SELF-ADAPTING PREDICTION MODEL FOR TRAFFIC FLOW STATUS

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ABSTRACT

The purpose of the study was to develop a method for making a self-adapting short-term prediction model for the flow status. The model was based on field-measured travel time data and self-organising maps. The test site was Ring Road I in the Helsinki metropolitan area. The forecasts were based on the outcomes of previous moments when the traffic situation was similar to the present. The forecast was set to the most common outcome in the cluster of these similar samples. The model was allowed to work online and its performance was studied. The proportion of correct forecasts was 93.8–96.3% over the entire trial period and 80.9–82.3% in congested conditions for the model in normal weather and road conditions. The average daily change in the proportion of correct forecasts was positive over the whole trial period: +0.3–0.4%. Two naïve comparison models were made. Both comparison models performed considerably poorer than the self-adapting model.

Keywords: prediction, traffic flow status, self-organising map

INTRODUCTION

Drivers can benefit from static and dynamic information of traffic situations on alternative routes by making more informed travel decisions, which allow them to improve their time management with ensuing reductions in cost and stress (Kitamura et al. 1999, Wunderlich et al. 2001). Information on travel time reliability is an important factor in addition to the travel time itself. Nevertheless, the impact that information provision has on route choice, for example, also depends on other things like the driver's familiarity with the road and complexity of the recommended route. The compliance of driver information varies with gender, standard of living and driving experience.

The provision of advanced driver information can have positive impacts at the transportation network level. Specifically, advanced traveller information can reduce congestion in transportation networks and even slightly decrease the number of injury accidents (Khattak et al. 1999, Aittoniemi 2007). However, traffic information may also have negative impacts if the driver cannot deal with all the information available or the information provider does not predict or take into account the response of drivers to the information (Ben-Akiva et al. 1991).

In the future, cooperative information systems could help reduce this problem (Kulmala 2007).

The value of information depends on the situation the user is in and on what kind of problem the information is supposed to solve (e.g. Herrala 2007). Information is more valuable when it is used to solve a problematic situation rather than a normal one. The type and length of the journey, the route and travel mode chosen, and traffic conditions all affect the value of information.

The accuracy of information is a critical factor. An aberration in system performance will not turn away users but consistently poor information will (Iida et al. 1999). The accuracy of the given traffic information has been shown to affect the route-choice compliance and departure times (Srinivasan and Mahmassani 1999, Chen et al. 1999, Chorus et al. 2007). The more reliable the information, the higher the rate of compliance. Results have also shown that compliance depends not only on how accurate the information is, but also on how frequently it is accurate. There is a certain threshold of error below which the information does not benefit drivers, and it depends on the location and time of day (Jung et al. 2003). However, there is also an upper threshold above which it is not worthwhile to improve the accuracy.

Road users will benefit more from accurate travel time information where travel times vary greatly (Jung et al. 2002). Hence, road users expect information to be up-to-date even if the actual travel time varies substantially. However, without short-term prediction, real-time information on travel time cannot be given. Much research has been done over the past 15 years in the field of travel time prediction (e.g. Park and Rilett 1998, D'Angelo et al. 1999, van Grol et al. 1999, Park et al. 1999, Lindveld et al. 2000, Suzuki et al. 2000, You and Kim 2000, Chen and Chien 2001, McFadden et al. 2001, Rilett and Park 2001, van Lint et al. 2002, Zhang and Rice 2003). However, all these models are stationary and share similar problems. Static models like the ones mentioned above cannot adjust automatically; instead, they occasionally require new, man-made calibration and new data. Unfortunately, there is often not enough time to collect the data for creating such a model, leading to a small number of samples that represent random incidents and consequently, a poor ability to predict their consequences.

Innamaa and Kosonen (2004) suggested that a step forward from models calibrated before any operational use would be a self-learning model that adjusts its own parameters while in actual online operation. The system should learn from its own mistakes and aim to perform better next time. Studies in which the models adjust themselves with time include Ohba et al. (2000), Otokita and Hashiba (1998), and Bajwa et al. (2003). These models are based on the principle that in order to learn and develop, the model should constantly add new samples to the traffic situation database. However, if all the samples are stored, the database grows fast and requires a powerful computer to run it online in real time. By contrast, if only those samples that differ from the samples in the database are stored, the database becomes skewed. Chung (2003) went about solving the problem by collecting the data into a database divided into segments by time of day (AM and PM), day of the week, holiday vs. non-holiday, and rainfall. However, although such segmentation does reduce the required computer time compared with non-segmented solutions, it does not overcome the underlying problem of ever-expanding databases. Consequently, there is a need for a prediction method capable of adapting itself but without storing all the samples in a database.

Van Lint (2006) had a different approach to fulfilling the need for online learning. He first presented an online-delayed (learning took place as realised travel times were available) version of the Extended Kalman Filtering (EKF) algorithm for training state-space neural networks for freeway travel time prediction. However, the performance of the online-delayed trained model was significantly lower than with offline EKF training and the Bayesian-Regulated Levenberg Marquardt method. Furthermore, van Lint (2008) presented an online-censored EKF algorithm, which could be applied online (before realised travel times were available) and offered improvements over the online-delayed version. However, the model based on it did not perform as well as the offline-trained comparison models. In addition, neither of the studies (van Lint 2006 and 2008) showed an improvement in the prediction performance of online-trained models in the course of time.

The above review shows that most of the prediction models made so far are stationary. The ability to learn while working online would be an evident improvement. The current literature includes only a few models that adjust themselves with time. To our knowledge, most of these are based on the principle that in order for the model to learn and develop, it should constantly record new traffic situation samples. This leads to large databases that must be used online in real-time. The larger the road network covered by prediction models and the more input variables there are — i.e. the more diverse the monitoring system — the larger the database and the faster it grows. Although computers are getting increasingly powerful, it would be practical to find a solution that does not involve the collection of these databases of increasing size. Hence there is a lack of knowledge as to how to develop a practical, self-adapting prediction model. Anyone providing real-time traffic information and making forecasts of the traffic situation could benefit from such models.

The purpose of the study was to develop a method for making a self-adapting short-term prediction model for the flow status (i.e. a five-step travel-speed-based classification). Specifically, the objective was to find a method that (1) could predict the flow status on a satisfactory level, (2) would learn by itself during online operation, and (3) would also be practical for long-term online use.

METHOD

Self-organizing maps

A self-organising map (SOM, Kohonen 2001) is, in its basic form, an unsupervised neural network method that can be used when the classification of the data is unknown or when the use of this classification is not desired. The approach can also be called cluster analysis, clustering, or profiling of data. A SOM consists of neurons (processing units or map units) organised on a regular low-dimensional grid. Distances between the map units can be measured with the distance of their weight vectors in grid coordinates.

The weight vectors connect each map unit with its counterpart in the pattern space and accordingly, each pattern vector (input vector of the model) with the map unit whose weight vector is closest to the pattern vector. The distribution of weight vectors tends to follow the distribution of the training data. Therefore the map can be used to generalise data when the number of map units is small. In pattern recognition, similar vectors tend to locate to map units that are close to one other on the grid. Consequently, similar samples are located close to one other.

A SOM is trained iteratively. The best matching map unit (BMU) and its topological neighbours on the map are moved according to the samples in the training set. The learning process contains following steps (Nauck et al. 1996):

1. A random initialisation of all weights w_{ij}.

2. Random selection of a training data set X.

3. Selection of the neuron with the minimal Euclidian distance to the training data set X.
   $c = \arg\min_j \left(\left\| X - W_j \right\| \right)$
   where $\left\| X - W_j \right\|$ is Euclidian distance between dataset X and weights of a neuron, c is the winner neuron and j is the index of neuron.

4. Change of winner neuron weights and weights of neighbouring neurons
   $W_j(t+1) = W_j(t) + \eta(t) \cdot h_{cj}(t) \cdot \left[X(t) - W_j(t) \right]$
   where neighbouring function $h_{cj}(t)$ describes how the neighbour is influenced by c and η(t) in monotonic decreasing constant.

5. Decrease of learning rate as well as the neighbouring constant. During the training less neighbours in the surrounding of the winner neuron are changed with a declining value.

6. Training process ends by reaching the number of predefined learning cycles, otherwise continue with step 2.

Supervised learning proceeds in the same way as the unsupervised basic method. However, the class information is added to the patterns in the training phase. Consequently, the separation of classes is better when compared to unsupervised learning.

SOM has been applied previously to traffic prediction. For example Asamer et al. (2007) used it in mid-term prognosis of traffic flow patterns. However, they found that with their prediction model very accurate prognosis is not possible. Their model was not self-adapting. Werner (2008) used SOM to the reduction of speed data patterns. They found that it is of advantage that a SOM generates virtual patterns which cover possible effects that have not been observed before. However, the lack in mapping the value range of really observed patterns was a disadvantage for their application.

Study site

The study site was Ring Road I in the Helsinki Metropolitan Area. The road was regularly congested during morning and evening peak hours on working days (Monday to Friday, **Figure 1**). The annual average daily traffic volume was up to 85,000 vehicles and the highest daily traffic volumes exceeded 100,000 vehicles on the busiest working days. The traffic volume exceeded 9,600 vehicles per hour for the busiest 100 hours of the year in the middle part of the road, being around 6,000 vehicles per hour in the western and eastern parts of the road.

The test road started from the west with 2+2 lanes. The number of lanes was 3+3 from the Otaniemi junction to main road 110 and from main road 120 to main road 45 (Figure 1). The road had an alternating bus lane in addition to the 2+2 lanes east from main road 4. The westernmost part of the road was connected to the street network with signal-controlled at-grade intersections, and only the main roads (marked on the map in Figure 1) were connected with grade-separated intersections. From main road 120 to main road 4, all intersections of the test road were grade-separated. In the easternmost part, the street and road network was connected to the test road with signal-controlled at-grade intersections, except for the road to Mellunkylä (marked on the map in Figure 1), which was connected with a grade-separated intersection.

Six camera stations (Figure 1) were used for automatic travel time monitoring on the test road. Cameras divided the road into 3.1-7.4 km-long sections. The results were analysed for the two most congested road sections (A and B, Figure 1). Section A extended from the third to the second camera station from the west; section B extended from the fourth to the third. On section A, there were on average 67.3 minutes of successful measurements of congestion per day and, respectively, 39.6 minutes per day on section B. Traffic flow was deemed congested if the average travel speed was under 75% of the free flow speed. On all other sections of the test road, the average amount of successful measurements of congested traffic was less than 20 minutes per day.

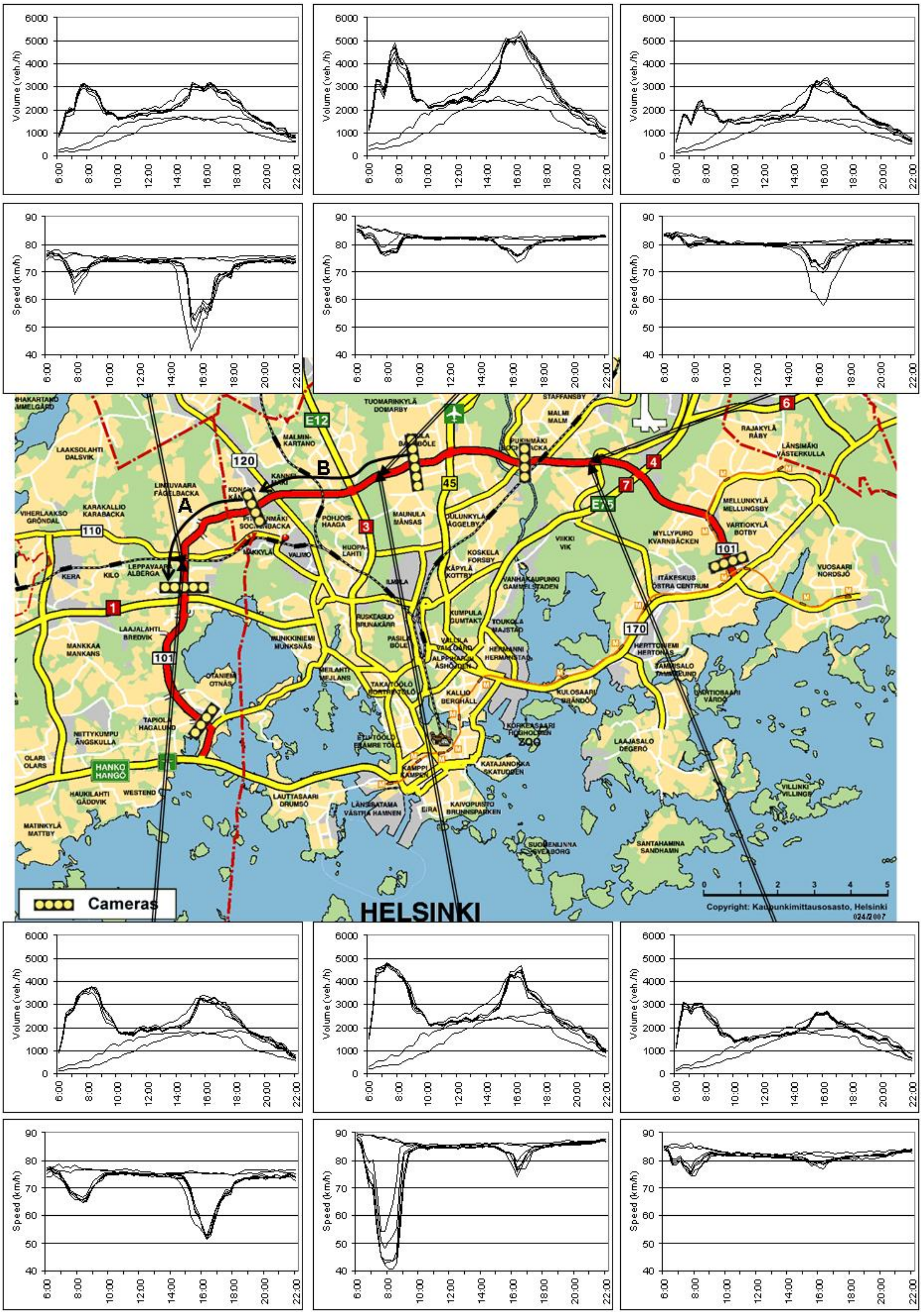

Figure 1. The location of camera stations and the traffic volume and mean speed for different weekdays in 2005 (westbound traffic above the map and eastbound traffic below).

Data

Raw travel time data collected by the travel time monitoring system were used in the study. Models were based on data collected during an 8-month period from January to August 2004. The prediction performance of the models was tested during a 250-day period starting in January 2005.

The raw travel time data were aggregated into median values of 5-minute periods. These data were filtered to avoid individual deviating observations affecting the median values too significantly. Several filtering methods were evaluated. This was done by visually checking which observations were filtered and which were not. As the filtering had to be performed online and its performance was critical, especially when the number of observations was small, a simple method based on two threshold values seemed to work better than more sophisticated methods using polynomial fitting. In the chosen filtering method, if the number of observations was less than three, the maximum difference from the latest accepted median was allowed to be 50%. Otherwise, the median was rejected.

$$\begin{cases} if\ \ n \geq 3, \quad \overline{T}_{new}\ accepted \\ if\ \ n < 3\ and\ \dfrac{\left|\overline{T}_{new} - \overline{T}_{latest}\right|}{\overline{T}_{latest}} \leq 50\%, \quad \overline{T}_{new}\ accepted \\ if\ \ n < 3\ and\ \dfrac{\left|\overline{T}_{new} - \overline{T}_{latest}\right|}{\overline{T}_{latest}} > 50\%, \quad \overline{T}_{new}\ rejected \end{cases}$$

where n is the number of travel time observations and $\overline{T}$ is the median travel time.

In addition to the travel time data, the prediction used the information on weather and road conditions from a measurement point near the test road on the intersecting main road 3. The weather and road conditions were classified into three categories: normal, poor and hazardous. The conditions were hazardous if both lanes were covered with snow or ice and if the road surface temperature was also below +2ºC on one of the lanes, if visibility was less than 150 m, or if the average wind speed was over 16.9 m/s. Conditions were considered poor if the visibility was 150-299 m or if the average wind speed was 12.0-16.9 m/s. In normal conditions, both lanes were dry, moist, wet or wet and salted, there was either no rain or little rain and the warning sensors showed no warnings. In addition, if none of the conditions above were fulfilled, the weather and road conditions were considered poor. Information on weather and road conditions was received in winter time every 20 minutes and in summer time every 60 minutes.

RESULTS

Principles of the model for the test road

A self-adapting prediction model was made for the test road. The forecasts were based on the outcomes of previous moments when the traffic situation was similar to the present. The forecast was equal to the most common outcome in the cluster of these similar samples (**Figure 2**). Forecasts were made for vehicles entering the road sections within the next 15 minutes on the basis of weather and road condition and travel time information. The forecast was given at 5-minute intervals for 5-minute periods, i.e. separately for vehicles entering the sections 0–5 min, 5–10 min, and 10–15 min ahead of the present moment.

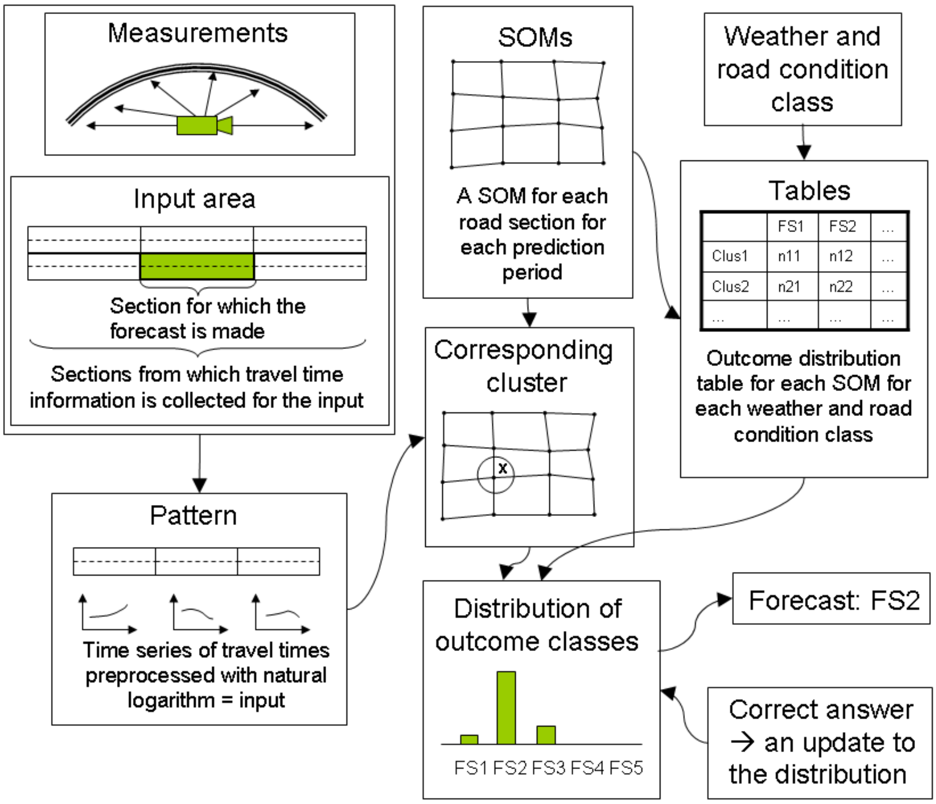

Figure 2. Principles of the prediction model.

The outcome of the model was defined as the traffic flow status class of the road section in question. The outcome of the traffic situation was described with five traffic flow status classes determined from the ratio of measured travel speed to the speed of free flowing traffic (Table 1). Traffic flow was considered congested if the flow status class was slow, queuing or stopped.

Table 1. Definition of flow status classes. These definitions are based on the driver's perception of the traffic situation (Kiljunen and Summala 1996).

Flow status	Travel speed / speed of free flowing traffic (%)
Free-flowing traffic	> 90
Heavy traffic	75–90
Slow traffic	25–75
Queuing traffic	10–25
Stopped traffic	< 10

The model input included a time series of the three latest measurements of 5-minute median travel times of the preceding road section, the road section in question, and the following road section. The input was pre-processed before making the SOM so that none of the input variables dominated over the others, i.e. long travel times over shorter ones. The natural logarithm separated travel times better than scaling or normalising and was therefore applied to the values.

For making the prediction model, the similarity of traffic situations (i.e. pattern vectors) needed to be determined and then clustered in a systematic way. Any method could have been chosen as long as it did not require original pattern vectors to be kept in a database. One solution for clustering was the SOM. SOMs along with the outcome distribution tables formed the prediction model.

To make the model learn from the traffic situations it encountered while working online, the distribution of outcome classes in which a dense version of the history data is stored was updated in the cluster used for making the forecast as soon as the "correct" answer was measured in the field. Consequently, there was no need to restore the samples to a database; rather, all that was needed was to increase the number of matches in an outcome distribution table. This table was as large as the number of clusters times the number of outcome classes. The flow status outcome tables were updated at 5-minute intervals. The updating is made by one observation at a time. If for some reason no observations were measured, the tables were left untouched.

SOM for the model

A separate SOM was made for each road section and for each of three prediction periods, based on the principles of supervised learning using a hexagonal map grid lattice. A sheet shape was selected for the map topology. The desired number of map units (*Munits*) was determined with the heuristic formula of Vesanto et al. (2000), where *dlen* was the number of samples in the training data.

$$Munits = 20 \cdot dlen^{0.54321}$$

The final map size was determined by calculating the two biggest eigenvalues of the training data and by setting the ratio of the side lengths equal to the ratio of these values. The final side lengths were set so that their product was as close to the desired number of map units as possible.

During training, a SOM was formed to present typical observations. In practice, the proportion of important cases (here, congestion) in the training set was small. Consequently, these cases might not be able to gain any ground of their own from the map. Therefore, the training data were collected by randomly selecting an equal number of 4,000 samples from each flow status class. This led to SOMs whose sizes ranged from 2,196 to 2,822 map units.

Sub-models

The effect of weather and road conditions on forecasts were investigated by comparing whether the performance of the model made without weather and road condition information differed depending on weather and road conditions. The results showed that the average performance of the model was similar for both normal and hazardous weather and road conditions. However, some differences were observed when the results were analysed by flow status class. Specifically, free-flowing traffic was predicted less accurately when the weather and road conditions were hazardous than when they were normal. For other flow status classes, the opposite occurred. When the weather and road condition class were poor, the performance of the model was similar to that for normal weather and road condition status, with the results falling between the performances for normal and hazardous.

The model was divided into sub-models according to the weather and road condition class (normal, poor, hazardous), although poor or hazardous conditions were rare on the test road because of the high flow rate and good maintenance in wintertime. On each road section, the same SOM was used for all weather and road condition classes for the same prediction period, but the flow status outcomes were collected on separate tables based on weather and road conditions.

The effect of day of the week was investigated similarly to that of weather and road conditions. On weekends, the proportion of free-flowing traffic was notable (95.9–100.0%, being above 99.0% on seven of the ten road sections). Because the free-flowing weekend traffic was predicted on average with more success than during the week, there was no need to integrate information on the day of the week into the model. Most of the very few, solitary observations of congested weekend traffic were not predicted correctly.

Practicality in long-term use

The practicality of the model in long-term online use can be assessed from e.g. the number of carry bits it takes to restore the history of traffic situation samples. In long-term use, the model should be able to run for several years if no significant changes are made to the road network. In 5 years, the dynamic online model presented in this study stores a condensed version of the same history in ten tables of a fixed size not exceeding 14,110 items. By comparison, this would lead to a database of 63,072,000 items (34,560 items per day, Table

2) if the entire history were stored for a site with ten road sections, and nine inputs and three outputs to store per road section.

Table 2. Number of carry bits it takes to restore the history of traffic situation samples. The site had ten road sections, and nine inputs and three outputs to store per road section.

Time frame	All items stored	Condensed history stored
1 day	34,560	141,100
1 week	241,920	141,100
1 year	12,441,600	141,100
5 years	62,208,000	141,100

Online trial

An online trial was conducted on the test road. The input information received from the field was aggregated, filtered and pre-processed with a natural logarithm (Figure 2). The Euclidian distance from the input to each map unit of SOM (presented as a matrix of weight vectors of map units) was calculated. The map unit with the shortest distance was selected as the BMU. The forecast was determined as the most common flow status outcome of that particular map unit and weather and road condition class. Finally, when (if) the correct answer was measured in the field, the corresponding outcome distribution table was updated for the corresponding map unit and weather and road condition class.

The model was allowed to work online and its performance was studied as a function of time for a 250-day period. The proportion of correct forecasts was 93.8% over the entire trial period and 80.9% in congested conditions for the model of road section A in normal weather and road conditions. Corresponding proportions were 96.3% and 82.3% for road section B.

As expected, the effect of the day of the week (Saturday-Sunday vs. others) was statistically significant. Weekend (Saturday-Sunday) traffic was mostly free-flowing and those forecasts were more successful than the ones made during the week (during weekends, road section A: 96.8%, road section B: 99.6% vs. during the week, road section A: 92.5%, road section B: 94.9%). According to Student's t-test, the difference in performance between workdays and weekends was statistically significant for both road sections (road section A: p = 0.001, road section B: p = 0.000). During congestion, the proportion of correct forecasts on workdays was 83.2% for road section A and 84.2% for road section B. On weekends there were very few, solitary observations of congested traffic on both road sections, and for the most part, these were predicted incorrectly.

It was hypothesized that the performance of the model improves with time, as it is able to adapt itself. The average daily change in the proportion of correct forecasts was indeed positive over the whole trial period: +0.4% for road section A and +0.3% for road section B. Student's t-test was used to determine whether this difference was statistically significant. The equality of variances was tested with Levene's test. The performance of the first 30 days of the trial was compared with that of the last 30 days. The test showed that the difference in performance was statistically significant for the model of road section A (p = 0.000) but not for that of road section B (p = 0.089).

Two naïve comparison models were made. The first one based the forecast on average travel time for the 5-minute period and day of the week in question for each road section. These average values were calculated from the same 2004 data used to make the model. The second comparison model used the latest measurements directly as forecasts. Both models were tested over the same trial period in 2005 as above. The latest measurements (83.2% for all conditions, 53.1% for congestion) performed better than the averages on road section A (83.7% for all conditions, 1.7% for congestion). On road section B, the reverse was true (averages: 89.7% for all conditions, 49.6% for congestion; latest measurements: 88.6% for all conditions, 40.5% for congestion). Both comparison models performed considerably poorer than the self-adapting model (Table 3).

Table 3. Proportion (%) of correct forecasts over the entire online trial period and in congested conditions for the comparison models.

Road section	Naïve model based on averages		Naïve model based on latest measurements		Self-adapting model	
	All conditions	Congested conditions	All conditions	Congested conditions	All conditions	Congested conditions
A	83.7	1.7	83.2	53.1	93.8	80.9
B	89.7	49.6	88.6	40.5	96.3	82.3

DISCUSSION

This study was designed to develop a method for making a self-adapting short-term prediction model for the traffic flow status. The objective was to develop a method that could predict the flow status on a satisfactory level, would learn by itself during online operation, and would also be practical for long-term online use. The method was tested in the Helsinki metropolitan area.

The main results showed that it was possible to develop a successful prediction model that is capable of learning while working online. The results indicated that the self-adapting principle improved the performance of the model over time. Specifically, the average daily change in the proportion of correct forecasts was positive over the whole trial period: +0.4% and +0.3% for the studied road sections. This difference was statistically significant for both road sections. The results showed that the difference in the performance of the first and last 30 days of the trial was statistically significant for one of the two studied road sections while being marginally not significant for the other (p = 0.089). Specifically, the structure of the model (clustering and updating of the outcome tables) made it possible for the model to learn by itself without the need to save all the data and that made the model practical for long-term online use. As the overall performance of the self-adapting model was successful (proportion of correct forecasts 93.8% and 96.3% over the entire trial period and 80.9% and 82.3% in congested conditions), the objectives could be considered fulfilled.

The performance of the prediction model is highly dependent on factors like the regularity, frequency and amount of congestion and the structure of the detector network – regular phenomena and fluent traffic being easier to predict than random incidents and severe congestion, and the prediction task being easier for a model based on densely rather than sparsely spaced detectors. Due to application specific circumstances, a numeric comparison between models developed for and tested at different sites is not very meaningful. The task of creating models for the same site using the same data is laborious; therefore, only naïve comparison models were made. These naïve models performed far poorer (83-90% of correct forecasts over the whole trial period and 2-53% in congested conditions) than the self-adapting model. In addition, this model performed better as self-adapting than the stationary version (i.e. without the self-adapting feature), as the model presented in this paper continually improved its performance during the online trial.

The structure of the self-learning model, especially the updatable condensed history in table form, was an essential contribution of the study. A simple practical solution produced a great measurable advantage. The power of the approach is that the classification of new measurements can be made online, without querying the historic data. The model was also more practical for long-term online use from the viewpoint of number of carries it requires to restore the history of samples of traffic situations. Compared with models developed elsewhere, there is now no need to store all the samples of traffic situations. For example, at the site of this study, storing all the samples would have led to a database of 62 million items in 5 years. By comparison, the condensed version of the same history was stored in 10 tables of fixed size of at most 14,000 items. This is a substantial difference, although the number of input parameters was rather small at the site, as was the number of road sections for which the forecasts were made. It is likely that the same principle can be applied to much more complex systems and extensive sites. As the history has to be used online in real time, a condensed version of it sets fewer requirements on the computer running the model and is therefore more practical to use.

Online computation of the model is very inexpensive because, besides processing of the input and the updating procedure, the model only needs to determine Euclidian distances to the map units and the most common outcome of the distribution table of the map unit with the minimum distance. Making a SOM requires more computational power – especially when the input vector contains many variables and a large training data set is used. However, once the SOM is ready, its use sets no special requirements on the computer running the model.

The model does not react fast to changes in traffic patterns, i.e. situations where a certain traffic pattern starts to lead to a different outcome than previously. Hence, if there are considerable changes in the road network or traffic management (e.g. new signal timing at an entry to the motorway), it is better to reinitialise the outcome tables and start the collection of historic information anew. Slow changes like annual growth in traffic volumes change the most commonly used map units, but as the outcome is the same as previously with the same traffic volumes, there is no need to initialise the tables. However, if a major change (e.g. structural improvement of the road) is made, it is advisable to collect a new training data set and create new SOMs and outcome distribution tables for the model.

It could have been assumed that the inclusion of weather and weekday (working day vs. weekend) information improves forecasts considerably. The results showed that the average performance of the model was similar both for normal and hazardous weather and road surface conditions. However, there were some differences in the results when they were analysed by flow status classes. Specifically, free-flowing traffic was predicted less accurately when the weather and road surface conditions were hazardous than when they were normal. For other flow status classes, the opposite occurred. These results suggested that the separation of weather and road surface condition classes was beneficial. Consequently, the inclusion of weather information improved forecasts. However, as poor and hazardous weather and road surface conditions were rare on a road like the test road because of the high flow rate and good winter maintenance, the effect on the average performance of the model was modest – although it would probably be significant in cases where such conditions occur more frequently.

Weekend traffic was mostly free-flowing at the study site. Specifically, the flow was free-flowing 96–100% of the time during weekends, being above 99% on seven of the ten road sections. On average, weekend forecasts succeeded statistically significantly better than during the week. However, during congestion, the proportion of correct forecasts was on a satisfactory level during workdays and the very few, solitary observations of congested weekend traffic were usually predicted incorrectly. However, the more seldom and probably more random the congestion, the more difficult it is to predict. As the proportion of weekend congestion was so small, even considerable improvement in the ability to predict it would not have influenced the average numbers significantly. In addition, as the most common cause for weekend congestion is probably incidents, one could ask whether a considerable improvement in the ability of the model to predict their consequences can be achieved. Therefore it was not possible to determine whether the inclusion of weekday information would considerably improve forecasts – at least for sites with practically no weekend congestion.

In conclusion, if the flow status outcome classes are well separated into clusters, a model based on the principles described in this chapter should be able to detect even the impacts of incidents on flow status with increasing accuracy over time. Also of importance is that there is no need to save all the data into databases, which makes long-term online use practical in terms of the number of carry bits it takes to restore the history of samples of traffic situations.

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