Network Monitoring and Personalized Traffic Control: A Starting Point based on Experiences from the Municipality of Enschede in the Netherlands

Tom Thomas and Sander Veenstra

Center of Transport Studies, University of Twente, P.o box 217
7500 AE Enschede, The Netherlands

Abstract. An increasing number of cities have severe traffic problems. We identify three main challenges for managing these problems. The first one is to achieve a proper amount of monitoring. Secondly, predictions of the effects of network wide management measures require knowledge of the underlying travel behaviour. Finally, measures should be in line with needs and expectations of travellers to be effective. In this paper we focus on these challenges. We use loop detectors near traffic lights in the Dutch city of Enschede to monitor the traffic situation in its network. We developed a method to estimate delays from these measurements. We also use a simple forecasting algorithm to predict flows and travel times for different time horizons. Regarding travel behaviour, we used a license plate survey to study route choice. We discuss how the results from these studies may be used to improve urban traffic management.

1 Introduction

Congestion has increased significantly in the last few decades. This has led to serious problems, especially in urban areas. Travel times for travellers have increased and the livability in residential areas has declined due to pollution and issues concerning safety. The efficient use of existing infrastructure is one of the strategies to reduce these problems. This requires sufficient monitoring of the traffic status of (parts of) the network. Only recently systematic data collection by roadside systems like loop detectors and cameras has increased significantly in urban areas. As a result, several traffic management centers have been applied for urban networks, e.g. [1], [2], [3].

In large cities in developing countries and Eastern Europe, however, still only few roadside sensors are available to collect the necessary traffic data. At the same time, an increasing number of travelers use smart devices which enable them to trace their position by e.g. GMS or GPS. With these devices traffic information, such as travel time or amount of congestion, can be provided to users in real-time. Increasingly, this is done by private companies. However, the underlying data they use, is often not freely available. It is therefore likely that in the near future, traffic managers will still need to use some roadside systems combined with limited amount of floating car

data. One of the challenges will be to generate sufficient traffic data in cities which have a limited amount of sensors.

With sensors throughout the network, network wide control scenarios can be developed for managing the network. For unsaturated flows, local vehicle actuated controls can minimize delays, and green waves, e.g. [4], at a main arterial road can reduce the number of stop and go moments, but in large cities with many congested roads these measures are often not sufficient. However, optimization of network wide strategies is a complex task, especially when real-time data are used. Simplification of the network therefore appears to be inevitable. In that regard, a hierarchical network architecture, in which controls are clustered in a tree structure, appears to be a promising approach, e.g. [5].

Although a lot of progress has been made in adopting network wide control strategies, their possibilities would be greatly enhanced when historical data and underlying traffic patterns, i.e. origin destination flows and route choice behavior, would be included. From historical traffic data, (short term) predictions of the traffic status can be made, for example by pattern matching, e.g. [6]. These predictions enable controllers to anticipate on the (near) future. Moreover, information about OD patterns and route choice can be used to simulate the outcomes of many different control scenarios in advance, e.g. [7]. These simulations may cover whole periods, like complete rush hours. In this way, timely measures to control the amount of traffic on access roads, may for example prevent congestion in the city center at a later time. In addition, dynamic assignment models may be used to improve forecasts of route choice fractions under different circumstances, e.g. [8].

Another challenge is that individual travel advice is sometimes not aligned with the objective of a traffic manager. For instance, a navigation tool may advise a traveler to drive through the center, while the objective of road authorities may be to reduce through traffic in the city center. It is therefore important to align the objectives of travelers and traffic managers. Through intelligent communication devices, road authorities may communicate their control strategies to individual travelers. Not only will this help travelers to anticipate certain measures, but if travelers understand the reasons behind certain control strategies, they might also follow advice that enhance these strategies. Such a win-win situation will only be successful if road authorities are informed about the needs and expectations of travelers. Hence, some knowledge of underlying travel behavior appears to be crucial for providing tailor made traffic control to different types of users.

In this paper, we will touch some of these issues. In section 2, we present some results of a route choice study based on a license plate study in the city of Enschede. The results could be used as input for specific control strategies in Enschede. In section 3, we describe a simple method to estimate travel times from detection loops at signalized intersections in Enschede. Together with volumes, these travel times describe the traffic status on the network. In section 4, we describe how we can use historic data to predict volumes and travel times, which enable traffic managers to anticipate on certain bottlenecks. In section 5, we conclude with a short discussion.

2 Route Choice from a License Plate Survey

Route choice plays an important role in predicting traffic flows. For given origin (O) and destination (D) pairs, route choice behavior determines how trips are distributed over the network. Hence, description of route choice behavior is essential in estimating traffic loads. Initially, travelers were assumed to choose the shortest travel time route, e.g. [9]. In general, both travel advice and traffic control are often still based on this assumption. However, many other attributes are found to be important, such as for example directness and number of intersections and turns, e.g. [10], [11].

The influence of these many different attributes on route choice can be evaluated by all kinds of observations. A rather indirect way to calibrate a route choice model is with the help of aggregate, instantaneous data like traffic volumes and travel times. It is not trivial, however, how individual preferences match with aggregate states of the transport system and many combinations of attribute values in the model might lead to link volumes that are reasonably comparable to observed volumes.

Most authors therefore prefer to gather observations from which route choice can be derived in a more direct way. Revealed preference techniques are probably most suited for this task, because they measure the actual choices of participants. Like stated preference, many of these revealed preference studies have been carried out by questionnaires, e.g. [12], [13]. Questionnaires enable the researcher to study individual preferences in detail, but the small samples are often not representative for the whole population. Routes can also be observed by floating car data, e.g. by GPS tracking, e.g. [14], [15], [16]. GPS tracking is in some sense complementary to questionnaires. Although fewer individuals are usually in the sample, partly due to privacy restrictions, individuals can be followed over longer time periods which enables researchers to describe dynamic aspects of route choice behavior. In addition, observed routes are often represented by a unique path in the network. However, like in questionnaires, samples are quite specified, i.e., aimed at a small group of individuals and hence a small set of arbitrary OD pairs.

Roadside systems can also be used to estimate route choice behavior. We used a license plate survey in the municipality of Enschede to study route choice. Although license plate surveys have been used for this purpose before, e.g. [17], this remains quite rare. License plate surveys are however complementary to questionnaires and GPS data. A license plate survey does not provide the explanatory power from a questionnaire or the details from GPS data. However, it provides a complete dataset with which average route choice behavior of many users and different types of OD pairs can be estimated.

2.1 License Plate Survey

The city of Enschede has about 130.000 inhabitants. Although the city is rather small and compact in an international context, it can be considered a large city (13th in the Netherlands) in the Dutch context. The monitoring stations were positioned in concentric circle cordons, covering all main roads. We distinguished main roads from residential streets. A main road has a speed limit of 50 km/h or larger. Residential streets have a speed limit of 30 km/h. Car license plates and their time passages were

registered during the off peak and evening rush hour on a Tuesday, and on a Saturday afternoon. These time slots represent periods with different traffic situations, e.g., on Saturdays a significant fraction of traffic consists of shoppers visiting the city center. Within each period the traffic situation is quite stable. The registrations were carried out by human observers.

Figure 1 illustrates the cordons around the central part of the city. The stations with the labels STK are on the ring road, and the stations with labels CK and CTK are on roads through the city center. The network in the figure consists of all main roads.

Trips were defined as a sequence of measurements of the same license plate. We used certain criterion to split sequences in separate trips when it was quite likely a driver actually had multiple destinations. However, due to significant variations in travel times, e.g. due to the unpredictability of traffic control phases encountered during a trip, it is quite difficult to distinguish multiple trips when the time at an intermediate destination is short. Actually, this problem also plays an important role in GPS data from which modelers want to identify different destinations and trip purposes. In some cases, it will remain difficult to distinguish between a stop at a destination and a traffic related stop. Although we do not know the exact number of these cases, they probably only constitute at most a few percent of all trips. For general trends, this issue is therefore not very relevant. However, it may be important for modeling route choice probability distributions. Probabilities for long routes may then be overestimated, because some of them actually constitute multiple trips.
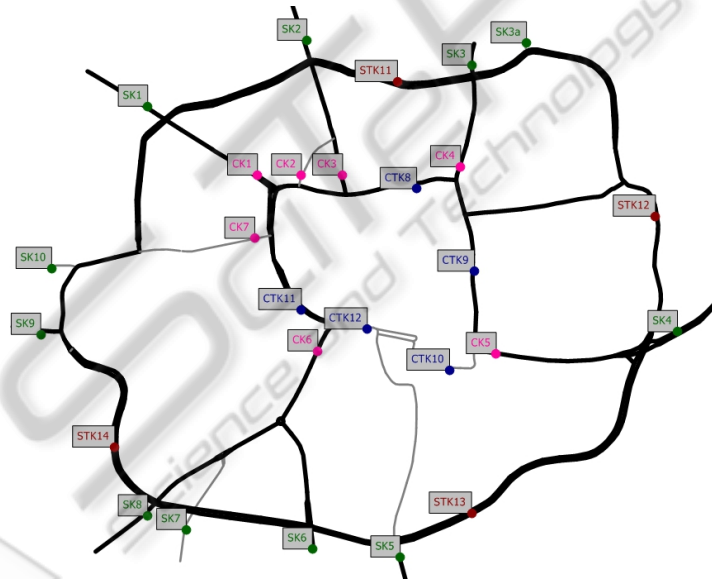

Fig. 1. Network of main roads and monitoring stations (labels) for the central part of Enschede.

Because travel times between consecutive stations are quite variable, we used the average travel time rather than the individual travel times. For each pair of consecutive stations, we estimated the average travel time and standard deviation of all observed trips containing that pair, irrespective of origin, destination or route. Due to
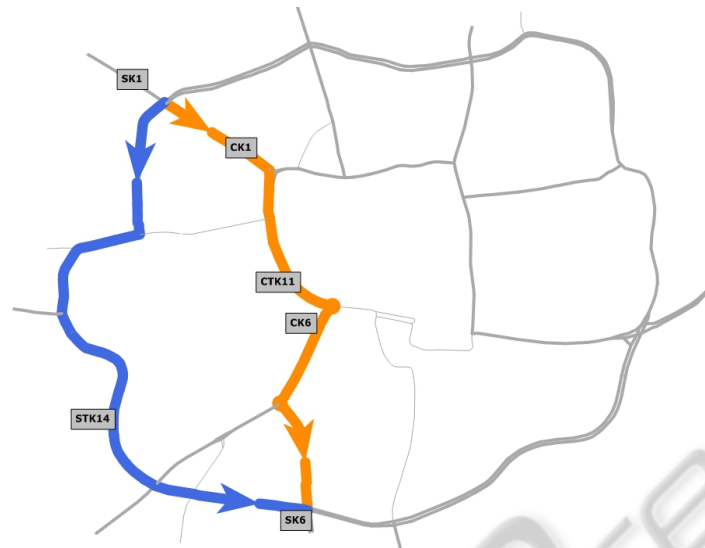
Fig. 2. Observed routes for sequences between SK1 and SK6.

the large number of observations, average travel times are quite accurate. By adding the average travel times between all consecutive stations in a sequence, the travel time of the corresponding sequence was obtained.

For some individual trips, deviating travel times are the result of something atypical going on, for example, a driver who makes a stop at a petrol station or just an error in the registration process. These so-called outliers were identified when the travel time between two stations deviated more than 3 times the standard deviation from the average travel time. As a result about 10% of trips were removed as outlier. However, as suggested in the previous paragraph, some "bona fide" trips were probably also removed, while short activities in between two trips, like collecting or delivering someone or something, may not have been filtered out.

Figure 2 shows an example of the trips that were observed between station SK1 and SK6. The blue route is along the ring road, and the orange route through the city center.

2.2 Route Set

Route assignment models use either implicit or explicit path generation. In explicit path generation, the generation of the choice set and the assignment of choices (by choice probabilities) are clearly distinct processes. Several authors (see for a review, [18]) have argued that both should be done independently, because choice probabilities may be affected by choice set size and composition.

However, even when paths are generated explicitly in advance, the alternatives will always be biased in some way, because the modeler determines which "logical" paths, i.e. those likely to be chosen, will be selected. For instance, large detours may be perceived as illogical, but it is not certain whether they may not occur in some

cases. It is the purpose of route choice studies to reveal how likely both logical and illogical routes are chosen in practice. This bias of using "a priori knowledge" may even be enhanced when requirements are set to include used (observed) paths in the route set, while equally valid unobserved paths may be left out. In such a bias against "unseen" data, the occurrences of observed events are over estimated.

The aforementioned issues are in particular relevant for our survey. We do not observe paths. Instead, our so called observed routes only consist of sequences of monitoring stations. In between these locations, multiple paths are still possible. Fortunately, this problem can be dealt with, because the following is true for this survey. First, most drivers take main roads. The use of residential streets is quite rare. Secondly, between consecutive stations, there is often one unique path of main roads. If there are multiple paths, these can be considered as overlapping, which means they are actually considered as the same by the driver. Thirdly, different sequences are considered to be non-overlapping, because they contain different key intersections, which make the corresponding routes quite distinct. Hence, each observed route (sequence of links) can be represented by one unique underlying path.

Since link sequences represent unique paths, our route set only consists of link sequences. We do not need to know the paths, and therefore do not need a network of roads. This will simplify the route set generation enormously, but also has the advantage that observed routes can mapped one-on-one to routes in the route set. Another advantage is that we almost do not need to make assumptions about the plausibility of certain routes in advance. Thus, almost all possible routes are selected, including unobserved routes. This means that we are careful not to introduce biases against "unseen" or "illogical" routes.

We used a simple route set method in which new routes, i.e. sequences, were created by appending stations to the last station of the previous sequence. Each sequence only contained pairs of consecutive stations which also appeared in observed sequences. Also, (sub) circular routes were not allowed, and a time limit relative to the shortest time route was used to stop the creation of very long alternatives. Yet, with these restrictions still about 80 alternative routes per OD pair were found, which is much more than in other route set generation methods.

2.3 Main Results

We found that most drivers use the shortest time route. However, 25% of the trips did not use the shortest time route, but a detour route. This is quite a significant fraction, but it is smaller than typically found in the literature, e.g. [13], [14], [15]. In those studies, typically fewer than 50% of the drivers take the shortest time route. The difference may be related to the relatively "low resolution" of our data, which does not allow us to distinguish different, but resembling, paths. On the other hand, the samples sizes of participants and corresponding OD pairs were relatively small (in order of magnitude of 100) in the aforementioned studies. Moreover, in most studies the samples only contained university staff members and / or commuters. Even if we would consider the samples in these studies to be representative, they are far from complete. It should be noted, however, that while our sample may be complete for the city of Enschede, it only contains city trips and no highway trips. It is therefore not

unlikely that the sample differences may be responsible for differences in results.

For a subsample of OD pairs, which cut the city center, we found that even more drivers, i.e. 88%, took the shortest time route when the ring road was faster than the route through the center. However, we found that only 14% took the shortest time route when the ring road was slower than the route through the center. Travelers thus preferred the route along the ring road even if it was not the fastest route. For this particular network constellation, road hierarchy appears to be crucial, and just as important as travel time. We also conclude that it is only useful to compare route choice fractions over shortest time routes when the context is the same.

Whereas route frequencies are quite sensitive to the characteristics of OD pairs, overall detour times are much more robust. We found that the average detour time is about 8% of the average travel time over the shortest time route. This results is quite comparable with the literature, e.g. [14], [16]. This can be explained by the fact that for OD pairs with only long alternative routes, a relatively small percentage of trips over these alternatives will be offset by larger detour times for these alternatives.

3 Travel Time Estimates for Signalized Intersections

The municipality of Enschede has the objective to reduce the number of vehicle kilometers by 5%. Consequently, the accessibility will be improved. For this purpose, travelers may be given incentives to change their behavior. This can for example already be done by confronting them with their "bad" travel behavior in comparison with that of other travelers. Another way is to inform travelers about the traffic status, and provide them with alternative modes or routes, which may yield more sustainable trips.

In the latter case, travel times and volumes in the network should be estimated. Travel times can be observed by floating car data, e.g. by GPS tracking. Roadside systems can also be used to estimate travel times. For example, Bluetooth data may provide quite reliable travel time estimates, e.g. [19]. We used data from inductive loops near all important signalized intersections in Enschede to estimate travel times or delays. These data were obtained from January 2010 till June 2011. Although travel times can only be estimated in an indirect way by inductive loops, they provide a complete dataset of all drivers who passed these intersections. They therefore also provide volumes, which are typically not observed from GPS data alone. The advantage of volume measurements is that they enable an assessment on why travel times deviate. In some cases, travel times increase, for example due to bad weather, while volumes remain constant or even decrease. In other cases, for example at the start of a normal rush hour, travel times increase due to increasing road volumes. If an explicit distinction can be made between capacity and demand related travel time deviations, this may yield more reliable short term travel time predictions.

3.1 Loop Data

A signalized intersection consists of 4 to 12 signal groups, indicated by the traffic

light symbols in figure 3. The figure shows that a signal group consists of 1 to 5 inductive loops. The loops associated to a signal group all have particular functions. The loop closest to the stop line (stop line loop) is mostly used to detect vehicles at the stop line and to estimate the volume of vehicle passing through. The second loop (long loop, if present) is generally situated 10 to 15 meters upwards from the stop line and is used to detect the first hints of a queue. The other loops (distant loops) are used to detect approaching vehicles. These loops can also be used to count the inflow of vehicles at a particular arm of the intersection. Most inductive loops are connected to one signal group, but distant loops can sometimes be associated with more than one signal group.
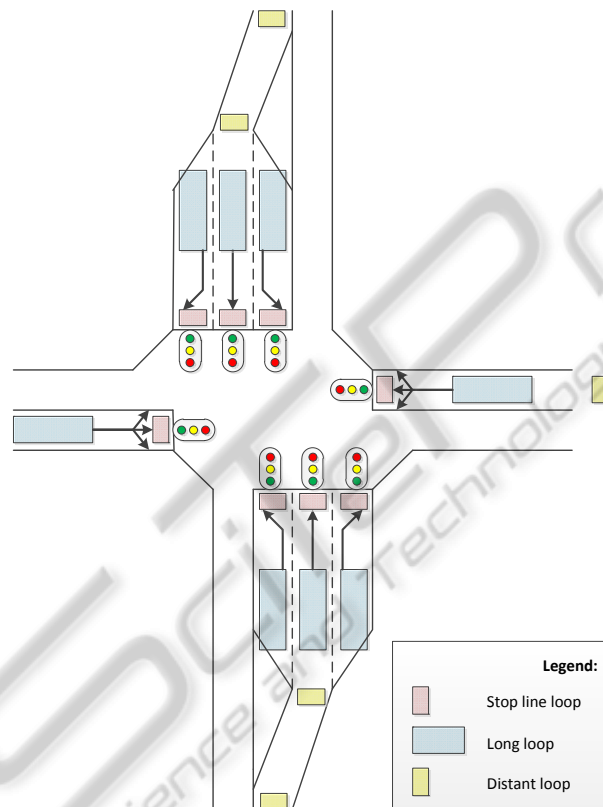

Fig. 3. Example of an intersection and its inductive loops.

The data were aggregated in 5-minute intervals. For different types of loops the data were further aggregated to the signal group level. Although we plan to use all the data, especially for estimating delays of oversaturated flows, so far we only used information from stop line loops. Flow volumes were estimated by adding vehicle counts from stop line loops belonging to the same signal group, and signal group occupancy rates were estimated as the weighted (by vehicle count) average over the corresponding loops. Also, the total red time and number of times the signal group

switched from red to green were recorded. Finally, we also kept record of the occupancy time during red as fraction of the total time (5 minutes).

Unreliable data were flagged. This was done as follows. If the volume was 0 or the vehicle count of at least one loop exceeded a maximum limit, the observation was flagged (flag = 0) as unreliable. The limit was set such that the time headway between two vehicles during green time should not be smaller than 1.5 seconds. Smaller values are unrealistic and indicate rapid and artificial variation in the loop's induction current. A volume of 0 does not necessarily have to point to a malfunctioning of the loops. In fact, in the middle of the night it is possible that no cars are passing during a five minute period. However, it is no problem to flag these "bona fide" measurements, because they are not relevant to the traffic manager, and cannot be used to estimate the travel time anyway.

We mapped the signal groups to a network of roads. This enabled us to provide route travel times by combining (free flow) travel times on road segments with the estimated travel times or delays at the signalized intersections. For intersections without measurements, we estimated the travel time by using a macroscopic traffic model.

3.2 Delay Estimation

Because delays cannot be measured directly from loop data, queuing theory is often used to estimate delays, e.g. [20]. If we assume a homogenous arrival rate of vehicles near saturation (green time is just sufficient to let all queuing vehicles through), the average delay per vehicle is half the red time of one cycle. For a random arrival rate, the delay increases somewhat, but the largest delays occur when cars arrive in clusters, i.e. the intensity during arrival is the same as the discharge intensity. In other words, all drivers will wait the same amount of time for a red traffic light. Near saturation, this would yield an average of the red time of one cycle.

In figure 4, we show the case in which arrival intensities are the same as discharge intensities for an arbitrary average 5 minute flow volume. The figure shows that all cars have the same waiting time. Hence, the average delay is the delay of the first car in the queue. This delay can be calculated by multiplying the occupancy rate during 'red' and the red time per cycle. Both quantities can be derived from the recorded observations.

We deviated from standard assumptions in queuing theory, because urban traffic flows are quite clustered. This may in particular be true when controls are vehicle actuated, such is the case in Enschede. Both in quiet traffic conditions and conditions near saturation, these estimations may therefore be quite accurate. For intermediate conditions the delay is probably somewhat over estimated. These simple estimates could therefore be improved by including a flow dependent factor between 0.5 and 1 for under saturated flows.

3.3 Accuracy of Delay Estimations

To test the accuracy of our delay estimates, we compared our estimates with other data sources. For the city of Enschede, a database with average speed profiles based
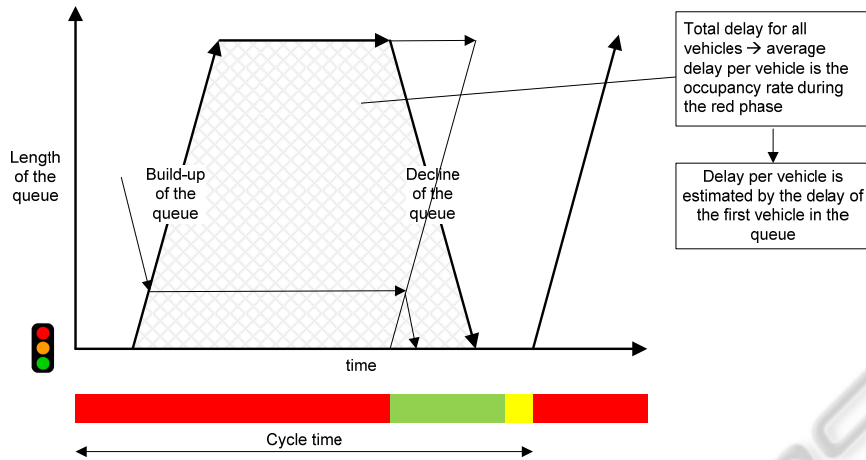
Fig. 4. Illustration of queuing when cars in under saturated flows arrive in clusters.

on floating car data (called ViaStat) is available. From this database average travel times on road sections can be extracted. We converted our delay estimates per signal group into travel times by assuming free flow travel times on the corresponding road segments. We chose the urban ring road for comparison. For both directions on the urban ring road we estimated the travel time on an average Thursday morning peak hour (between 8 and 9 AM).

In table 1, we show the comparison. The table suggests that our results are quite valid. However, we should be careful interpreting these results. The comparison consists of aggregates over many signal groups. Systematic errors in individual delays could still be present. In particular, over estimation of delays in under saturated conditions, could have been offset by an underestimation of delays in potential saturated conditions. So far we did not consider saturated traffic conditions. In a saturated condition the delays will increase dramatically when vehicles have to wait several cycle times. For the estimations of these travel times, we might use data from previous 5 minute intervals to describe the growth of the queue, and apply correction factor larger than 1 to capture the increasing delays.

Table 1. Travel times based on ViaStat and our estimates.

	Based on ViaSTAT	Our estimate
Ring road 'right'	14 min 11 sec	13 min 35 sec
Ring road 'left'	13 min 50 sec	14 min 11 sec

4 Urban Traffic Flow Predictions

One of the objectives is to generate accurate information on flow volumes and travel times. Users need to be able to plan their journey based on this information. Thus not only real-time information should be generated, but also predictions for the (near)

future. Different approaches exist for predicting volumes and travel times. Extrapolation models (both spatial and temporal) are often used for short term predictions, e.g. [21], [22]. Extrapolations can give accurate predictions, but only for prediction horizons smaller than 15-20 minutes. For longer prediction horizons, volume measurements can also be matched to historical patterns. For these predictions neural networks, e.g. [23], [24], or clustering methods, e.g. [25], [26], are applied.

4.1 Base-line Prediction

Autoregressive models (e.g. ARIMA models) are common in time-series forecasts. Their forecasts are based on linear combinations of measurements from previous time-intervals. Travel demand variations are often non-linear. Several authors, e.g. [21], [22], [26], have therefore indicated that they prefer to use the average historical profile of a whole day for predictions of a future day. In this case, non-linear features may already be captured by the historical profile. Based on these results, our first prediction for day d, link l and time interval t is equal to the historical mean of the group to which day d belongs.

$$q_{dlt}^{base} = \overline{q}_{dlt} = \frac{\sum_{d' \in D} q_{d'lt}^{obs}}{n_D} \tag{1a}$$

$$D_{dlt}^{base} = \overline{D}_{dlt} = \frac{\sum_{d' \in D} D_{d'lt}^{obs}}{n_D} \tag{1b}$$

In equation (1a), we call q_{dlt}^{base} the base-line prediction, and q_{dlt}^{obs} is the measured volume on day d, link l and time interval t. Equation (1b) provides the base-line prediction for delay D. Figure 5 illustrates base-line predictions for 5 minute intervals of a particular traffic control during Mondays, Thursdays and Saturdays. The upper panel shows significant day-to-day variation. The characteristic morning rush hour peak is absent during Saturdays, while Thursdays show extra traffic in the evening due to extra shopping hours. The lower panel shows the average delay for these weekdays. The figure nicely illustrates that during busy periods, travel times also increase.

4.2 Short Term Predictions

When large events take place traffic flows may be influenced by the visitors of these events. At certain locations this will lead to a significant increase of traffic just before the event has started and after the event has finished. These events should be taken into account, implicitly by pattern recognition or explicitly by using historical data of events and knowledge about the occurrence of a new event. However, base-line predictions sometimes also do not follow the measurements in a regular situation. Apparently, traffic counts show systematic variations in time, which cannot be described by the regular day-to-day variation alone. Such variations can have different causes,
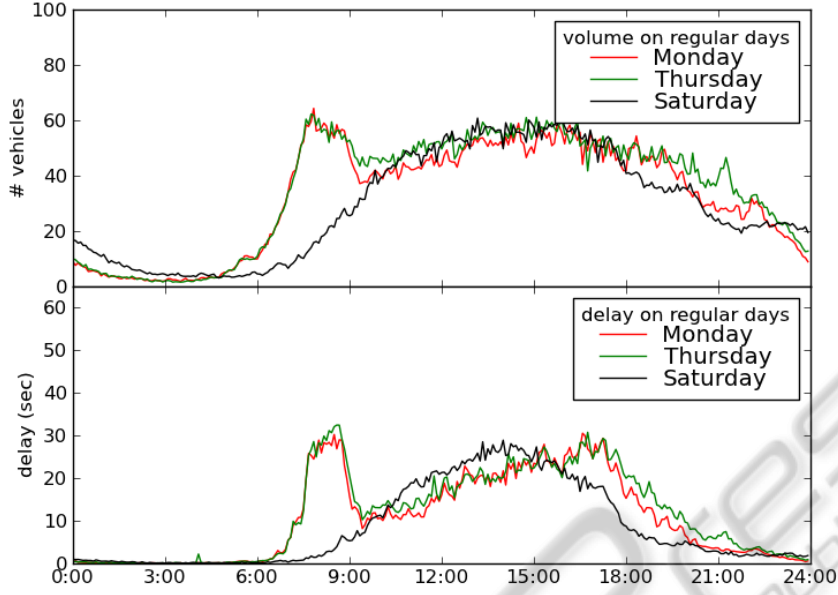
Fig. 5. Volumes (upper panel) and delays (lower panel) for a specific intersection and per 5 minute interval averaged over all Mondays, Thursdays and Saturdays.

like for example seasonal effects, changing weather conditions or road works.

From a visual inspection of time-series, we suspect that a large amount of the variation between successive time-intervals is random. This variation is called noise. The amount of noise is an important quantity. If the amount of noise increases, systematic variations can be detected less easily. It also gives an under limit for the predictive power, because noise cannot be predicted. Noise can have different causes. It can be caused by the random arrival process of cars. This process results in different headways between following cars, which is an important source of variation on highways. In urban areas traffic flows are interrupted by traffic signals. However, if green times of these signals are unknown, they may even contribute to the noise. In practice, all variations which have short time-scales and which do not follow a recurrent pattern can be considered as noise.

A measurement of quantity x on day d, at link l and in time interval t can thus be described in the following terms:

$$x_{dlt}^{obs} = x_{dlt}^{pred} + \varepsilon_{dlt} + v_{dlt} \tag{2}$$

with x_{dlt}^{pred} the prediction (e.g. the base-line prediction), ε_{dlt} the systematic variation between measurement and prediction, i.e. the prediction error and v_{dlt} the noise on day d, at link l and in time interval t.

The objective is to develop a prediction scheme that minimizes the systematic variation or prediction error. There are two extreme approaches to reach this objective. First, the external processes that lead to systematic variations can be studied in detail, so that the relation between the two can be modeled (e.g. the relation between weather and travel demand). The advantage of this approach is that it provides insight in the

variation of travel demand. The disadvantage is that it is complicated and requires many reliable data sources, which are often not available. Another approach is a black-box approach. In this approach correlations in historical data are found by certain mathematical techniques (e.g. neural networks, pattern matching) and these correlations are used in the prediction scheme.

We applied an intermediate approach. Our method is based on the following assumption. The single most important temporal correlation in the systematic variation is that between *successive* epochs (which can have different time-scales), i.e. there is a positive correlation between the systematic variation ε_{dlt} and $\varepsilon_{dlt+\Delta t}$. For example, due to seasonal effects, we assume that if there is more traffic than average on a particular day, than the probability is high that the next day will also show more traffic. The improvement of the base-line prediction is quite simple in this case. The relative systematic variation c (with $\varepsilon = cq^{pred}$) results from the ratio between the observation and base-line prediction. Suppose that this ratio is 1.10, i.e. c is estimated to be 10%. Dependent on the strength of the correlation between the relative systematic variation of successive time intervals, the updated prediction then lies between 1.00 (in case of no correlation) and 1.10 (in case the correlation coefficient is 1) times the base-line prediction.

Hence, the short term predictions up to 24h ahead can be described as:

$$q_{dlt+\Delta t}^{pred} = \overline{q}_{dlt+\Delta t} * \left(\frac{q_{dlt}}{\overline{q}_{dlt}} \right)^{\beta_q} \tag{3a}$$

$$D_{dlt+\Delta t}^{pred} = \overline{D}_{dlt+\Delta t} * \left(\frac{D_{dlt}}{\overline{D}_{dlt}} \right)^{\beta_D} \tag{3b}$$

In which the base-line prediction at $t + \Delta t$ is updated by the ratio between real-time observations and base-line predictions at t. We used hourly volumes to estimate this ratio. In doing so, we reduced the influence of noise, while still capturing most of the changes in the systematic variation. As mentioned, the update factor β depends on the strength of the correlation between the relative systematic variation at t and $t + \Delta t$. In Figure 6, we show the relative systematic variation of successive days for volumes (upper panel) and delays (lower panel) for a particular traffic control. We did this for each hour of the day between 6.00 and 22.00h. The figure shows positive correlations (with correlation coefficient 0.79 for volumes and 0.68 for delays). The correlation is less strong for the delay, because of the larger amount of noise in the delay estimations. These correlations yield βs of around 0.7.

Besides seasonal influences, which can be used to make predictions on a longer timeframe (i.e. one to two days ahead), real-time data may be used to improve predictions for shorter time horizon. We estimated the correlation between systematic variation in successive hours, and found these to be comparable to that of successive days.

These are still preliminary results. Due to the high noise level, in especially delay estimates, systematic variations are not easily resolved. As a result, at the moment short term predictions are only slightly better than base-line predictions. However, short term predictions can be improved when the noise in the observations are filtered [27]. Without a noise filter, the quality of the prediction quickly reaches an upper limit set by the amount of noise in the observations.
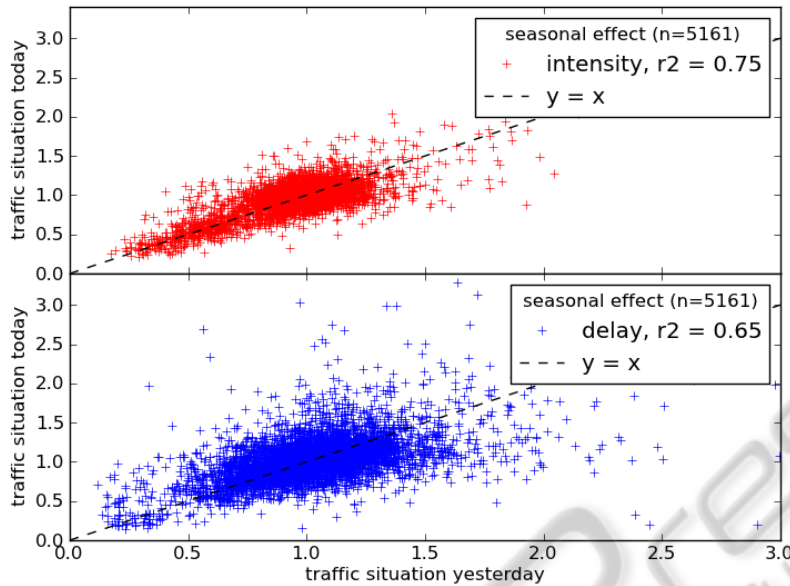
Fig. 6. Correlation between relative systematic variations of successive days for volumes (upper panel) and delays (lower panel).

5 Discussion

Traffic management has developed significantly in the last few decades. However, especially for urban areas, future developments are required.

The first development concerns monitoring. Network wide measures can only be effective if the traffic situation is monitored throughout the whole network. This poses a challenge. Roadside sensors do not always cover the whole network. For example, in sections 3 and 4 we used data from detection loops to monitor the traffic situation in the Dutch city of Enschede. Because some (important) intersections are not equipped with sensors, our estimates and forecasts are incomplete. Ideally, roadside measurements could be supplemented by floating car data, e.g. by GPS, from individual travellers. GPS data alone are probably not sufficient either, because traffic is quite dispersed in urban networks, which implies GPS data from a high fraction of motorists are needed. A fusion between the different data types might be the solution, and could be one of the challenges in a new project.

Floating car data may also be used to improve travel time estimates throughout the network. We used a quite simple algorithm to estimate delays at signalized intersections using occupation rates and red times. However, in particular for saturated condition, delays are probably underestimated by this simple method. We therefore need to improve the travel time algorithm. In addition, car floating data can be useful for validation purposes.

Monitoring in itself is not sufficient. Predictions about the traffic situation enable controllers to anticipate on the (near) future, such that timely measures to control the

amount of traffic in one part of the network may prevent bottlenecks in other parts. In section 4, we used a simple prediction algorithm to forecast volumes and travel times in the near future. The predictions can however be improved. First, noise filters could reduce the noise in the observations and as a result yield better predictions. Secondly, so far we only considered single time series. However, volumes and delays may be spatially correlated. We might improve the predictions by including spatial correlations between sensors, but this will only be effective when most adjacent intersection are equipped with sensors. Unfortunately, this is not always the case. Finally, we focus on slow changing systematic variations in traffic. However, for managers, sudden changes due to events or incidents are often more relevant. The related traffic situations may in those cases be better predicted by pattern matching algorithms. It may be possible to develop a hybrid method, which combines pattern matching and forecasts of slow changing variations.

The second development concerns personalized traffic control. Predictions are not only useful for traffic control managers, but also for road users. If they are informed about future traffic flows and control strategies, they may make choices that enhance those strategies. This will only be possible if personal needs and expectations of road users are taken into account by traffic control strategies.

For this purpose, we need to explore travel behavior. We used a license plate survey to study route choice in the municipality of Enschede. We found that most drivers use the shortest time route, but that 25% of the trips did not use the shortest time route. Moreover, we found that most travellers took the ring road instead of the route through the city centre, even when the ring road was slower. This result suggest that travellers do not need to take the fastest route, but that they may prefer larger roads (higher up in the hierarchy). Many traffic managers would like to see drivers to take the ring road instead of small roads through the city center. These results suggest that strategies to increase the use of ring roads are probably acceptable to users and may also be quite successful.

References

1. Hasberg, P., Serwill, D.: Stadtinfoköln – a global mobility information system for the Cologne area, 7th World Congress on Intelligent Transport Systems, Turin, Italy (2000)
2. Kellerman, A., Schmid, A.: Mobinet: Intermodal traffic management in Munich –control centre development, 7th World Congress on Intelligent Transport Systems, Turin, Italy (2000)
3. Leitsch, B.: A Public-privat partnership for mobility – Traffic management Center Berlin, 9th World Congress on Intelligent Transport Systems, Chicago (2002)
4. Nagatani, T.: Vehicular traffic through a sequence of green-wave lights, Physica A: Statistical Mechanics and its Applications, Vol. 380, (2007) 503-511
5. Vrancken, J., Van Schuppen, J.H., Dos Santos Soares, M., Ottenhof, F.: A HierarchicalNetwork Model for Road Traffic Control, Proceedings of the 2009 IEEE International Conference on Networking, Sensing and Control, Okyama, Japan, (2009) 340-344
6. Hodge, V.J., Krishnan, R., Jackson T., Austin, J., Polak, J.: Short Term Traffic Prediction Using a Binary Neural Network, 43rd Annual UTSG Conference, Open University, Milton Keynes, UK (2011)

7. Wismans, L.J.J, Van Berkum, E.C., Bliemer, M.C.J.: Comparison of Evolutionary Multi Objective Algorithms for the Dynamic Network Design Problem. ICNSC – IEEE conference, Delft (2011)

8. Mitsakis, E., Salanova, J.M., Giannopoulos, G.: Combined dynamic traffic assignment and urban traffic control models, Procedia - Social and Behavioral Sciences, Vol. 20, (2011) 427 – 436

9. Wardrop, J. G.: Some theoretical aspects of road traffic research, Proceedings, Institute of Civil Engineers, PART II- 1, (1952) 325-378.

10. Bar-Gera, H., Mirchandani, P., Fan, W.: Evaluating the assumption of independent turning probabilities, Transportation Research part B, Vol. 40, (2006) 903 - 916

11. Chen, T.Y., Chang, H.L., Tzeng, G.H.: Using a weight-assesing model to identify route choice criteria and information effects, Transportation Research Part A, Vol. 35, (2001) 197 – 224

12. Mahmassani, H.S., Jou, R-C.: Transferring insights into commuter behavior dynamics from laboratory experiments to field trials. Transportation Research Vol. 34A(4), (2000) 243-260

13. Prato, C. G., Bekhor, S.: Applying Branch-and-Bound Technique to route choice set generation. Transportation Research Record, Vol. 1985, (2006) 19-82

14. Jan, O., Horowitz, A. J., Peng, Z. R.: Using global positioning system data to understand variations in path choice. Transportation Research Record, Vol. 1725, (2000) 37 – 44.

15. Zhu, S., Levinson, D.: Do people use the shortest path? An empirical test of Wardrop's first principle, 4th International Symposium on Transportation Network Reliability, July Minneapolis, USA (2010)

16. Papinski, D., Scott, D. M.: A GIS Toolkit for route choice analysis, Journal of Transport Geography, Vol. 19, (2009) 434 – 442

17. Hamerslag R.: Investigation into factors affecting the route choice in "Rijnstreek-West" with the aid of a disaggregate logit model. Transportation, Vol. 10, (1981) 373 – 391.

18. Bovy, P. H. L.: On modeling route choice sets in transportation networks: a synthesis, Transport Reviews, Vol. 29 (1), (2009) 43 – 68

19. Tarnoff, P. J., Wasson, J. S, Young, S. E., Ganig, N., Bullock, D. M., Sturdevant, J. R.: The Continuing Evolution of Travel Time Data Information Collection and Processing, Transportation Research Board Annual Meeting, Paper ID: 09-2030 (2009)

20. Mak, W. K., Viti, F., Hoogendoorn, S. P., Hegyi, A.: Online travel time estimation in urban areas using the occupancy of long loop detectors, 12th IFAC symposium on transportation systems, Redondo Beach (2009)

21. Wild, D.: Short-term forecasting based on a transformation and classification of traffic volume time series, International Journal of Forecasting, Vol. 13, (1997) 63 – 72

22. Van Grol, R., Inaudi, D., Kroes, E.: On-line traffic condition forecasting using on-line measurements and a historical database, 7th World Congress on Intelligent Transport Systems, Turin, Italy (2000)

23. Dia, H.: An object-oriented neural network approach to short-term traffic forecasting," European Journal of Operational Research, Vol. 131, (2001) 253 – 261

24. Yin, H., Wong, S. C., Xu, J., Wong, C. K.: Urban traffic flow prediction using a fuzzy-neural approach, Transportation Research Part C, Vol. 10, (2002) 85 – 98

25. Chung E.: Classification of traffic pattern, 10th World Congress on Intelligent Transport Systems, Madrid (2003)

26. Weijermars, W. A. M,: Analysis of urban traffic patterns using clustering, Ph.D. Thesis, University of Twente, Enschede, The Netherlands (2007)

27. Thomas, T., Weijermars, W. A. M, Van Berkum E.C.: Predictions of Urban Volumes in Single Time Series, IEEE Transactions on Intelligent Transportation Systems, Vol. 11 (1), (2010) 71 – 80