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Different methods of traffic forecast based on real data

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Abstract

Different methods to forecast traffic are analysed and discussed. An elementary approach is to develop heuristics based on the statistical analysis of historical data. Daily traffic demand data from 350 inductive loops of the inner city of Duisburg over a period of 2 years served as input. The sets of data are organized into four basic classes and a matching process that assigns these sets into their class automatically is proposed. Furthermore, two models for short-term forecast are examined: the constant and the linear model. These are compared with a prediction based on heuristics. The results show that the constant model provides a good prediction for short horizons whereas the heuristics is better for longer times. The results can be improved with a model that combines the short- and long-term methods.

Keywords: Traffic; Statistical analysis; Heuristics; Matching; Forecasts

1. Introduction

In recent decades growing traffic problems have become an increasing disturbing factor. The existing road network is not able to cope with the demand leading to congestion which is both: a social and an economic inconvenience. Nevertheless, the construction of new roads is often socially untenable. Since current estimates propose that the traffic demand will grow further [17], there is a seek for new traffic management and information systems to solve these problems. One vital component of such systems is the prediction of traffic states. The information of future demand can be provided to traffic control centres in order to prevent a break-down of the flow in advance, e.g., using traffic lights or variable message signs. In the same way, it is possible to pass information to the drivers by means of radio broadcasts or dynamic route guidance systems. However, predictive information offers a new degree of freedom for the road users since they have the option of changing the departure time.

In general, the prognosis horizon is the first and most important parameter, since it determines which procedure proves as the most effective forecast method. A second important detail is the input data, i.e., the number and the location of the sources of the data. Different approaches have been proposed in the past. Neural networks often are used for predicting traffic flow, speed data or

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travel times up to 15 minutes [1,6,7,16]. To forecast traffic jams spatial correlations can be used taking into account, e.g., the dynamics of a moving jam [10,11]. For a useful long-term prediction the current traffic data loose their weight and it is more important to use experience about the past, so-called heuristics, in form of a statistical data base consisting of traffic time series [3–5,12,20].

The main problem creating such data bases is the collection and availability of data. The first methods based on the collection of data counting manual during a few hours a day. The growing number of inductive loops, infrared sensors, and video systems installed on the roads offers the possibility to create larger and consequently more effective data bases about past experiences. To be effective this information has to be combined with data about the current situation.

The remainder of the paper is structured as follows. In the next section results of a statistical analysis of 2 years of data from over 350 urban inductive loops are presented. The traffic demand data are filed into sample classes. In Section 3 a procedure to match a set of data in the right class is proposed. In the following section, two different methods for a short-term forecast are analysed and compared with a forecast based on historical data. In Section 5 a new method for arbitrary horizons is proposed which combines the advantages of the different models. The paper closes with a summary and an outlook.

2. Analysis of historical data

In order to develop heuristics for traffic forecast, i.e., experience about recurrent events, historical data have to be analysed. Therefore, it is useful to classify certain days and events in categories [4,13,20,21]. Two different characteristics can be distinguished: daily and seasonal. Seasonal differences arise due to school holidays. On the other hand, there are daily differences: on working days a sharp morning peak is found which is absent on Sundays or holidays. Additionally, there are special events like football games. The following conclusions are drawn from a statistical analysis of data from over 350 loop detectors in the inner city of Duisburg during the years 1998–2000. The data are provided by a permanent connection to the centre of traffic control of the municipal authority of Duisburg.

2.1. Daily characteristics

In order to classify days, the daily traffic demand, i.e., the flow of vehicles vs. time, has to be investigated. Therefore, the flow per minute $J_{\text{nm}}(t)$ of every loop detector $N_{\text{LD}}(t)$ at a certain time t is accumulated. Then the data are summed over all days, where data are available $N_{\text{days}}(t)$, this result is divided by $N_{\text{LD}}(t)$ and $N_{\text{days}}(t)$:

$$J_{\text{dem}}(t) = \frac{\sum_{n=1}^{N_{\text{days}}(t)} \sum_{m=1}^{N_{\text{LD}}(t)} J_{\text{nm}}(t)}{N_{\text{days}}(t) N_{\text{LD}}(t)}. \quad (1)$$

One advantage of this procedure is the opportunity to analyse even days with an incomplete set of data. The resulting traffic time series are subdivided in seven classes, taking into account the different demand during the weekdays.

Obviously, the demand of many days is quiet similar, since the activity patterns on most working days do not differ very much. However, this is also true if Fridays and days before holidays are compared. Therefore, the number of classes can be reduced. For the decision which traffic time series can be merged into one class a matching process is used which compares the traffic patterns on the basis of an error measure (Section 3). Finally, the following distinct classes are defined:

- Monday until Thursday, except holidays or days before holidays (Mo–Th),
- Friday and days before holidays (Fri),
- Saturday except holidays (Sat), and
- Sunday and holidays (SunHol).

Fig. 1 shows the daily traffic demand of these four groups. The highest number of vehicles during one day is generally measured on Fri. If this value is set to 100%, the other classes are as follows: Mo–Th 97%, Sat 71%, and SunHol 51%. Analysing the traffic time series in more detail yields for the graph of Mo–Th (solid line in Fig. 1) a rough division into four regions:

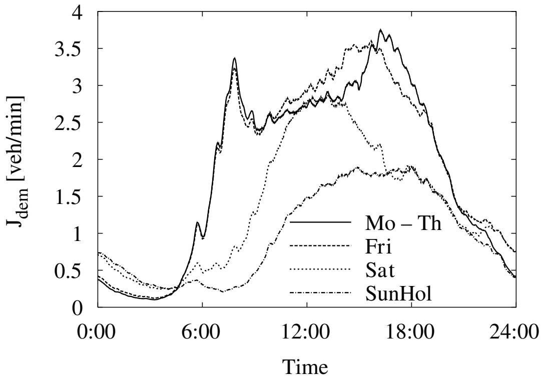

Fig. 1. No. of cars vs. time. The data are stemming from all inductive loops and are averaged over days with a similar traffic demand. The four classes are distinct.

- a sharp morning peak located at 7:51 with a small standard deviation of 3 minutes,
- a region which is approximately a straight line but with many fluctuations like the peaks at about 9 or 10 o'clock,
- a peak in the afternoon located at 16:21, which is higher and broader than the morning peak, and
- a relatively smooth curve during the night with a minimum at 3:09.

This classification reflects the daily life, for a detailed discussion (see [5]). However, for a traffic forecast the standard deviations of the peaks are an expressive feature. They reflect the quality of a heuristic. Since the standard deviation of the morning peak is about three minutes, it will appear with a high probability in this interval of time (Table 1).

2.2. Seasonal differences

For the analysis of seasonal differences, only working days, i.e., the classes Mo–Th and Fri, are considered. On average the highest number of vehicles is measured in May. If this value is set to 100% the other months are: June 99%, April and November 98%, March, February and December 97%, September 95%, August and October 94%, July 89%. Most of these differences are due to school holidays. In general, the structure of the traffic demand stays the same during school holidays, i.e., traffic patterns are not changed. But in July the absolute values are reduced by 10%. Unfortunately, no data are measured in January during the three years due to problems of the data connection.

2.3. Special events

Similar to holidays or long vacations, there are sometimes special events which influence traffic patterns drastically. For this kind of events two examples are presented in the following. In Fig. 2(a) and (c) the influence of the football match between Germany and the United States of America during the World Championship 1998 is

Table 1
Summary of the empirical data

Class	Feature	Cars [veh/minutes]	Std. dev. [veh/minutes]	Time	Std. dev. [minutes]
Mo–Th	1. Morning shift	1.16	0.05	5:44	2
	2. Morning shift	2.24	0.10	6:53	2
	Morning peak	3.38	0.21	7:51	3
	Afternoon peak	3.82	0.15	16:21	24
Fri	1. Morning shift	1.14	0.04	5:44	2
	2. Morning shift	2.19	0.11	6:53	4
	Morning peak	3.28	0.26	7:52	3
	Afternoon peak	3.69	0.13	15:09	32
Sat	1. Morning shift	0.61	0.04	5:44	3
	2. Morning shift	0.61	0.03	6:46	7

The height and the width of the peaks as well as their standard deviations are measured. Additionally, the times the structures occur and their standard deviation is given.

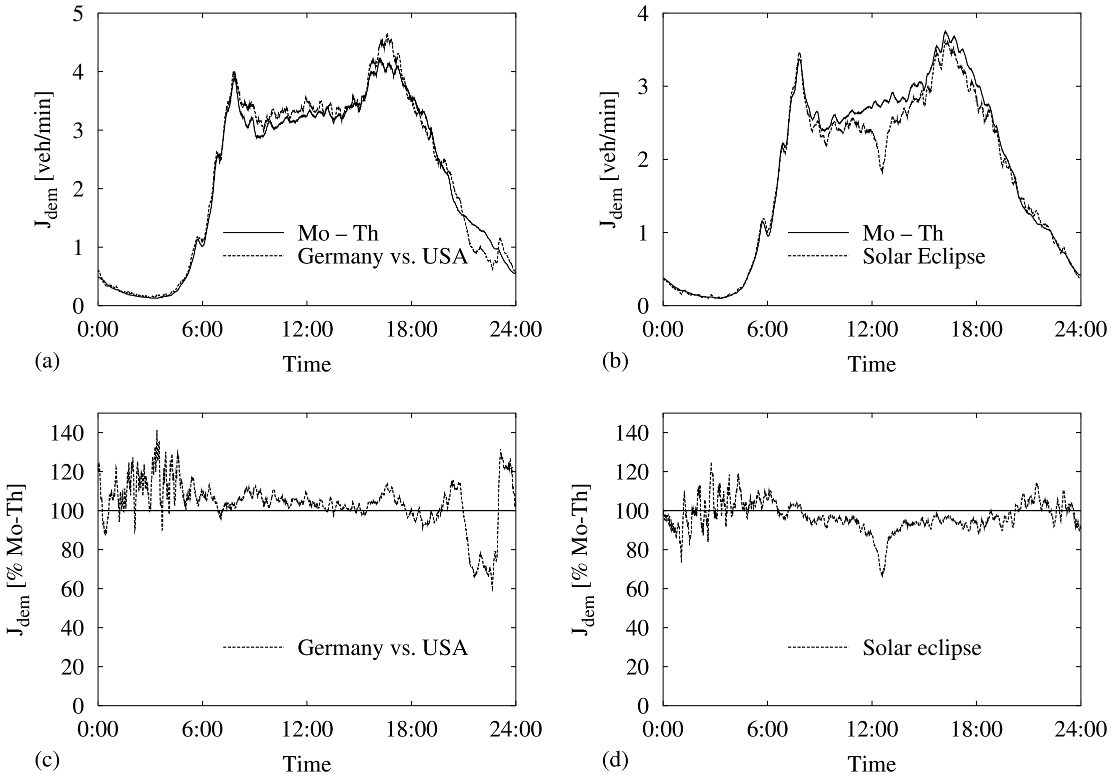

Fig. 2. Daily traffic demand for special events: (a) football World Championship match Germany–USA; (b) solar eclipse on the 11th of August in 1999. The football match results in a sharp breakdown at 21:00 whereas the solar eclipse influences the whole day; (c) and (d) are the same curves in percental graphs.

shown. Ten minutes after the kick-off at 21:00 the flow is only at 88% of the average traffic time series of a working day. Shortly before the end of the game it decreases further to only 61%. Averaged over the interval from 21:10 until 22:50 a flow of 72% of a working day is measured. Note that the activity during the whole day is remarkably higher.

A different characteristic shows a very special event: the solar eclipse at the 11th of August in 1999 during 11:11–13:50 (see Fig. 2(b) and (d)). Although the total eclipse could not be seen in Duisburg, even a partial eclipse of 97% influenced the traffic pattern dramatically. From the morning peak until the peak in the afternoon only 93% of the usual number of vehicles is found. The minimum of the dip is located at 12:36 with only 67% of the averaged graph of this class. It is quite remarkable that the solar eclipse influences a whole day.

2.4. Dependence on direction

Up to now, graphs resulting from all inductive loops have been studied, i.e., the traffic pattern of the whole city. But every street has its own characteristic. Therefore, a single street is selected which exhibits typical commuter flows: the Mülheimer Straße. It connects the Autobahn A3 (Cologne–Oberhausen) with the inner city of Duisburg. For the investigation of the flow towards the A3, 10 inductive loops are employed in the other direction eight.

The result for the class Mo–Th is shown in Fig. 3. The traffic time series of this street differs strongly from the traffic pattern of the whole city. This is due to a huge number of commuters coming to Duisburg in the morning and leaving in the afternoon. The morning peak to Duisburg is shifted to 7:59. Such data can also be helpful

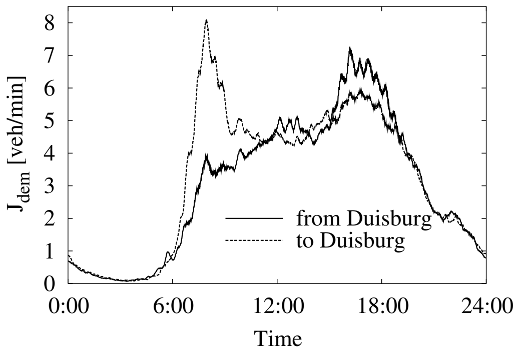

Fig. 3. Traffic time series for different directions. A flow of commuters can be observed: Into the city in the morning and out of the city in the evening.

for the identification of origin–destination matrices.

3. Matching process

In the previous section, daily and the seasonal differences have been analysed by classifying days. In order to assign traffic time series in the correct class automatically, a basic approach is examined in this section: matching. In the matching process two sets of data with a certain length N and positive elements x_n, y_n, are compared using different measures of discrepancy. There are various measures, which rate the deviations differently. In the following, we discuss results for two examples of such measures, whereby x_n and y_n are the data of two different traffic time series:

- the mean absolute deviation (MAD),

$$\mathrm{MAD} = \frac{1}{N}\sum_{n=1}^{N}|x_n - y_n|; \tag{2}$$

- and the mean relative deviation related to the measured value (MRD),

$$\mathrm{MRD} = \frac{\sum_{n=1}^{N}\frac{|x_n - y_n|}{x_n}}{N} \times 100\%. \tag{3}$$

3.1. Consistency of classification

In Section 2.1 we already mentioned that matching allows for an estimation whether the allocation into four classes is sufficient or, e.g., holidays have to be put in a new class. Therefore, the data of the years 1998 and 1999 are compared with the corresponding sample classes. It is determined whether a time series is matched to its own sample class or not. In Table 2 the results for holidays, which are matched to the class SunHol, and days before them, which are matched to the class Fri, are shown.

Results for the other days are depicted in Table 3(a). Some of the data sets are incomplete because the local network was down or the connection to the host system of the city broke off. However, an advantage of the matching process is that even with the a lower number of values a correct matching can be achieved. The results are divided into groups taking into account the number of the measured values (Table 3).

For entire or almost entire sets only one measure of discrepancy is necessary to get satisfying matching results, either the MAD or the MRD. Indeed, some of them are not useful alone like the mean error which is only a measure for the traffic demand of the whole day. Since the demand within the classes Mo–Th and Fri is very similar, these are often mixed up.

Table 2
Results of the matching process for two holidays and days before them using MAD

	Mo–Th	Fri	Sat	SunHol	Id
Holidays					
04/10/1998 (Good Friday)	1.29	1.34	0.62	0.19	SunHol
05/01/1998 (Labour Day)	1.24	1.28	0.55	0.13	SunHol
Before holidays					
04/09/1998	0.19	0.18	0.76	1.21	Fri
04/30/1998	0.36	0.30	1.03	1.49	Fri

The assignment yields that holidays belong to the class SunHol and days before them to Fri.

Table 3
Results of the matching processes

	Measure	Percentage of correct matching, when x minutes are missing						
		$x = 0$	$x < 240$	$x < 480$	$x < 720$	$x < 960$	$x < 1200$	$x < 1440$
(a)	MAD	99	99	99	99	98	97.5	96
	MRD	97	95	95	95	95	95	92
(b)	MAD	100	100	100	100	100	100	100
	MRD	100	95	96	97	98	98	98
(c)	MAD	100	96	96	96	95	94	91
	MRD	49	37	37	40	41	45	47
(d)	MAD	100	96	96	96	95	94	88
	MRD	49	40	40	43	44	48	42

Since some of data sets are incomplete, they are subdivided according to the number of measured values. (a) The data of the years 1998 and 1999 are matched to the corresponding sample classes. A high percentage is matched correctly. (b) Matching of 52 data sets of the year 2000 with the sample traffic time series of the years before. (c) and (d) Matching of the local data of the Mülheimer Strasse (c) in direction inner city and (d) in direction outskirts. The data are not as stable as those of the whole city.

3.2. Automatic matching

An open question is: how does this method operate with data which are not used to generate the sample classes? Nevertheless, the earlier an incomplete set of data can be assigned to the correct sample class the earlier a first automatic prediction can be provided. To examine how "new" data can be assigned to the given classes data sets of 52 days of 2000 are compared with the classes generated by data of 1998 and 1999. Table 3(b) shows the results. Using the MAD all days are assigned to the correct sample class regardless of the number of measured values.

However, the accumulated data of the whole city have a very stable structure in the sense that fluctuations are averaged. This is the reason for the high percentage of correct matching. Since also incomplete data sets are matched correctly, it is possible to automatize the process of forecast. Measuring data during a few hours of a day allows to decide, which sample graph is suitable to forecast the remaining day.

Data of a single inductive loop differ more from day-to-day. Therefore, it is more difficult to match the data with the sample graphs. Results for the network of inductive loops of the Mülheimer Strasse (Section 2.4) are shown in Table 3(c) and (d) for both directions. In this case, some error measures are not as useful as others. The fluctuations cause a high MRD during time intervals with low traffic, e.g., at night. In future, we will examine possibilities to merge the measures of discrepancy to get a better matching result.

4. Short-term forecast

The traffic time series already provide predictive data for all days of a sample class. In order to take the current data into account two methods of short-term forecast are examined: the constant model and the linear model.

4.1. Constant model

In this model, the forecast for all horizons is a constant value. However, in the literature different approaches to determine this value are proposed [3,14,18]. The value can be the last value measured (Naive Model) or better an average over, e.g., the last 10 values (moving average). In the following a Single-Smoothing model is used, based on an exponential adjustment. The forecast value $J_c(n)$ at the discrete time-step n is calculated by two equations:

$$\begin{aligned} &J_c(1) = J(1), \text{for the first value,} \\ &J_c(n) = \alpha J(n) + (1-\alpha)J_c(n-1), \text{each other.} \end{aligned} \tag{4}$$

An example for different prognosis horizons $\Delta\tau$ can bee seen in Fig. 4. α is the smoothing coefficient, with $0 < \alpha < 1$. The higher the value of α the less is the influence of the past. To give a rough idea: the cumulative weight (weight of the last l values) of 99% is reached within the last $l = 13$ values for $\alpha = 0.3$ and within the last $l = 4$ values for $\alpha = 0.7$.

So the first task is to choose a suitable value for α. To answer this question the MADs of short-term forecasts during the years 1998 and 1999 are calculated and minimized by varying the coefficient α in steps of 0.01. This is done for each sample class and for five different horizons individually. The results can be seen in Table 4. The longer the horizon $\Delta\tau$ the higher is the optimal α. In other words, if one wants to look further into the future, more importance should be attached to the current data. Besides, the optimal α depends on the sample class. This is due to the different sizes of fluctuations in the graphs.

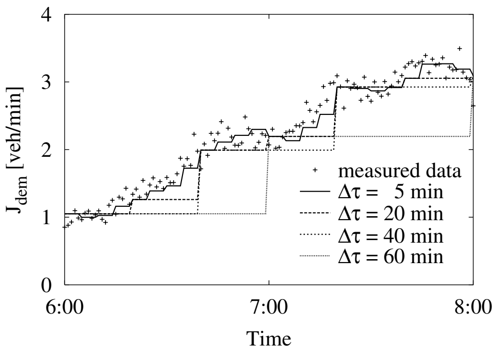

Fig. 4. Short-term forecast using the constant model with different horizons $\Delta\tau$, and $\alpha = 0.5$.

4.2. Linear model

This model is based on the linear curve fitting by use of the last N measured values. The trend of this linear fit is extrapolated into the future and used for the forecast. For this model it is important to determine the optimal number of values N starting from the current data point. Similar to Section 4.1 the MADs of a prediction are calculated and minimized by varying N in steps of 1. This is also done for five prognosis horizons and for the four sample classes.

The results are presented in Table 5. The longer the prognosis horizon $\Delta\tau$ the more values should be used for the prediction. Thus, the further one goes into the future the more values should be used from the past. This is a remarkable difference to

Table 4
Optimal smoothing coefficients α for minimizing the MAD

$\Delta\tau$ [minutes]	Mo–Th	Fri	Sat	SunHol
5	0.32	0.30	0.28	0.23
20	0.46	0.45	0.38	0.30
40	0.55	0.55	0.41	0.33
60	0.52	0.53	0.32	0.36
120	0.64	0.81	0.39	0.44

The longer the prognosis horizon $\Delta\tau$ the higher is the optimal α. Furthermore, the coefficient depends on the sample class.

Table 5
Optimal number of measured values N used for the fit

$\Delta\tau$ [minutes]	Mo–Th	Fri	Sat	SunHol
5	32	28	34	52
20	42	44	66	68
40	53	55	72	70
60	59	53	77	72
120	63	63	69	76

Note: A value is measured every minute, e.g., 60 values represent 1 hour.

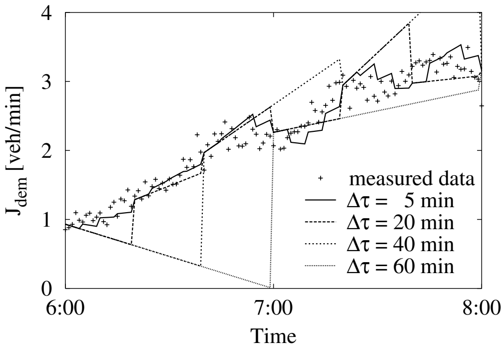

Fig. 5. Short-term forecast using the linear model with different horizons $\Delta\tau$ and $N = 20$.

the constant model. The reason for this is the fact that the more points are used for the fit, the lower is the gradient in general. However, with a steep gradient large deviations might occur, e.g., in case a trend changes (Fig. 5). A larger N leads to a prognosis less susceptible for deviations due to fluctuations.

4.3. Comparison of methods

In order to compare both short-term methods with each other and with the heuristics the MAD is calculated for different prognosis horizons $\Delta\tau$. Results are presented in Fig. 6 for an ordinary weekday and the day of the solar eclipse. The MAD for the heuristics is constant regardless of $\Delta\tau$. It represents the MAD of the complete day. For α and N the optimal values determined in the previous sections are used.

One can see that at an ordinary day the constant model is the best forecasting method up to $\Delta\tau \approx 18$ minutes. The linear model is in any case worse than the constant model. In the special case of the solar eclipse, the constant model is the optimal method even up to $\Delta\tau \approx 40$ minutes.

5. Combination of methods

Hitherto, two forecast methods have been examined: the heuristics in form of sample graphs for long-term predictions and the short-term predictions based on the current data, like the constant model. The former lacks the influences of the current situation whereas the latter does not take into account the experience and the knowledge about previous events, i.e., historical data.

For a good forecast both methods should be combined. Therefore, we propose a method that uses the constant model for small $\Delta\tau$ and with increasing $\Delta\tau$ the heuristics. Therefore, the data of the point in time a prognosis is rendered t_0 loose their influence with increasing $\Delta\tau$. Based on this consideration the following formula is proposed:

$$J_{\text{pred}}(t_{\text{p}}) = J_{\text{dem}}(t_{\text{p}}) + k \cdot \Delta J(t_0) \tag{5}$$

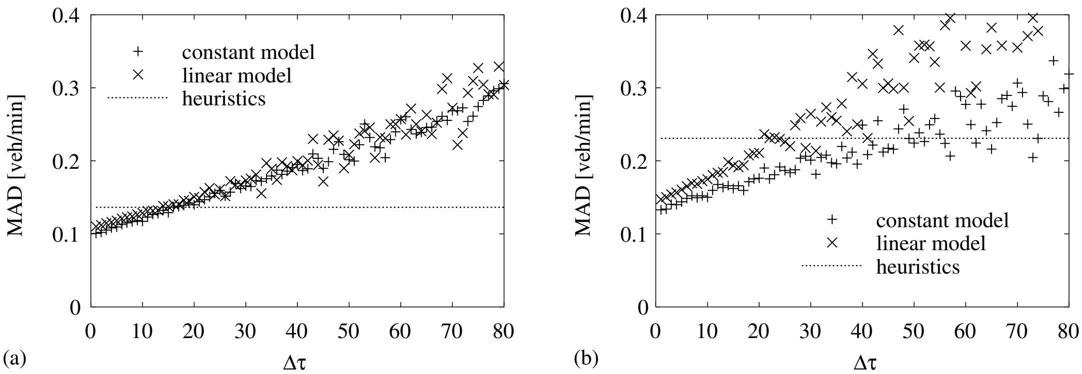

Fig. 6. The MAD of the prognosis from the current data using different forecast models: the linear model (×), the constant model (+), and the heuristics (dotted line). (a) An ordinary day. The constant model is the most useful method up to a $\Delta\tau \approx 18$ minutes. (b) The day of the solar eclipse. In this special case, the constant model is the optimal prognosis algorithm up to about $\Delta\tau \approx 40$ minutes.

with

$$\Delta J(t_0) = J_c(t_0) - J_{dem}(t_0),$$

$$k = \begin{cases} \eta\left(1 - \frac{\Delta\tau}{\Delta\tau_{max}}\right), & \text{if } 0 < \Delta\tau \leqslant \Delta\tau_{max}, \\ 0, & \text{if } \Delta\tau > \Delta\tau_{max}, \end{cases}$$

$$\Delta\tau = t_p - t_0.$$

The variables are defined as follows:

$J_{pred}(t_p) \widehat{=}$ predicted traffic flow,
$J_{dem}(t_p) \widehat{=}$ flow of the sample graph, (1),
$J_c(t_0) \widehat{=}$ value of the constant model (4),
$t_0 \widehat{=}$ point in time the prediction is made,
$t_p \widehat{=}$ point in time predicted,
$\eta \widehat{=}$ weighting of current and historical data, and
$\Delta\tau_{max} \widehat{=}$ maximum horizon for constant model.

Obviously, for $\Delta\tau > \Delta\tau_{max}$ the heuristics is used as forecast. The factor η is a coefficient for the relationship between current and historical data. Reasonable is $0 < \eta < 1$; for $\eta = 0$ only the sample graph is used, for $\eta = 1$ the prognosis curve starts at the current value.

In order to find the optimal η and $\Delta\tau_{max}$, they have been varied and the prognosis is compared with the real data for all days of the year 1999. The optimal parameter values are depicted in Table 6. The parameters chosen differ a little bit depending on the used measure.

In order to test this model for extreme values, data from the day of the solar eclipse has been chosen to demonstrate the quality of the model. Results are depicted in Fig. 7. There is a large anomaly of the traffic flow, which cannot be predicted by heuristics. However, the combination of the short-term forecast with the heuristics improves the quality of the prediction obviously.

Table 6
The parameters η and $\Delta\tau_{max}$ that minimize the difference measures of discrepancies of the prognosis and the real data

	MAD	MRD
η	0.57	0.66
$\Delta\tau_{max}$ [minutes]	37	29

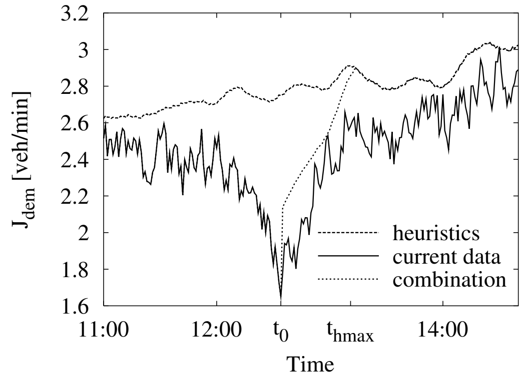

Fig. 7. The irruption of the traffic flow during the solar eclipse as an example for the combination of short-term- and long-term forecasting. The current data loose their influence at a prognosis horizon $\Delta\tau_{max}$. There it merges with the curve of the heuristics. The combination of both methods offer an improved prediction.

6. Summary and outlook

In this contribution different methods of forecasting using 2 years of real-world data from the inner city of Duisburg are presented. Firstly, the historical data are examined taking into account seasonal and daily differences, dependency on direction and special events. At the end four basic classes are found: Mo–Th, Fri, Sat and SunHol. Additionally, an automatic matching process is proposed that verifies the consistency of classification. In the same way it is able in future to assign the data to different classes automatically. The results of two measures of discrepancy are presented.

Two methods of short-term forecasting are discussed: the constant and the linear model. The former sets a constant value, an exponentially smoothed value, for all horizons $\Delta\tau$. Depending on $\Delta\tau$ optimal smoothing coefficients α are found. The linear method extrapolates the gradient of the past N values into the future using a curve fitting. The optimal number of N for different $\Delta\tau$ exhibits that the further one wants to look into the future, the more values of the past are needed. In the constant model it is the other way round.

A comparison of these models with a prediction using the heuristic yields, that the most promising forecast method for short terms $\Delta\tau \approx 18$ minutes is the constant model and then the heuristic. Therefore, a method combining both models is proposed. This methods shows good results even for special events like the solar eclipse.

In future, this method will be used in supplementation with on-line simulations, e.g., of the freeway network of NRW [9] or the inner city network of Duisburg [8,15]. The simulations describe the dynamics in a network but are lacking information about the boundaries [5]. Therefore, the forecast will be used to predict the flow of the sources. However, every forecast is confronted with a fundamental problem: the messages are based on future predictions which themselves are affected by drivers' reactions to the messages they receive [2]. Therefore, an anticipatory traffic forecast is needed which takes into account the reaction of the road users to the prediction [19].

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