval of the OD-matrix is reduced to 5 minutes. This procedure, called *dynamizing*, is described in detail in section 5.
- **Adapt speed-density functions**: Based on historical induction loop data a speed density function is estimated for each road type in the network. The measured data is fitted to the function using a least square minimization. This procedure is described in detail in *De Romph (1994)*.
- **3DAS**: The 3DAS model is a dynamic assignment model. The model calculates the traffic flows, densities, speeds and travel times for each link in the network and for each period of the total time span. The 3DAS model is described briefly in section 6 and in detail in *De Romph (1994)*.

Above description accounts for sections 4, 5 and 6. The other sections of the paper contain a description of the input data (section 2), the research approach (section 3), the data preparation (section 7), the results (section 8), and the conclusions (section 9).

2. **Input data**:

2.1 **Network**

The study area is the Amsterdam beltway. The beltway-network representation consists of a list of nodes and a list of directed links, extracted from ‘basisnetwerk Nederland’, *DVK (1974)*. The total length of the beltway approximates 30 kilometres. The network has two tunnels and four major motorway intersections. The network contains 286 nodes and 430 links of which 76 are on- or off-ramps. A small part of the arterial network is present near on- and off-ramps. This makes it possible to combine clockwise and anti-clockwise on-ramps or off-ramps in one origin or destination node. In total there are 21 origins and 21 destinations.

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**Insert figure 2 about here**

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2.2 **Induction loop data, the MTM system**

This section summarizes the properties of the input data that are available at this moment as a basis for dynamic traffic prediction in the Netherlands. The limitations of these data are essential to the choices that need to be made in view of the OD-prediction module.

Data were obtained from MARE, a research facility connected to the national MTM system. For three weeks data were collected at 141 locations on the Amsterdam Beltway. Motorway sections on which MTM is installed are equipped with dual induction loops on all lanes with intervals of approximately 500 meters. One of the primary objectives of MTM is the upstream warning for congestion and slow traffic. It is claimed that this leads to a significant decrease in risk of pile ups and incidents (-50%), an increase of flow (+5%) and a decrease of traveltime (-15%) (Source: *AVV, 1994*).

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1. In this specific pilot this has not been done, the actual measured on-ramp volumes were used.
Not all collected data are available at a central computer. Data is aggregated and smoothed in road-side processors (substations) before transmission to the central computer. Therefore dynamic traffic management applications using MTM collected data intended for use in the near future are bound to certain input data limitations, of which the most important are:

- Data are aggregated to one minute periods.
- Arithmetic averages of observed speeds are stored whereas harmonic averages are needed to compute average travel-times.
- Missing observations of entry and exit volumes. In general, motorway on- and off-ramps are not explicitly monitored. The detectors of the monitoring system are located on the through lanes of the motorway. At an aggregate level on- and off-ramp volumes can be reconstructed from the observations at the adjacent links, if present. Applying this technique to one minute data however, introduces significant errors, regularly leading to negative flows. A factor that makes the problem worse is that the accuracy of induction loop detectors decreases in areas with many lane changes, which is typical for on- and off ramps.
- The possibility of faulty detectors. The probability of all detectors working at a time is very small.
- Large observation errors in case of slow traffic and in case of traffic characterized by a high frequency of lane changes.
- Unreliable counts of low traffic volumes. A minimum of 4 vehicles per minute is ‘observed’ in every substation. For some technical reason the predecessor of the MTM system generated dummy vehicles every 15 seconds in absence of real vehicles. This property is preserved in the present version of MTM and is a constant source of errors, especially at night and on less frequently used links such as on-ramps.
- Poor positioning of induction loops. Some loops are located halfway an on-ramp or off-ramp. The exact number of vehicles using the ramps cannot be determined in this case, as the point where vehicles change between ramps and main lanes varies between motorists, and might be up- or downstream of the detector.

3. Research approach:

The primary objective of this pilot study was to find answers to the following two questions:
- Can the system give a sufficiently accurate prediction of the future traffic conditions?
- Can the system react to changing conditions, such as accidents and weather changes?

The Amsterdam beltway was selected as the pilot area. This network is well equipped with induction loops, has a manageable size, and several dynamic traffic management instruments are in operation or planned for operation in the near future.

To answer the questions given above, data was collected for three weeks at 141 locations in the Amsterdam network. The data was collected using induction loop detectors. The data was screened for errors and two days, April 14th and April 28th, were selected to be reproduced by the prediction system. A historical database was setup using data of five other days.

It was decided to consider three different scenario’s to answer the questions above:

I. The first scenario tried to reproduce the morning rush hour of Thursday, April 28th. The data on this day has few errors and no major accidents or other disturbances. It was decided to reproduce the rush hour from 06:00h in the morning until 09:00h in the morning. The period length used in the calculation is five minutes. This period length was chosen, because a total of 36 periods could be managed by the software, and resulted in a feasible representation of the dynamics in the network. A shorter period length would suggest an accuracy that cannot be reached, and with a longer period...
length, the interaction between time periods diminishes. An impression of the capabilities of the system can be achieved by comparing the prediction with the actual measured flows.

II. The second scenario tried to reproduce the morning rush hour of Thursday, April 14th. On this day an accident occurred on one of the freeways which blocked the freeway for 20 minutes. The same time span and period length as in the first scenario was used. The prediction is again compared with the actual measured flows for this scenario.

III. To get an impression of the relevance of a system for making predictions, a third scenario was considered that does not use the system to make a prediction, but used the collected induction loop data to make a prediction. The measurements were summed and averaged for five measured days, with similar conditions. This scenario represents the historical average traffic pattern.

The first question of the research approach was answered by the first scenario (see section 8.1), and the second question was answered by the second scenario (see section 8.2). Section 8.3 gives the results of a comparison between the first two scenario’s and the historical average.

During this research, various computers, including a parallel computer (see Van Grol, 1992) were used to make the calculations. Most modules of the system can work independently. The OD-estimation model and the dynamic assignment model are the most computational intensive modules.

4. OD-Estimation:

The estimation of Origin-Destination (OD) tables is a classical subject in transportation engineering. The main characteristic of the problem is that many OD-tables satisfy the constraints posed by observations taken from a transport system, usually volume counts. Therefore the unique reversion of this assignment is impossible, unless one uses a ranking of the underlying OD-matrices. Such a ranking can be based on different principles for example compliance with a model of travel demand, closeness to a prior matrix, maximization of the number of micro states or minimization of the total travel time in a system. See for relevant publications among others Van Zuylen and Williamsen (1980), Maher (1983), Cascetta and Nguyen (1988) and Hamerslag and Immers (1988).

Most of the work until now concentrates on static OD-tables, i.e. all traffic volumes are considered at an aggregate level. For dynamic traffic predictions, travel demand should be specified in a time differentiated manner. For this purpose we define a dynamic OD-table as a series of OD-tables, ordered with respect to departure time. Because of differences in spatial aggregation and time differentiation, these methods deviate significantly from the ones that were developed for static OD estimation.

The great majority of dynamic OD-estimators is based on the prediction error minimization principle: inferences about OD-patterns are made on the basis of similarities between the up- and downstream traffic flows. Examples of methods based on this principle are described in Cremer and Keller (1981), Nihan and Davis (1987), Keller and Ploss (1987), Bell et al. (1991), Cascetta et al. (1993), Van Der Zijpp and Hamerslag (1994b). Platoon dispersion and congestion have an adverse effect on methods based on prediction error minimization, and limit their applicability to simplified networks like intersections and motorway corridors.

These theoretical considerations, together with practical considerations such as limitations
posed by input-data and a limited time-budget for data preparation necessitate other methods for large or complex networks. Considerations related to input data are the existence of accurate observations on all on-ramps, knowledge of the exact location of induction loops, synchronization, accuracy etc., see section 2.2 for more details on data availability on the Dutch motorway system.

In this paper the generation of synthetic time dependent OD-matrices is addressed. The problem of determining an OD-matrix from an under-specified set of traffic counts is solved by the use of a model of travel demand. In literature the field of synthetic dynamic OD-estimation is relatively unexplored. This is probably due to the disaggregate nature of the problem and the fact that a motorway network rather than a complete transport network is considered. These considerations invalidate most of the models of travel demand.

At least two references to synthetic time differentiated OD-estimation can be found. Willumsen (1984) describes an extension of ME2 which is based on the entropy model. VanAerde et. al. (1993) describe a procedure referred to as QUEENSOD. Relative to previous research this paper presents three novelties:

- A derivation of a static model of travel demand motorway networks
- A time dependent extension of this model
- An efficient procedure for solving the unknown variables

These elements are treated in the subsections 4.1, 4.2 and 4.3 respectively. The output of the procedure that is described in the following sections is a time dependent OD-table with time intervals of thirty minutes. A typical period length for dynamic traffic prediction is five minutes. Therefore the thirty minutes estimates are converted to five minute intervals that match the observed on-ramp volumes. This process, referred to as ‘dynamizing’ is described in section 5.

4.1 A model of travel demand for subnetworks

This section derives a static model of travel demand for motorway networks on the basis of a general accepted model of travel demand for the surrounding network. In this context, a motorway network is referred to as a subnetwork. As a point of departure the well known gravity model with an exponential deterrence function is used, see e.g. Ortúzar and Willumsen (1990) for more background on this model. If $T_{rs}$ denotes the number of trips from ‘true’ origin to ‘true’ destination then this model prescribes the following relation:

$$T_{rs} = A_r B_s \exp(-\beta c_{rs})$$ (1)

where:

- $A_r$ production ability for zone $r$,
- $B_s$ attraction ability, for zone $s$,
- $\beta$ parameter in deterrence function,
- $c_{rs}$ generalized travel costs from zone $r$ to zone $s$

Define the assignment map $\tau$ with:

$$\tau_{rsij} = 1 \text{ if flow } rs \text{ contributes to flow } ij \text{ on the subnetwork}$$

$$\tau_{rsij} = 0 \text{ otherwise}$$ (2)

In addition the validity of (1) assume that $m$ disjunct sets origins $O(i), i=1,2,...m$ exist that jointly cover all origins in the surrounding network, and that similar sets of destinations $D(j), j=1,2,...n$ exist, and that for this sets the assignment map satisfies:
\[ \tau_{rsij} = \tau_{ri} \tau_{sj} \]

where:

\[ \tau_{ri} = 1 \text{ if } r \in O(i), \tau_{ri} = 0 \text{ otherwise} \]

\[ \tau_{sj} = 1 \text{ if } s \in D(j), \tau_{sj} = 0 \text{ otherwise} \]  

(3)

Condition (3) is satisfied if the entry where an arbitrary OD-path enters the subnetwork only depends on the trip-origin and the exit only depends on the trip destination. This is the case for example if the subnetwork under consideration is embedded in a network that may be represented by a directed tree, see figure 3.

The last assumption is that the generalized travel costs are \textit{additive}, i.e.:

\[ c_{rs} = c_{ri} + c_{ij} + c_{js} \]  

(4)

This is in accordance with the usual assumptions.

From combining (2) and (3) it follows that the subnetwork EE-flows are given by:

\[ f_{ij} = \sum_{r \in O(i)} \tau_{ri} \sum_{s \in D(j)} \tau_{sj} T_{rs} \]  

(5)

Combining this with (1) enables the simplification:

\[ f_{ij} = a_i b_j \exp(-\beta c_{ij}) \]  

(6)

with:

\[ a_i \text{ entry production ability, } a_i = \sum_{r \in O(i)} A_r \exp(-\beta c_{ri}) \tau_{ri} \]

\[ b_j \text{ exit attraction ability, } b_j = \sum_{s \in D(j)} B_s \exp(-\beta c_{sj}) \tau_{sj} \]

Above derivation shows that under certain conditions usage of model (1) on a subnetwork is justified.

4.2 Time dependent extension of the static model

In this section the time dependent case is considered. As a time dependent extension of model (6), we propose:

\[ f_{ijt} = a_i(t) b_j(t+c_{ij}) f(c_{ij}) \]  

(7)

with:

\[ f_{ijt} \text{ flow from entrance } i \text{ to exit } j, \text{ departing period } t \]

\[ c_{ij} \text{ average travel-time from entrance } i \text{ to exit } j \]

\[ a_i(t) \text{ production ability related to entrance } i \text{ in period } t \]

\[ b_j(t+c_{ij}) \text{ attraction ability related to exit } j \text{ in period } t+c_{ij} \]

\[ f(c_{ij}) \text{ deterrence function, distributed in classes; } f(c_{ij}) = \sum_k F_k \delta_{ij}^k, \delta_{ij}^k = 1 \text{ if } c_{ij} \text{ is in class } k, \text{ and zero elsewhere.} \]

Note that the interpretation of \( c_{ij} \) has changed from generalized travel costs to average travel time, and the continuous deterrence function is replaced by a discretized deterrence function. The latter replacement was done to facilitate computational procedures.

A second element of a time-dependent model description relates to the trip execution. Since
travel time can no longer be neglected flows with a certain departure period contribute to link flows in different periods. For this purpose we introduce a time dependent assignment map:

\[ \pi_{ijap} \]

Proportion of flow \( f_{ij} \) travelling over link \( a \) in period \( p \)

As a result, to the observed link flows applies:

\[ y_{ap} = \Sigma_{i,j,t} f_{ijt} \pi_{ijap} \] (8)

with:

\[ y_{ap} \quad \text{observed flow on link } a \text{ in period } p \]

### 4.3 Solution procedure

The above described model converts the under-specified problem into an over-specified problem, i.e. generally it will not be possible to compute a set of production and attraction abilities in such a way that all observations are exactly matched by the model predictions. To obtain an optimal fit between model prediction and observed link volumes a weighted least squares error approach is proposed. In this approach the errors are weighted with their approximated variances, which in turn, are approximated by their observed values. This results in the problem of minimizing:

\[ \Sigma_a \Sigma_p (y_{ap} - \Sigma_{i,j,t} f_{ijt} \pi_{ijap})^2 / y_{ap} \] (9)

using:

\[ f_{ijt} = a_i(t) b_j(t+c_{ij}) (\Sigma_k F_k \delta_{ij,k}) \] (10)

The solution procedure is expressed in the following vectorized notation. Let:

- \( m \) number of entrances to the subnetwork
- \( n \) number of exits of the subnetwork
- \( A \) number of links on which the volumes are observed
- \( T,P \) number of departure periods, number of observation periods

and:

- \( \tilde{y} \) vector of observed flows for all periods (length \( AP \))
- \( \tilde{f} \) vector of subnetwork flows for all periods (length \( mnT \))
- \( U \) dynamic subnetwork assignment map (height \( mnT \), width \( AP \)).
- \( U_{rs} \) is the proportion of the \( r \)th element of flow vector \( \tilde{f} \) that contributes to the \( s \)th component of the observation vector \( \tilde{y} \).
- \( Y \) a diagonal matrix containing the elements of \( \tilde{y} \) (height \( AP \)).

The equivalent of (9) in vectorized notation is:

\[
\text{minimize: } J(\bar{a}, \bar{b}, \bar{F}) = (\tilde{y} - U\tilde{f})' Y \frac{1}{2} (\tilde{y} - U\tilde{f})
\]

with:

- \( \bar{a} \) vector of production abilities for all periods, \( \bar{a}_{i(t-1)j(t)} = a_i(t) \)
- \( \bar{b} \) vector of attraction abilities, \( \bar{b}_{j(t-1)k(t)} = b_j(t) \)
- \( \bar{F} \) vector of deterrence values, \( \bar{F}_k = F_k \)

The minimization of this expression is a nonlinear problem, subject to nonnegativity constraints. In a first attempt to solve this problem a conjugate gradient method was used, see Bazarra et al. (1993). Although this method converged, computation times were too high to yield results for problems of realistic size within reasonable time. To overcome this problem
an alternative solution algorithm is proposed. This algorithm sequentially solves the production abilities, $\bar{a}$, the attraction abilities, $\bar{b}$, and the coefficients in the deterrence function, $\bar{F}$. Each time two sets of parameters remain constant while the third set is solved. This results in the following iterative procedure:

$$\bar{a}^{n+1} = \text{argmin}_{\bar{a}} J(\bar{a}, \bar{b}^n, \bar{F}^n)$$ (12a)

$$\bar{b}^{n+1} = \text{argmin}_{\bar{b}} J(\bar{a}^{n+1}, \bar{b}, \bar{F}^n)$$ (12b)

$$\bar{F}^{n+1} = \text{argmin}_{\bar{F}} J(\bar{a}^{n+1}, \bar{b}^{n+1}, \bar{F})$$ (12c)

Provided that the function $J$ is convex, this procedure can be shown to yield the solution to the minimization problem (11). As each of the subproblems (12a-c) is quadratic, the solution to these subproblems can be determined in one step. For example if in (12c) the vectors $\bar{a}^{n+1}$ and $\bar{b}^{n+1}$ are fixed diagonal matrices $A$ and $B$ exist such that holds:

$$f = AB \bar{F}^n$$ (13)

And expression (11) is converted into:

$$\text{minimize: } J(\bar{F}^{n+1}) = (\bar{y} - UA \bar{F}^{n+1})' Y (\bar{y} - UA \bar{F}^{n+1})$$ (14)

The value of $\bar{F}^{n+1}$ that minimise expression (14), for fixed values of $\bar{a}^{n+1}$ and $\bar{b}^{n+1}$ can be determined directly using:

$$\bar{F}^{n+1} = (BAU^{-1}U'AB)^{-1}BAU^{-1}\bar{y}$$ (15)

An identical approach can be used to solve (12a) and (12b). This procedure of sequential solving of $\bar{F}$, $\bar{a}$ and $\bar{b}$ turns out be much more CPU-time efficient for this particular problem then the conjugate gradient method.

5. Dynamizing:

As there is a gap between the ability of the OD-prediction module (thirty minutes aggregation) and the need of a dynamic prediction system (five minutes aggregation), additional steps are necessary. Reducing the aggregation interval of the OD-prediction module would invalidate the underlying model. Therefore a heuristic procedure is followed to convert the thirty minute estimates into five minute estimates. This procedure, referred to as ‘dynamizing’, is based on the assumption that processes resulting into travel demand have a constant or slowly changing influence.

Due to the, from an observation point of view, random nature of traffic, local and temporary deviations from the general traffic pattern may occur. This deviations may emerge as peaks or drops in on-ramp volumes, but also as deviating distribution of trips over the off-ramps. The first phenomenon can be observed directly and prior to the execution of trips, while the second phenomenon can only be observed indirectly and posterior to the execution of trips.

As traffic predictions need to be made prior to the execution of trips, it is not realistic to assume knowledge on the second phenomenon. To obtain a ‘best’ guess of the OD-matrix at the time an on-ramp volume is observed, the on-ramp volumes are multiplied by split propor-
tions that are derived from the thirty minutes aggregated matrices.

6. Dynamic Assignment:

The dynamic assignment model, 3DAS, is based on the work initiated by Hamerslag (1989). The basic feature of a dynamic assignment model is the partitioning of time in small time-slices, usually referred to as periods. Over the last two years the model has been improved, in particular towards its dynamic aspects. The 3DAS model is described in detail in De Romph (1994).

The model determines the flow distribution in the network by an iterative process. In each iteration the shortest-paths in the network are calculated for all OD-pairs and for every departure period. The link parameters are defined separately for each period. The properties of the network and travel demand are presumed given.

The basic iteration scheme in figure 4 is essentially the same as is used for static assignment models. The difference lies in the “all-or-nothing-in-time” module. In this module an extra iteration over the departure period is needed, and the shortest-pathfinding and the assignment have to be performed in real time.

The paths are defined using the traveltime on a link in the period in which the traffic actually traverses the link, i.e. the trajectory the traffic follows in time is calculated. The network is loaded, based on these trajectories. During the assignment the contribution of a traveller to the traffic-load on a link in a certain period is determined by calculating the duration of presence on that link in that period. If we focus on one traveller then two situations can occur:

1. Several links are covered in one period. In this case the traveller is present on a link only for a part of the period, and therefore should only be assigned for this part.
2. One link is covered in several periods. The traveller is present on the link during multiple periods and should be assigned entirely for each individual period.

At the start of each iteration the traveltimes on the links are derived from the load of the previous iteration. For each link the traveltime is calculated with a speed-density function. Speed-density functions are used instead of traditional traveltime-intensity functions to be able to model a decreasing flow in case of congestion. The conservation of traffic and the continuity of flow is maintained. In case of overflow, the overflow is assigned to the preceding link of the path in the same period. The stop criterion is reached when there is no difference between two successive iterations.

The 3DAS model has been tested on several small networks [De Romph et al. (1992)]. Several parameters of the model were calibrated using these networks. The initial settings of these parameters followed from these tests and were not changed for this study. A speed-density function of the following form is used:
In which $v_{\text{max}}$ is the free-flow speed, $\rho_{\text{crit}}$ is the critical density and $\rho_{\text{max}}$ is the maximum density. The maximum density represents a no-motion traffic-jam. The value of $\phi$ is chosen to make the function continuous at $\rho_{\text{crit}}$. The parameter $\alpha$ influences the steepness of the first linear part of the function, the parameter $\beta$ influences the curve of the second part of the function. For each link in the network different parameters are possible.

7. Data Preparation:

The data sets that are available for implementation of the traffic prediction system in the pilot area were described in section 2.

For the proper functioning of the OD-estimation module several additional items need to be specified:

- A list of link-number/loop-number pairs, specifying the correspondence between MTM loop-numbers and beltway-network link-numbers. This list was made on the basis of detailed maps of the area, Rijkswaterstaat (1993).
- A list of origin nodes and a list of destination nodes.
- An ‘origin/on-ramp’ table, specifying which are the feeder links corresponding with the origin zones. The specified links will be used in the ‘dynamizing’ procedure, see section 5.
- A ‘missing ramps’ table specifying which monitored link volumes should be added or subtracted to obtain a certain non-monitored link volume. The use of this table is twofold: firstly the table is needed to compute on-ramp volumes that are required by the ‘dynamizing’ procedure, see section 5, secondly the table can be used to replace two largely overlapping observations by two observations with a lower degree of redundancy. For example, two inner link volumes are replaced by one inner link- and one exit volume.

After specification of these items, a number of automated actions is performed:

- Preparation of the MARE data. The MARE data consist of a series of one-minute data. Occasionally data are missing or erroneous, this can be detected via the time-stamp and the error-status attributes. Missing data are replaced with averages of previous periods.
- Calculation of the assignment map based on shortest paths for use in the OD-estimation module.
- Merging redundant data. If one link has several induction loops, these loops generate largely redundant data. This fact can be established by inspection of the assignment map. If certain pairs of induction loops only have a combined appearance in the assignment map, these loops are merged by averaging.

Another part of the data-preparation consisted of the visual inspection of network and input data. All elements relevant to the OD-estimation and dynamic assignment procedures have been made available in a graphical environment that contains visualisations of network, origins, destinations, routes, loop-data, distributions functions, assigned link volumes, and predicted speeds.

Visual inspection of the network has revealed a number of shortcomings in the original input
data. Induction loops producing improbable data were dropped. Via a selected link analysis routes containing U-turns were detected. Routes containing U-turns are regarded as a highly unlikely phenomenon on a motorway network, which can only occur because of omission of the secondary network. By addition of dummy links these routes were prevented from being optimal.

8. Results:

The results of the three scenario’s proposed in section 3 are described in the next three sections.

8.1 Morning Rush Hour at Thursday, April 28th.

A dynamic assignment was carried out based on the dynamic OD-matrix, and the speed-density functions. Calculation started at 06:00h. At this time the network was almost empty. During calibration numerous modifications were made to the network. A wrong number of lanes at one location can disturb traffic flow over a large part of the network. Several on-ramps were not well represented, and at some locations individual speed-density relationships were required. Detailed maps were required to figure out the exact lay-out of the network. Finally a fairly good reproduction of the actual traffic flow was achieved. Two different locations in the network are showed to give an impression of the results. Figure 5 gives flow and speed at two locations near the Coentunnel, referring to the network shown in figure 2.

The left side of figure 5 shows a location with traffic queuing before entering the Coentunnel. The flow pattern is reproduced fairly well, except in the last 6 periods, speed increases, while in reality speed remains low. The right side of figure 5 shows a location in the other direction with traffic leaving the Coentunnel and travelling north. This location shows a free flow situation and is a good reproduction.

8.2 Morning Rush Hour at Thursday, April 14th

A dynamic assignment was made for the morning rush-hour of April 14th based on the dynamic OD-matrix of April 28th. Calculation started at 06:00h. At 06:50h an accident occurred north of the Nieuwe Meer intersection northbound, see figure 2. This accident shows clearly in the induction loop data. Downstream flow is almost zero and a large traffic jam has built up in several directions. At 07:35h, a larger downstream flow was again measured and the traffic jam builds down from the start point, but it still builds up from the tail of the traffic jam. At 08:00h the tail of the traffic jam reached the Watergraafsmeer intersection. The accident was introduced into the model by setting the maximum density to 1 veh/km during the accident for the appropriate section. The traffic flow was reproduced fairly well, but not as good as April 28th. Two different locations near the accident are shown in figure 6 to give an impression of the results near the traffic jam.
The left side of figure 6 shows a location downstream of the accident, and shows a restored flow and speed. Flow is low for the first twenty periods. Around the twentieth period (07:35h), the freeway is clear again and flow increases. The right side of figure 6 shows a location upstream of the accident. The flow pattern is quite complicated here. The first decrease in speed around the 18th period is the result of the accident. The second decrease in speed, around the 27th period is the result of a traffic jam that appears east of Nieuwe Meer, for trips going east and has nothing to do with the accident. This traffic jam was not reproduced exactly by 3DAS, and for this reason speed is somewhat underestimated around the 30th period.

8.3 A Prediction Based on the Historical Average

The two scenario’s described were validated with data measured for three weeks by induction loop detectors at 141 locations. Five days were selected from this data collection which contained no major disturbances. The traffic patterns for these days were summed and averaged. The resulting data set represents the “average traffic pattern” for the morning rush hour from 06:00h until 09:00h for a “normal” weekday.

Including the data of the two scenario’s described earlier, there are now five different sets of speeds and intensities for the morning rush hour;

I. The first set represents the actual measured situation from 06:00h until 09:00h with 36 period of 5 minutes at Thursday, April 28th.

II. The second set represents the results of the prediction system of Thursday, April 28th.

III. The third set represents the actual measured situation from 06:00h until 09:00h with 36 period of 5 minutes at Thursday, April 14th.

IV. The fourth set represents the results of the prediction system of Thursday, April 14th.

V. The fifth set represents the average traffic pattern for a morning rush hour from 06:00h until 09:00h in 36 period of 5 minutes.

A comparison can be made between the results of the prediction system and the historical average for a normal day and for a day with an accident.

As a measure of effectiveness we use the discrepancy between the predicted or averaged travel times and the observed travel times, i.e. comparisons take place between the sets I and II, I and V (normal day), III and IV, and III and V (accident scenario).

This discrepancy is expressed for each location/link separately. The absolute error for a specific link between scenario I and scenario II can be computing according to equation (17).

\[ \sum_p \left| t^p_I - t^p_{II} \right| \]  

(17)

Where \( p \) is the period number and \( t^p_i \) the travel time in period \( p \) for scenario \( i \). Figure 7 shows these absolute errors for each location and each period. The absolute error for the predicted values II is represented by a bar, and in the same figure, the absolute error for the historical average V is shown as a solid line.
Figure 7 shows that the prediction system is capable of reproducing the actual situation of April 28th, as for most links the absolute error in travel time summed over the entire time span is only a few minutes. The same figure, however, shows that the historical average is at least as good. To make a prediction for the morning rush hour of April 28th, it might be better to use the historical average of several similar days.

Figure 8 shows the same entities as figure 7, but now for April 14th. The absolute error for the prediction IV is represented by a bar for each location, and in the same figure, the absolute error for the historical average V is shown as a solid line.

Figure 8 shows that the prediction system is also capable of reproducing the actual situation on April 14th, while the historical average gives a bad estimate for several locations.

9. Conclusions:

This paper illustrates that the proposed traffic forecasting system can be used to make predictions of traffic flows in a network. OD-estimation and the 3DAS model are capable of reproducing a traffic pattern on a specific day, including accidents. Correct representation of the network and speed-density functions is very important. Specifying the wrong number of lanes at a road section can have consequences for the entire network. These errors can be located easily and corrected using the available graphic software.

The model was tested on two different days. One day represented a “normal” morning rush hour, the other day represented a morning rush hour with an accident which blocked all lanes for 45 minutes.

Comparing the traffic flow pattern of a specific day with the historical average pattern, it can be concluded that for “normal” days, the system can reproduce the situation, but that the historical pattern is at least as good. This is explained by the fact that predictions obtained from historical data are not hindered by mis-specification of OD-demand and network characteristics.

The day with the accident however, was better reproduced by the prediction system than by the historical data. These results suggest that the ideal forecasting procedure is a combination of both approaches.

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10. References:


Hamerslag, R. (1989a) Dynamic Assignment in the Three Dimensional Timespace, Transportation Research Record 1220


Rijkswaterstaat (1993) Portalen MCSS, Rijkswaterstaat Directie Noord Holland


Van Der Zijpp, N.J. and Hamerslag, R. (1994b) An Improved Kalman Filtering Approach to Estimate Origin-Destination Matrices for Freeway Corridors, Transportation Research Records, No.1443, pp.54-64


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Figure 1: Framework of the prediction system
Figure 2: Map of the study area (Amsterdam beltway)
Figure 3: hierarchical network structure
Figure 4: The iteration scheme
Figure 5: Model results (bars), compared with the actual measured traffic flow (solid line) at two locations near the Coen tunnel.
Figure 6: Model results (bars), compared with actual measured traffic flow (solid line) at two locations near the accident: left figures is downstream of the accident, travelling north and, the right figures is upstream of the accident travelling east.
Figure 7: The absolute error in minutes for the prediction system (set II) in bars, and for the historical average (set V) as a solid line. The observed data of April 28th (set I) are used as a reference.
Figure 8: The absolute error in minutes for the prediction system (set IV) in bars, and for the historical average (set V) as a solid line. The observed data of April 14th (set III) are used as a reference.
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