

# **ON-LINE TRAFFIC CONDITION FORECASTING USING ON-LINE MEASUREMENTS AND A HISTORICAL DATABASE**

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## **SUMMARY**

Knowledge of future traffic conditions is important for travellers —to improve their journey planning (with or without congestion)— as well as for traffic managers —to improve the effectiveness of their control actions, and their planning.

In recent years, a lot of effort has been put into investigation towards models that can predict, on-line, the short-term development of traffic conditions. The results obtained to date have been somewhat disappointing, especially considering the effort and the complexity of the model systems. We have not come across convincing evidence that even advanced models have been capable of consistently outperforming much simpler methods.

This paper reconsiders the use of a simple historic database to provide short-term forecasts. Results show that only slight improvements can be achieved by using on-line measurements. The 'historic forecasts' are however very useful, especially when information can be provided about the certainty of the forecasts.

# INTRODUCTION

Up-to-date knowledge of traffic conditions is important in nowadays traffic systems. The users of the traffic system, the travellers, benefit by the information provided because it allows them to plan their journey better; benefits can be found both in mode choice, route choice and time planning (short term and long term). The suppliers of the traffic system, the traffic managers, benefit by the information because it allows them to use traffic control instruments more effectively, and to improve for instance roadwork planning.

During the last two decades a lot of research has gone towards the development of quite complicated and sophisticated traffic model systems that allow the prediction of the short-term development of traffic conditions. To date the results have been somewhat disappointing when they are compared to the use of the simplest models available.

In our view it was useful to move a step back, in order to rethink the objectives and the feasibility of proposed solutions. In this paper some steps in this process are taken. First of all the objectives will be discussed in combination with the model systems typically used. Then the use of a simple model system will be discussed. Results will be presented from some tests that have recently been conducted in The Netherlands.

Our view has been based upon experience built up over the last decades and during several large European project, e.g. DYNA (1) and DACCORD (2), but also on numerous national projects conducted in both Italy and The Netherlands.

## PREDICTABILITY OF TRAFFIC CONDITIONS

The need to predict unexpected congestions (for now we ignore the “recurring problem”: how to define congestion) is strong, but on the other hand also the most difficult to realise, with or without sophisticated models. Sophisticated traffic models can more easily predict reoccurring congestion (recurrent congestion), but in fact, this is not too difficult even with a simple model (e.g. based on a database system).

To bring this discussion to a higher level a somewhat deeper analysis is required. To support the following discussion it is important to classify traffic conditions into:

- Free flow condition — the traffic flows unhindered (speed > 80 km/hour).
- Recurrent congestion — regular recurrent congestion at broadly the same time and location in the network.
- Incidental congestion — unexpected congestion; unexpected in both time and location.

These three traffic conditions (for instance defined in terms of speeds) will now be discussed in respect to the use of traffic models to predict them:

**1. Free flow condition** — Forecasting is not required. Because the traffic is flowing at so-called “free-flow speed”, which is assumed to be time-invariant, it could suffice to measure the average speed once at different locations.

**2. Recurrent congestion** — Also recurrent congestion does not require sophisticated

forecasting models. Recurrent congestion re-occurs at (approximately) the same time and (approximately) the same location. Therefore it can be forecasted by maintaining a database to record the phenomenon (time and place) as well as the variation over time (over the days). A somewhat more sophisticated database model with a certain degree of differentiation in terms of distinguishable situations is likely to outperform the currently available traffic simulation models.

**3. Incidental congestion** — Naturally this is the most disturbing type of traffic jam. The problem is that congestions of this kind occur unexpectedly. Accidents can simply not be predicted. The likelihood of a congestion to occur might be partially predictable, but the manifestation of incidents, and the congestion they may cause, remains unpredictable. So, with or without a sophisticated model, the incidental congestion remains unforeseen (accidents may and do in reality even occur at the least busy time of day and in the least busy location).

Based on the above analysis the reader might come to the conclusion that there is no sense in developing traffic (simulation) models for forecasting traffic conditions for the very short term at all. At best a congestion table should be used. However, this is not the entire story. The problem with incidental congestions has only partially to do with when and where they occur. More important is how to deal with them. Prevention is naturally the best, but no matter what precautions are taken accidents will always happen. A severe congestion might block the entire network. To help with the latter problem a database would not be very helpful (unless the particular congestion would occur very often at the same time and place (in which case it will become a form of recurrent congestion.)). A traffic (simulation) model that would allow the analysis of the solution space would in this case be much more helpful. Hence the development of traffic models in this context remains important, not so much for preventing the incident but rather for minimising the delays when solving the consequences of an incident once it has occurred.

Although the further development of traffic simulation models should clearly continue, the need for information about recurrent congestion should also be recognised. This paper investigates the use of a database model (in contrast to a traffic simulation model) to provide information about recurrent congestions.

## USING HISTORICAL DATABASES

The use of a historic database in traffic modelling is not new. Some such model systems exist for quite some time now and others have already been proposed in the distant past (3). The objective of using a historical database is to measure and record most of the systematic variation in traffic conditions by means of classification. The traffic conditions are therefore stored in the form of time series. The first important differentiation is a differentiation by location (for each location a separate historic database). The second is a differentiation by time (hence time series). Time series capture the “within day” variation. Next, two basic ways of recording traffic conditions can be distinguished:

- Classify the traffic conditions by day-type (the “between day” variations);
- Classify the traffic conditions by type of traffic condition.

In the first case the time series of the speeds measured by a loop detector is stored by day-type and time. For instance, separate databases may be created for the different days of the week

(in general for days for which the traffic conditions are different). In the second case, see (4), a database is kept for time-series under different traffic conditions (independent of the day-type). When a new time series is recorded it is stored in the database together with time-series that resemble it most closely. Combinations of both methods can be possible as well. The first method, which uses day-type as proxy for traffic conditions, is straightforward and easy to implement, and it forces the recognition of trends. In other words, it provides the user with insight in the development of the traffic situation over time (days, weeks, months). The second method is more complicated as it requires a classification of traffic conditions. But it allows a better classification (closer to the observations). On the other hand, it is more difficult to forecast the traffic conditions for an upcoming day, because first the condition class needs to be predicted. In this paper we describe an application of the first type of method.

## HISTORICAL DATABASE MODELS — SETTING UP THE SYSTEM

Historic patterns of traffic measurements are stored in the form of time-series, differentiated by day-type. At this point we limit our selves to a database using a classification of different weekdays (7 separate time-series). When a new time-series is obtained from the measurement system it is combined with the historic time series for that day of the week.

Although the idea of a historical database is simple and easy to implement, there are a number of questions that need to be answered in setting up a historical database system.

- **What should be the time-basis?** In the Netherlands average traffic flow and speed data is available per minute. The minute-by-minute variations can be fairly strong. Better results may be obtained using 5 or 10-minute aggregates.
- **How do we construct the database from day-to-day?** The underlying requirements are that the system should keep the databases up-to-date. In other words, if the characteristics of the Monday traffic are changing this should be captured by the historical database.

For the database system under consideration a method of exponential forgetting has been used, such that the system can be called self learning.. The historic value  $X_{daytype}(t)$  at time  $t$  is updated with a new measurement  $Y(t)$  according to the following equation:

$$X_{daytype}^{new}(t) = (1 - \alpha)X_{daytype}^{old}(t) + \alpha Y(t) \quad (1)$$

Hereby  $\alpha$  determines how much influence the new measurement has on the historical database. With a large  $\alpha$  the database will strongly resemble the most recent day which was put in to the database. With a very small  $\alpha$  the most recent day will have hardly any influence. If there is a trend this will only be picked up very slowly by the database. The value of  $\alpha$  should be chosen in such a way that the desired trends are captured, without undermining the historic characteristics.

## FORECASTING — USING THE HISTORICAL DATABASE

The simplest way of forecasting the traffic conditions is by using the historical database as if it corresponds exactly to the current day. In principle there are now limits to this type of forecasting. One could make a forecast months ahead as long as the type of day is known, and presuming that there is a historical database for that type of day available. Naturally the relevance of the forecast may diminish if the forecasting horizon grows, but for what historical databases are worth, there are no limits. So, the forecast for a certain type of day at time  $t$  could be written as follows:

$$F_{daytype}(t) = X_{daytype}(t) \quad (2)$$

When looking days ahead there is probably no better way to make a forecast. However, when we look one minute ahead the best forecast will most likely be the measurement of the current moment:

$$F(t+1) = Y(t) \quad (3)$$

If the current measurement corresponds with the historical database value, then there will be no difference, but as soon as the current measurement differs from the historical database, the current measurement will be a better predictor. In terms of equations this means that:

$$|F_{daytype}(t) - Y(t)| > |F(t) - Y(t)| \quad (4)$$

Obviously there must be a transition point where current measurement no longer prevails over the historical database. Equation (3) assumes that nothing changes in the coming minute. When extending the time horizon of the forecast, one cannot maintain that theory, as it is clear that eventually (and unfortunately in traffic: very quickly) the traffic conditions will change. In any case, it is clear that apart from the historical knowledge the current prevailing traffic condition should be utilised in preparing the forecast as well. One way to do this is presented in the following paragraph.

### **FORECASTING — USING TEMPORAL CORRELATION**

The historical database provides the historic value for each individual minute on a particular day-type. Another way of looking at it is to view the historical database as a historical day-pattern, thereby concentrating on the form of the pattern during the day. By assuming that not the absolute values themselves are repeated, but rather the shape of the pattern, the current measurement could be used by extrapolating the current difference between measurement and historical database into the future. Experience, however, has shown that in 30 to 60 minutes ahead the historical database itself is more reliable (or accurate) than the extrapolated difference. A useful methodology has shown to be one that slowly reduces the contribution of the difference when the forecast horizon is growing. Assuming that on a horizon of T minutes the historical database is the best forecast, the following equation shows the method.

$$difference(t) = (1 - \beta) * difference(t-1) + \beta * (Y(t) - X_{daytype}(t)) \quad (5a)$$

$$F_{extrap}(t+h) = X_{daytype}(t+h) + (1 - \frac{h}{T}) * difference(t) \quad (5b)$$

Hereby  $h$  is the prediction horizon ( $h \leq T$ ) and  $\beta$  a damping factor (between 0 and 1). In equation (5) the absolute error is extrapolated. Another method could be to extrapolate the relative error. Both methods have advantages and disadvantages that will not be discussed further here. Both methods assume that patterns embedded in the historical database will be replicated in future.

The forecasts resulting from the methods presented so far can be evaluated on-line. A 30-minute ahead forecast can be evaluated after 30 minutes. If the error made would be constant, than the forecast could potentially be improved using the method described above. In practice the errors show very strong variation over time. As we will demonstrate later in this paper, the temporal correlation between what happens at the moment and what happens in 30 minutes ahead is not very strong.

## FORECASTING — USING SPATIAL CORRELATION

Rather than looking at the temporal relation, it is also possible to look for a spatial correlation. The difference between the current measurement and the historical database somewhere upstream is expected to correlate with the difference locally some time later (as it propagates with the speed of the traffic. With an increasing distance to the upstream location (and thus an increasing time for the error to travel downstream) the correction might be used for longer forecast horizons. Naturally the assumption is made that the spatial correlation exists.

$$F_{spatial}(t+h) = X_{daytype}(t+h) * \left(1 + \beta \left( \frac{Y_{upstream}(t-\tau) - X_{daytype,upstream}(t-\tau)}{X_{daytype,upstream}(t-\tau)} \right)\right) \quad (6)$$

In which  $\beta$  is a damping factor (between 0 and 1) and  $\tau$  the travel time between the location upstream to the current location.

As with the temporal relation, the range of influence is however fairly limited, meaning that only over relatively small distances improvement can potentially be made. With increasing distances the correlation is not strong enough.

## EVALUATING THE FORECAST METHODS

We have tested the different simple forecasting methods that were described in the previous sections using real data from a database implementation on a motorway network near Amsterdam in The Netherlands. The quality of the forecasting methods has been evaluated by comparing the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{N} \left( \sum_{t=start}^{start+N} (F(t) - Y(t))^2 \right)} \quad (7)$$

for  $N$  minutes starting at 'start'. However, to evaluate the quality of the forecasting there is no substitute for a visual inspection of the time series themselves. The RMSE ignores the time of day (e.g. during the night the predictability decreases due to the increased variations).

## RESULTS

Some results are shown in Figure 1, Figure 2, Figure 3 and Table 1. The historical database is composed out of 10 time series of Wednesdays. The time-basis used is 10 minutes. The damping factor  $\beta$  is 0.25. Figure 1 shows the effect of using the historical database as forecast (green line), see equation (2). The red line in Figure 1 is the measurement for a Wednesday, which is not part of the database. In Figure 2 the results of making use of temporal correlation in preparing the forecast is shown (green line), see equation (5). The red line in Figure 2 is the on-line measurement again. In Figure 3 the results of making use of spatial correlation in preparing the forecast is shown (green line), see equation (6). The upstream station is located at 2-km distance. In the top-half of each figure the speed is shown, and in the bottom half the traffic flow. Overall, the quality of the forecasts can be judged from the figures, but to compare the quality between forecasts a more quantitative approach is required. The quality is more easily read in Table 1, which shows the Root-Mean-Square-Error for the different forecast methods, for two locations in the network near Amsterdam (a location travel south on the A9, and a location on the A10 west), for different time-basis and forecast horizons.

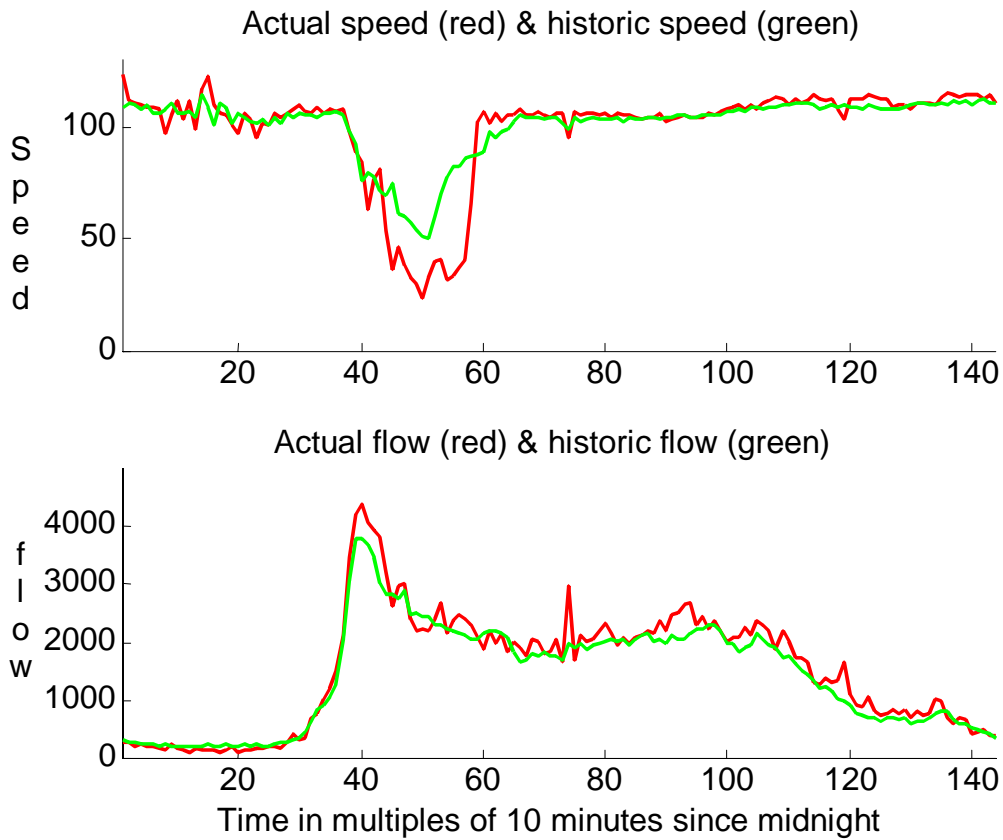


Figure 1. The historical database as forecast (green) compared with the measurement (red)

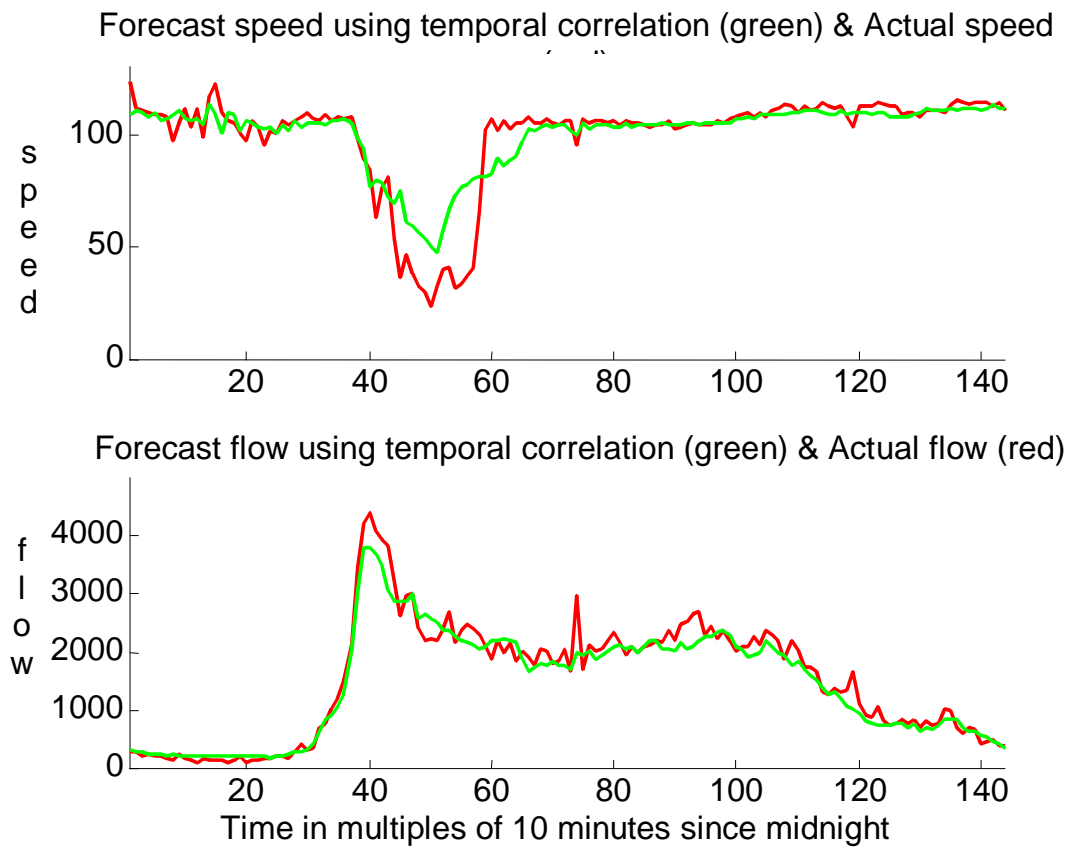


Figure 2. Results using temporal correlation

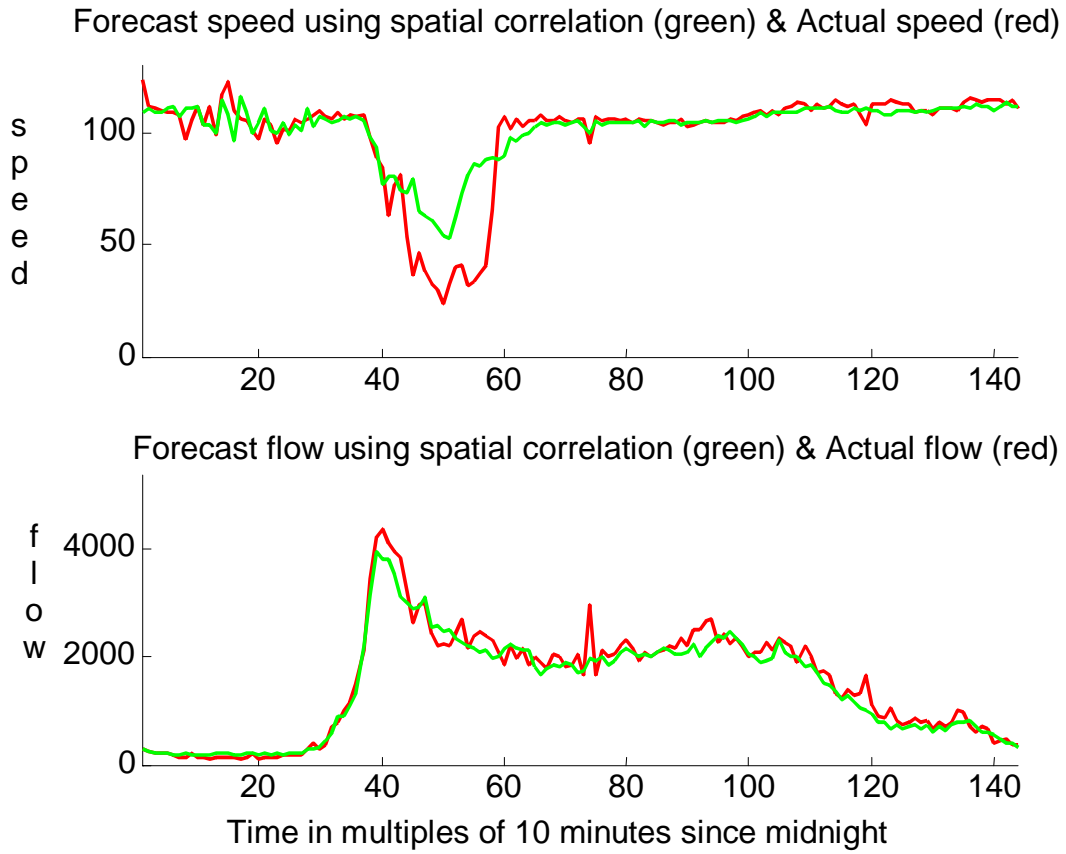


Figure 3. Results using spatial correlation

<i>Root Mean Square Errors for SPEED forecasts</i>						
location	time basis	historic forecast	forecast using temporal correlation (T=80)			forecast using spatial correlation
			10 ahead	30 ahead	60 ahead	
A9	1	13.74	11.52	12.64	13.41	14.44
	5	11.81	8.90	10.59	11.41	12.73
	10	11.04	8.28	9.28	10.71	11.93
A10 west	1	15.62	12.80	16.38	15.55	—
	5	14.44	12.15	14.49	14.15	—
	10	13.54	11.11	13.15	13.22	—

<i>Root Mean Square Errors for FLOW forecasts</i>						
location	time basis	historic forecast	forecast using temporal correlation (T=80)			forecast using spatial correlation
			10 ahead	30 ahead	60 ahead	
A9	1	465	456	459	466	473
	5	275	238	253	269	262
	10	230	188	206	221	212
A10 west	1	506	532	504	513	—
	5	311	302	304	313	—
	10	233	210	224	232	—

Table 3. The root-mean-square-errors for different method at two locations (A9 and A10), three time basis (1, 5 and 10 minute aggregates) and different prediction horizons (10, 30 and 60 minutes ahead)



## DISCUSSION

The results shown above indicate that historic forecasts provide a useful starting point for predicting traffic conditions in the near future. They also show that the use of temporal correlation enables us to make only a limited improvement over use of the historical forecast alone. And the improvement clearly reduces with increasing forecasting horizon (after 10 to 30 minutes no significant improvement is noticeable). The use of spatial correlation brings no benefit at all in some of the cases, a marginal improvement in some other cases.

Historical data can be very useful in providing insight in what happens on certain types of days. Obviously one could further improve the historical databases by incorporating for instance weather types to capture additional systematic variation in traffic conditions. In that way Monday traffic would be split into separate databases for different weather conditions on Mondays. However, we also have to realise that it is simply a very difficult task to produce consistently accurate forecasts of the traffic conditions. In a way, traffic forecasts resemble weather forecasts. It is easy to predict the weather when conditions are stable, but if we reside in a region at the border of a hot and a cold front, where the condition is unstable, than it is extremely hard to predict with confidence what weather it will be.

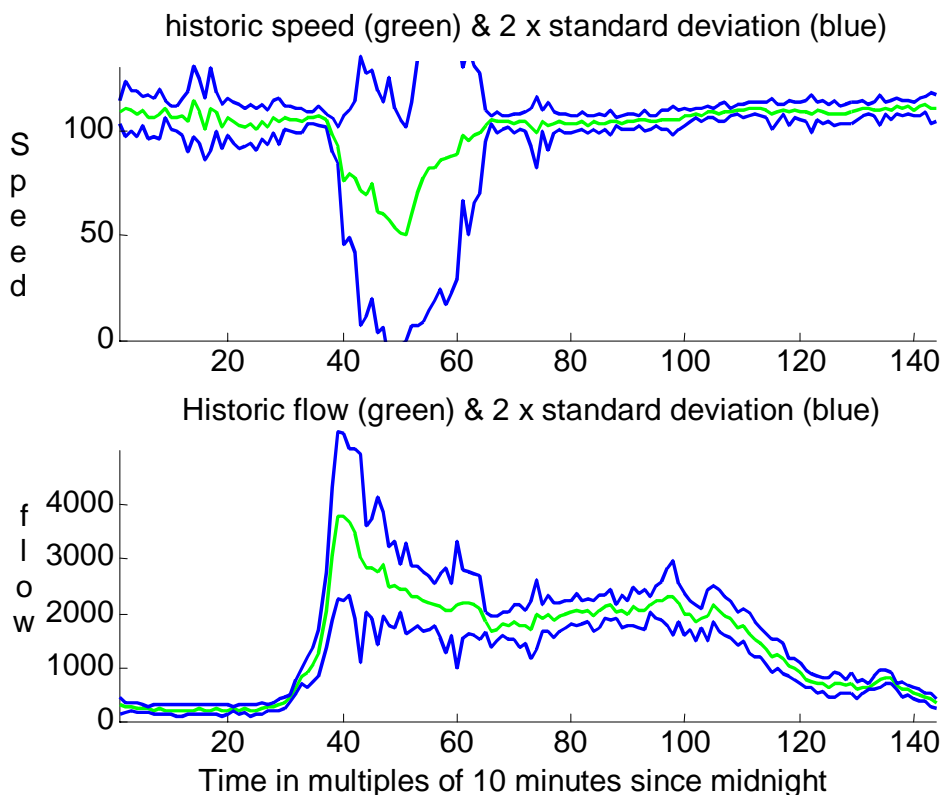


Figure 4. The historic speed and flow together with the uncertainty in time

It may seem as if we are giving up traffic forecasting here, but that is not the case. It is important to realise that at certain times the traffic conditions are actually quite unpredictable. However, at other times the conditions can be predicted accurately. And maybe even more importantly: the accuracy of the predictions can be predicted. In other words it is possible to accurately say when we can be certain of our forecast and when not. This is very important for travellers (especially business travellers and transport companies). They are not so much concerned with the existence of congestions as such, but much more with uncertain travel

times. If they could accurately know when the travel time could be predicted with a high certainty then this would help their planning a lot. This can easily be realised by storing not only the average values of traffic flows and speeds in the historical database, but also the standard deviation. Figure 4 shows an example of the historical database including a band of twice the standard deviation (>95% confidence interval). A visual inspection reveals the times when travel times are uncertain, but also the times when a historic value would provide an accurate forecast, quite easily.

## CONCLUSIONS

Historical databases that distinguish traffic conditions by type of day can provide valuable information about expected traffic conditions. With the results in this paper we have illustrated that only limited improvements can be obtained using on-line measurements (when looking at overall daily performance). The use of temporal and spatial correlation had, at least in our examples, only a very limited reach. Traffic conditions are simply hard to predict, and they cannot be predicted in all circumstances with the same accuracy. Nevertheless, the use of a historical database containing observed mean values of traffic flows and speeds, together with simultaneously recorded information about the standard deviations, provides very valuable information for planning purposes, be it short term or long term.

## ACKNOWLEDGEMENTS

The authors gratefully acknowledge the contribution from the Rijkswaterstaat Adviesdienst van Verkeer en Vervoer by allowing us to use the data presented in this paper. The views expressed in the paper are, however, entirely on the account of the authors alone.

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