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Travel time and incident risk assessment

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Summary

The goal of the project was to find methods for creating an accurate overall understanding of the current status of the transport system and to predict changes in traffic conditions. The most important task in achieving this was travel time prediction. Another goal was to find methods to assess the risk of incidents. In addition, an overall assessment of the monitoring system was performed considering specifically the needs of short-term prediction and incident risk assessment.

Best practices were sought among other road operators, in the literature and from small data pilots. Existing applications in use by the Finnish Transport Agency were evaluated based on theory and practice found in literature and in data pilot studies.

A slightly modified version of the dynRP travel time prediction model of the Danish Road Directorate was piloted on Ring I of the Helsinki Metropolitan Area. The main results showed that a 15-minute prediction model gave better travel time estimates than just using the latest measurement, especially in congested conditions. The model did not fulfil the threshold of keeping maximum errors between 10–25% prevalent in the literature. Nevertheless, if decisions must be made proactively, the use of this forecast, although not perfect, would lead to better decisions more often than when using just the latest measurement. Therefore the use of this model can be recommended.

Furthermore, shorter-than-15 min prediction models provided more accurate estimates than the 15 min model. However, with the former, the latest measurement served better as an estimate, and the difference from the prediction model was small if any, or even negative. Therefore, the use of these shorter-term models cannot be recommended.

The Dutch Rijkswaterstaat Traffic Management Centre has several procedures that can be considered best practice in incident risk assessment and management. It is recommended that a procedure be set up to systematically collect and use information on events that affect traffic. These annual forecasts should be studied in weekly meetings to detect abnormalities of traffic in the coming week and find solutions for (proactively) operating the traffic. The success of the previous week's operations should also be evaluated in order to perform better next time. The annual traffic forecast can also be used in the planning of timing of road works.

Incident data analysis for Ring I included road weather conditions in addition to traffic flow status information. The results indicate that some circumstances have higher incident risk than others, like evening rush hour, reduced visibility and moderate or abundant snowfall. However, the statistical significance of the results could not be studied here. This should be examined further with a larger dataset.

Travel time is a reactive measure, as it can be measured only with delay. Therefore it is recommended that in areas with regular congestion, the traffic flow be monitored using sufficiently densely-spaced cross-section specific detectors capable of monitoring reliably at least the traffic volume and speed. In areas where regular congestion does not take place, traffic monitoring serves incident management and traffic information (e.g. media). In such areas, travel time monitoring would be sufficient to indicate the consequences of incidents and the level of congestions. The system could be supplemented by road user notifications.

Satu Innamaa, Eetu Pilli-Sihvola ja Ilkka Norros: Matka-ajan ja häiriöriskin arviointi. Liikennevirasto, Liikenteen palvelut. Helsinki 2013. Liikenneviraston tutkimuksia ja selvityksiä 31/2013. 74 sivua ja 3 liitettä. ISSN-L 1798-6656, ISSN 1798-6664, ISBN 978-952-255-327-0.

Avainsanat: matka-aika, ennustaminen, häiriöriski, seuranta

Tiivistelmä

Hankkeen tavoitteena oli löytää menetelmiä tuottaa tarkka yleiskäsitys liikennejärjestelmän tilasta ja ennustaa liikennetilanteen muutokset. Tärkein tehtävä tavoitteen saavuttamiseksi oli matka-ajan ennustaminen. Toinen tavoite oli löytää menetelmiä, kuinka arvioida liikenteen häiriöriskiä. Lisäksi tehtävänä oli arvioida liikenteen seurantajärjestelmä yleisellä tasolla ottaen huomioon lyhyen aikavälin ennustamisen ja häiriöriskin arvioinnin tarpeet.

Hankkeessa etsittiin hyviä käytäntöjä muilta tienpitäjiltä, kirjallisuudesta ja pienten aineistotutkimusten perusteella. Liikenneviraston käytössä olevia järjestelmiä arvioitiin kirjallisuudesta ja aineistotutkimuksista löydetyn teorian ja käytännön tulosten perusteella.

Hieman muokattua versiota Tanskan tiehallinnon käyttämästä dynRP matka-ajan ennustemallista kokeiltiin Kehä I:llä Helsingissä. Päätulokset osoittivat, että etenkin ruuhkaolosuhteissa 15 minuutin ennustemalli antoi parempia matka-aika-arvioita kuin viimeisin mittaus. Mallin tarkkuus ei täyttänyt kirjallisuudesta löytynyttä kriteeriä, että keskimääräisen virheen suuruus saisi olla korkeintaan 10–25 %. Jos päätöksiä kuitenkin pitää tehdä ennakoivasti, mallia käyttämällä päästään parempiin päätöksiin kuin viimeisiä mittauksia käyttämällä, vaikkei malli täydellinen olekaan. Siksi mallin käyttöönottoa voidaan suositella.

Lyhyemmän aikavälin kuin 15 min ennustemallien antamat ennusteet olivat tarkempia kuin 15 min mallin. Lyhyemmällä aikavälillä myös viimeisin mittaus tarjoaa kuitenkin paremman estimaatin, ja ero ennustemalliin oli pieni, jos sellaista yleensä oli, tai jopa negatiivinen. Tästä syystä näiden lyhyemmän aikavälin ennustemallien käyttöä ei voida suositella.

Rijkswaterstaatin liikennekeskuksella oli useita hyviä käytäntöjä häiriöriskin arviointiin ja häiriön hallintaan. Suositellaan, että Liikennevirastoon luodaan järjestelmällinen menettelytapa kerätä ja hyödyntää tietoa tapahtumista ja muista liikenteeseen vaikuttavista, ennalta tiedossa olevista asioista. On suositeltavaa, että tätä vuosiennustetta katsotaan viikkokokouksessa aina seuraavan viikon osalta, jotta voidaan ennakoida liikennetilannepoikkeamat ja löytää niihin (proaktiiviset) keinot operoida liikennettä. Kyseisissä viikkokokouksissa olisi hyvä käydä läpi myös edellisen viikon operoinnin onnistuminen, jotta seuraavalla kerralla voitaisiin onnistua vielä paremmin. Vuositason liikenne-ennustetta voitaisiin käyttää myös tietöiden ajoituksen suunnitteluun.

Kehä I:n liikennehäiriöaineiston analyysi sisälsi tiesääolosuhteet liikennetilannetiedon lisäksi. Tulokset viittasivat siihen, että joissakin olosuhteissa häiriöriski tosiaan on korkeampi kuin toisissa, kuten iltaruuhkan aikaan, näkyvyyden alentuessa tai kohtalaisen tai runsaan lumisateen aikaan. Tulosten tilastollista merkitsevyyttä ei kuitenkaan voitu nyt tutkia. Tutkimusta tulisikin jatkaa suuremmalla aineistolla.

Matka-aika on reaktiivinen suure, joka voidaan mitata ainoastaan viipeellä. Tästä syystä on suositeltavaa, että säännöllisesti ruuhkautuvilla alueilla liikennevirtaa monitoroidaan riittävän tiheällä poikkileikkauskohtaisella liikenteenmittausjärjestelmällä, joka on kykenevä seuraamaan luotettavasti vähintään liikennemäärää ja nopeutta. Alueilla, joissa liikenne ei säännöllisesti ruuhkaudu, liikenteen seuranta palvelee häiriönhallintaa ja tiedotusta (esim. mediaa). Tällaisilla alueilla matka-ajan seurantajärjestelmä olisi riittävä indikoimaan häiriöiden seuraukset ja ruuhkan tason. Järjestelmää voitaisiin täydentää tienkäyttäjien ilmoituksilla.

Satu Innamaa, Eetu Pilli-Sihvola and Ilkka Norros: Restidsprognoser och bedömning av störningsrisken. Trafikverket, avdelningen trafiktjänster. Helsinfors 2013. Trafikverkets undersökningar och utredningar 31/2013. 74 sidor och 3 bilagor. ISSN-L 1798-6656x, ISSN 1798-6664, ISBN 978-952-255-327-0.

Sammanfattning

Målsättningen med projektet var att hitta metoder för att bilda en korrekt allmän uppfattning om nuläget i trafiksystemet och förutse ändringar i trafiksituationen. Den viktigaste uppgiften för att nå detta mål var att uppskatta restiden. Den andra målsättningen var att hitta metoder för att bedöma störningsrisken i trafiken. Därtill hade man som uppgift att utvärdera trafikens uppföljningssystem på ett allmänt plan genom att beakta kraven som ställs på de kortsiktiga prognoserna och på bedömningen av störningsrisken.

Man sökte efter god praxis bland övriga väghållare samt med hjälp av litteratur och mindre materialstudier. Systemen som används vid Trafikverket utvärderades utifrån den teori och de praktiska resultat som presenterades i litteraturen och materialstudierna.

En något omarbetad version av modellen dynRP som danska vägdirektoratet använder för restidsuppskattning testades på Ring I i Helsingfors. De huvudsakliga resultaten visade att man särskilt i rusningstrafik kunde uppskatta restiden bättre med en 15-minuters prognosmodell än med den senaste mätningen. Modellens noggrannhet uppfyllde inte kraven som ställts i litteraturen, dvs. att den genomsnittliga felmarginalen får vara högst 10–25%. Om beslutsfattandet ändå kräver förutseende, uppnår man bättre resultat genom att använda denna, om än ofullständiga, modell än att använda de senaste mätningarna. Därför kan man rekommendera att modellen tas i användning.

De prognosmodeller som var mer kortsiktiga än 15-minutersmodellen gav mer exakta prognoser än 15-minutersmodellen. På kort sikt ger också den senaste mätningen ett bättre estimat och om det överhuvudtaget fanns någon skillnad mellan mätningen och prognosmodellen, var skillnaden försumbar eller till och med negativ. Därför kan användningen av kortsiktiga prognosmodeller inte rekommenderas.

Vid Rijkswaterstaats trafikcentral har man ett flertal exempel på god praxis i fråga om bedömning av störningsrisken samt störningshantering. Det rekommenderas att Trafikverket skapar ett systematiskt tillvägagångssätt för att samla in och utnyttja informationen om händelser och övriga redan kända faktorer som påverkar trafiken. På veckomötena borde man alltid studera denna årsprognos för den kommande veckans del, för att man ska kunna förutse avvikelser i trafiksituationen och vidta (proaktiva) åtgärder för att leda trafiken. På veckomötena i fråga skulle det också vara bra att gå igenom hur trafikledningen fungerade föregående vecka, för att man nästa gång ska lyckas ännu bättre. En trafikprognos på årsnivå kunde också användas för tidsplaneringen av vägarbetena.

Analysen av materialet gällande trafikstörningarna på Ringväg I innehöll, förutom information om trafiksituationen, även information om vägvädersituationen. Resultaten visar att störningsrisken faktiskt är större under vissa förhållanden, som t.ex. i kvällsrusningen, vid nedsatt sikt eller vid måttligt eller ymnigt snöfall. Det var inte möjligt att ta med den statistiska betydelsen av resultaten i denna undersökning. Undersökningen borde fortsättas med en utvidgad materialbas.

Restiden är en reaktiv storhet, som bara kan mätas med en viss tidsförskjutning. Därför rekommenderas att man i områden med återkommande trafikstockningar övervakar trafikflödet i en specifik tvärsektion med hjälp av ett tillräckligt heltäckande trafikmätningssystem, som åtminstone klarar av en tillförlitlig uppföljning av trafikmängden och hastigheten. I områden utan regelbundna trafikstockningar betjänar uppföljningen av trafiken störningshanteringen och informationsspridningen (t.ex. medierna). I sådana områden skulle ett system för uppföljning av restiden vara tillräckligt för att indikera konsekvenserna av störningarna och trafikrusningens nivå. Systemet kunde kompletteras med trafikanternas meddelanden.

Preface

The Finnish Transport Agency is searching for a method that would give a situation-aware overall understanding of traffic on the road network at any given time to support the operative work of traffic management operators at Finnish traffic management centres. This understanding, or overall picture if presented in visual from, should also include short-term prediction of the traffic situation. VTT Technical Research Centre of Finland conducted a study that targeted finding methods for creating an accurate overall understanding of the current status of the transport system and to predict changes in traffic conditions.

Senior Scientist Satu Innamaa was the project manager at VTT. She was responsible for the deliverable, piloting of the Danish travel time prediction model, analysis of the Dutch incident management model, incident clustering, evaluation of the traffic monitoring system, and the discussion chapter. Research Scientist Eetu Pilli-Sihvola was responsible for literature reviews and evaluation of the incident information message content. Research professor Ilkka Norros was responsible for the incident data analysis. The project's steering group consisted of Aapo Anderson, Kari Hiltunen, Risto Kulmala and Michaela Koistinen of the Finnish Transport Agency. Sami Luoma of the Traffic Management Centre also participated in discussions on the recommendations given in the deliverable.

Helsinki, July 2013

Finnish Transport Agency

Table of content

1 Introduction

In managing the road network, taking action before traffic conditions become congested is often a more effective solution than just reacting to congestions as they take place and are observed. This approach to transport network management is generally referred to as proactive traffic management. To be able to manage traffic proactively, information about the status of the traffic flow (e.g. average speeds, travel times or traffic volumes) is needed. This information includes short-term forecasts of the traffic situation.

In Finland, the Finnish Transport Agency is searching for a method that would give a situation-aware overall understanding of traffic on the road network at any given time to support the operative work of traffic management operators at the Finnish traffic management centres. This understanding, or overall picture if presented in visual from, should also include short-term prediction of the traffic situation.

Because information on the predicted state of the traffic network would be used in operative traffic management activities, it is essential that the approach be practical, the output of sufficient quality, and information on the quality of forecasts easily accessible. Specifically, a key element in proactive traffic management is the prediction of travel time in different traffic and road weather circumstances. Certain combinations of traffic flow and road weather conditions could be more likely to result in incidents than others. In addition, ways to monitor and identify risk factors on the road network should be developed to be able to anticipate the potential emergence of accidents and other traffic incidents and to be able to predict their likely consequences.

The goal of the project was to find methods for creating an accurate overall understanding of the current status of the transport system and to predict changes in traffic conditions. The most important task in achieving this is travel time prediction. Another goal was to find methods for assessing incident risk. The final task was to carry out an overall assessment of the monitoring system considering the needs of short-term prediction and incident risk assessment.

2 Travel time prediction

2.1 Danish model – dynRP

2.1.1 Background

The Danish Road Directorate has used short-term forecasts of travel time as part of their traffic management system on the very busy M3 motorway near Copenhagen for years. The suitability of the prediction model was evaluated in Finnish conditions in 2006 (Innamaa and Silla 2006).

The results of the evaluation were satisfactory. The evaluation study recommended a travel time prediction model like the one used by the Danish Road Directorate, which is derived from a regression model based on latest measurements and historic averages for use on short road sections with regular heavy traffic or alternatively always freely flowing traffic. In addition, they recommended that the models be based on 5-minute medians. (Innamaa and Silla 2006)

The model used in the Copenhagen area was later replaced with the dynRP model. The drawback of the earlier model was that it required manual updating. The new model, described in detail in the following section, could be fully automated.

2.1.2 Description of the model

The Danish Road Directorate uses the dynRP model to predict travel times automatically in real time (Danish Road Directorate, no date). Their monitoring system is based on loop detectors; thus travel time is estimated from loop detector data. The forecast is given for 15 and 30 minutes ahead.

The model is based on two curves: one presenting free flow speed and the other historic averages. Through interpolation and extrapolation, the travel time is predicted assuming the ratio between measured travel time and historic average to be constant.

Historic averages are updated automatically daily using e.g. the past 6 months of data. All day types are treated separately: Monday, Tuesday/Wednesday/Thursday, Friday, Saturday, and Sunday/Holiday.

Historic averages are used only in normal traffic conditions. The normality of condition is determined from threshold values. If the traffic condition is considered abnormal, the last measurement is used as the best forecast. The dynRP flow chart is shown in Figure 1.

The Danish Road Directorate recommends that an automated system be created to accompany the dynRP method to compare given forecasts with true, measured outcomes and to give an alarm if certain thresholds are exceeded (poor quality of forecasts, usually a sign of abnormal traffic flow).

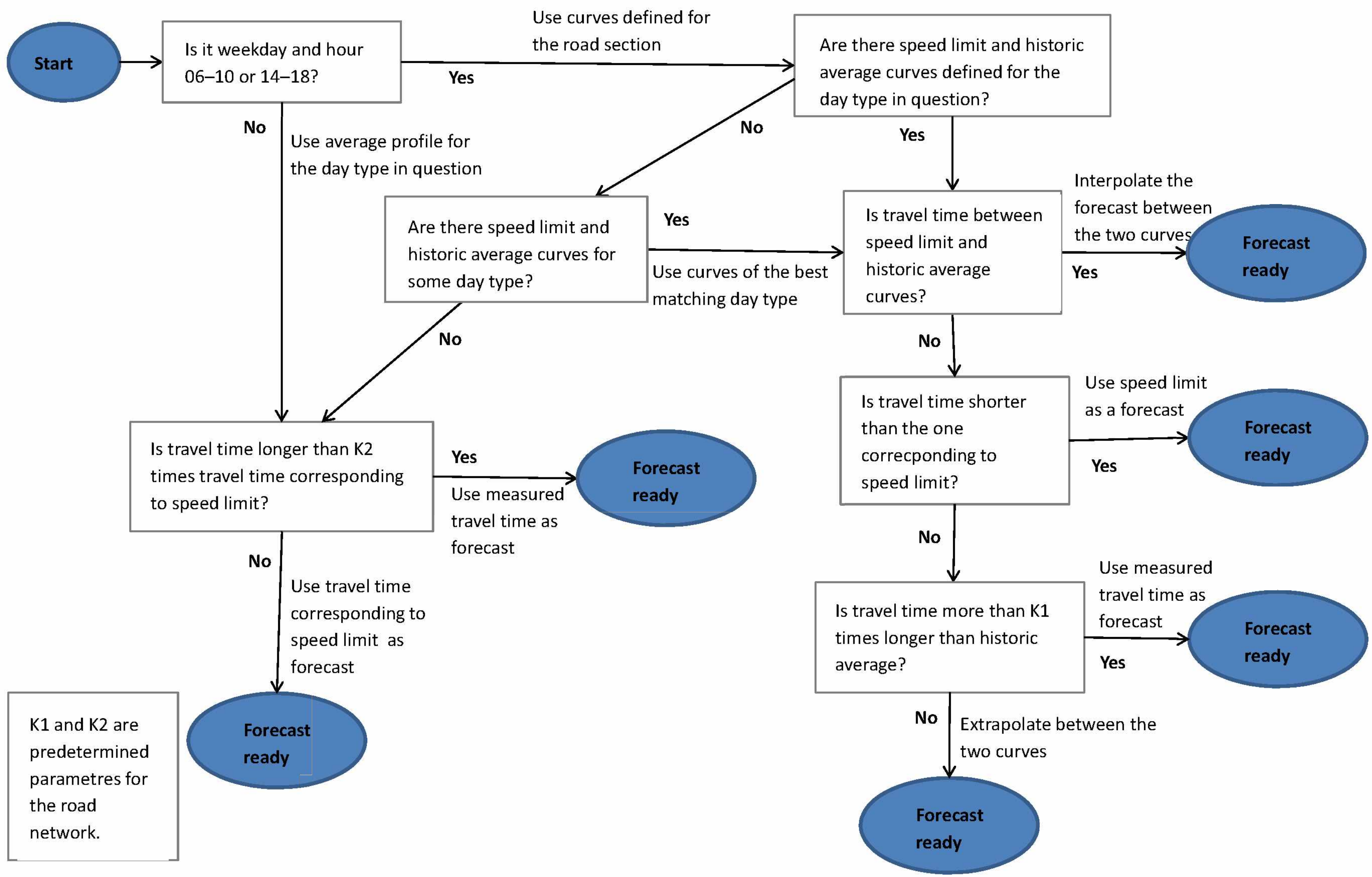


Figure 1. *Generation of travel time forecasts with the dynRP travel time prediction model (Danish Road Directorate, no date)*

2.1.3 Pilot on Ring I

Pilot area and data

The Danish dynPR travel time prediction model was piloted on Ring I in the Helsinki metropolitan area. As the traffic monitoring system on Ring I is based on a travel time camera system, dynPR needed to be slightly modified.

The pilot was conducted on two links of Ring I, Konala–Pakila (eastbound) and Pukinmäki–Konala (westbound). The Pukinmäki–Konala link (free flow travel time approximately 330 seconds) was longer than Konala–Pakila (approx. 180 seconds).

The piloted version of the model was based on direct travel time measurements monitored using the existing licence plate reader camera system. As travel time observations include outliers – both due to failures in the monitoring system and due to vehicles stopping on the way at e.g. a supermarket – the median is a more suitable indicator than an average value. Therefore, for these links a historic model was calculated as a median of the last 5-minute median travel times determined for every minute during 2011 and 2012. Data from 2011 was used in creating the model and that from 2012 was used in testing it.

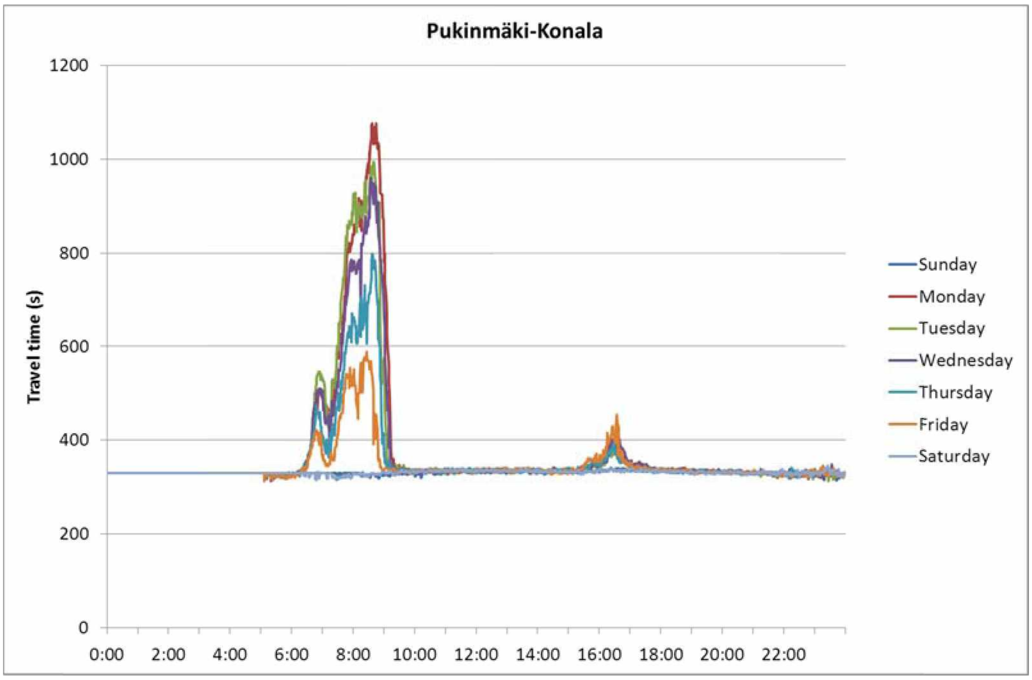
Due to outliers in the travel time data, small numbers of travel time observations also cause outliers to the median values. Therefore, it was decided that the median should be based on at least 5 observations before it could be included in the calculation or testing of the model. The proportion of time with a sufficient number of observations was 45.4–46.3% on test links (Table 1).

Table 1. Proportion of time with given number of observations per 5 minute period; months when travel time monitoring did not perform well are excluded

Sample size	Pukinmäki–Konala	Konala–Pakila
0	24.9%	26.9%
1	11.8%	10.4%
2	7.6%	6.7%
3	5.7%	5.1%
4	4.7%	4.1%
5	4.0%	3.5%
6	3.6%	3.1%
7	3.4%	2.8%
8	3.1%	2.5%
9	3.0%	2.2%
10+	28.3%	32.3%

Basic model

First the model was built for the 2011 using all travel time medians that were based on at least 5 observations (Figure 2). The model was calculated as the median value of median travel times measured for that particular moment in time (1 minute slot) and weekday. In the models, travel time was considered equal to free flow travel time if fewer than 5 medians were available for the corresponding minute and day.



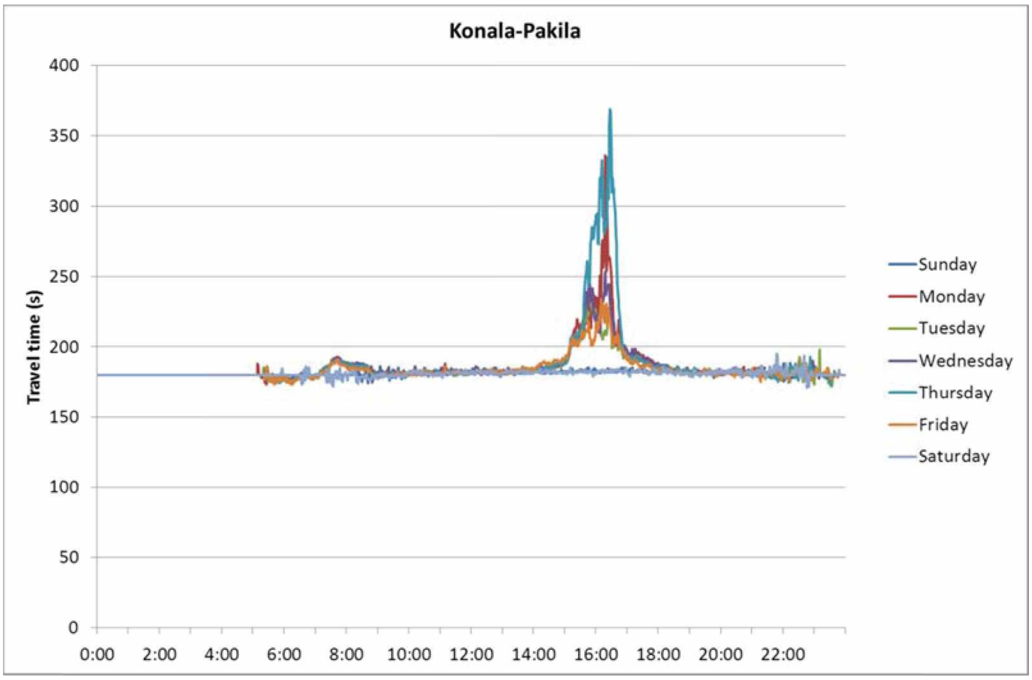


Figure 2. *Historic median models of 5-minute medians (based on at least 5 observations) determined for every minute and weekday, free flow travel time if there were less than 5 medians for the corresponding minute and day*

In Denmark, Tuesday, Wednesday and Thursday were combined into one average. However, based on the result all weekdays seemed to differ on Ring I (Figure 2) and keeping them all separate was justifiable.

The basic model was tested with 2012 data. Only those observations were included in the test data set that were based on at least 5 observations and were not measured during night-time (00–05).

The forecast was calculated as a product of historic median travel time of the current weekday 15 minutes ahead from the current moment and the ratio between the current travel time and corresponding historic median:

$$TT_{+15} = \frac{TT_{00}}{\overline{TT}_{00}}\overline{TT}_{+15}$$

If the measured travel time or forecast was faster than the free flow speed (330/180 s), the value was replaced with the free flow speed for the error calculation.

The results were calculated for moments at which the measurement value corresponding to the period of the predicted outcome existed. The average absolute value of the relative error was 3.2–4.1% for all traffic conditions and 13.3–15.2% for congested conditions, determined as traffic for which the travel time has risen to at least 10% above the free flow median (Table 2). As the proportion of congestion was rather small, the overall performance of the model was satisfactory (82.0–87.2% of the time the error was <5% and 96.5–96.9% of the time <20%), but the performance was clearly poorer in congested conditions (30.4–30.5% and 76.6–81.8%, respectively).

Table 2. Model test results based on 2012 data. Traffic was considered congested if measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		**Konala–Pakila**	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	4.1%	13.3%	3.2%	15.2%
Proportion of time when error <5%	82.0%	30.4%	87.2%	30.5%
Proportion of time when error <10%	91.9%	55.9%	93.6%	52.3%
Proportion of time when error <20%	96.5%	81.8%	96.9%	76.6%

The correspondence of predicted and measured outcomes as flow status classes were studied (Table 3, more detailed results in Annex A). The results show that most of the free flowing traffic (travel time at most 10% over free flow travel time) was predicted correctly (success rate 95.6–97.2%). In addition, most of the stopped traffic (travel time more than 90% over free flow travel time) was predicted correctly (78.7–82.0%).

However, the flow status classes between them were predicted more poorly, with 37.6–62.9% success rate for flow with travel time 10–75% over free flow travel time. The worse performance was for the flow status with travel time 75–90% over free flow travel time, with only 14.2–19.0% success rate. Large errors (at least two flow status classes) were most frequent for flow with travel time 25–75% or >90% over free flow travel time (11.0–13.6%). Large errors were least frequent for the two most fluent flow classes (0.7–2.7%).

Table 3. Test results as correspondence of flow status classes, the basic model

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**>90%**
Konala-Pakila link	**Correct class**	97.2%	43.6%	47.2%	14.2%	78.7%
	False by more than one class	0.7%	2.7%	13.6%	8.5%	11.9%
Pukinmäki-Konala link	**Correct class**	95.6%	37.6%	62.9%	19.0%	82.0%
	False by more than one class	1.3%	2.7%	13.1%	4.1%	11.0%

The classes when the measured travel time was 10-25% and 75-90% of the free flow travel time seemed always to perform the worst (Table 3). It is probably because these classes mainly exist as "passing" classes, between more stationary classes, i.e. congestion seldom remains (time-wise) in these classes but changes either for the better or worse, which is why they are hard to predict. This could also be typical, of course, for these sections.

As a comparison for the prediction model, the performance of use of the last measured value as a forecast was studied (Table 4). On the Konala–Pakila link the average relative value of relative error was equal to or almost equal to the prediction model above. On the Pukinmäki–Konala link the prediction model performed better than when using the last measurement (e.g. 13.3% vs. 17.7% average absolute value of relative error in congestion). When looking at correspondence of flow status classes (Table 5 and Annex A), it can be seen that the proportion of correct classes was worse with direct use of the last measurement for all classes, except free flowing class where the performance was very similar. In addition, the proportion of large errors was greater with direct use of the last measurement in these traffic conditions.

Table 4. Results when the last measurement is used as a forecast. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki-Konala		Konala-Pakila	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	4.8%	17.7%	3.2%	15.6%
Proportion of time when error <5%	81.1%	20.1%	87.1%	28.7%
Proportion of time when error <10%	89.9%	41.1%	93.5%	51.2%
Proportion of time when error <20%	94.7%	71.0%	96.8%	75.8%

Table 5. Test results when using the last measurement as a forecast, by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	96.9%	40.1%	43.0%	9.0%	77.2%
	False by more than one class	0.7%	2.6%	22.6%	11.8%	13.8%
Pukinmäki-Konala link	**Correct class**	96.0%	25.6%	41.2%	14.6%	76.3%
	False by more than one class	1.6%	4.3%	29.8%	7.7%	15.4%

In the results above, the forecast was calculated from the historic median curve independent of the ratio between the current state and the curve value. However, the Danish Road Directorate suggests using a threshold above which the last measurement is used instead of the forecast. Such a threshold value was sought by studying the proportion of time when the forecast would have been a more accurate choice as a function of the ratio between current state and historic curve (Figure 3). Nevertheless, the historic median based forecast was more reliable than the latest measurement, even if the difference between the latest measurement and the historic median was 100%. Therefore it is recommended always to extrapolate the forecast from the historic value.

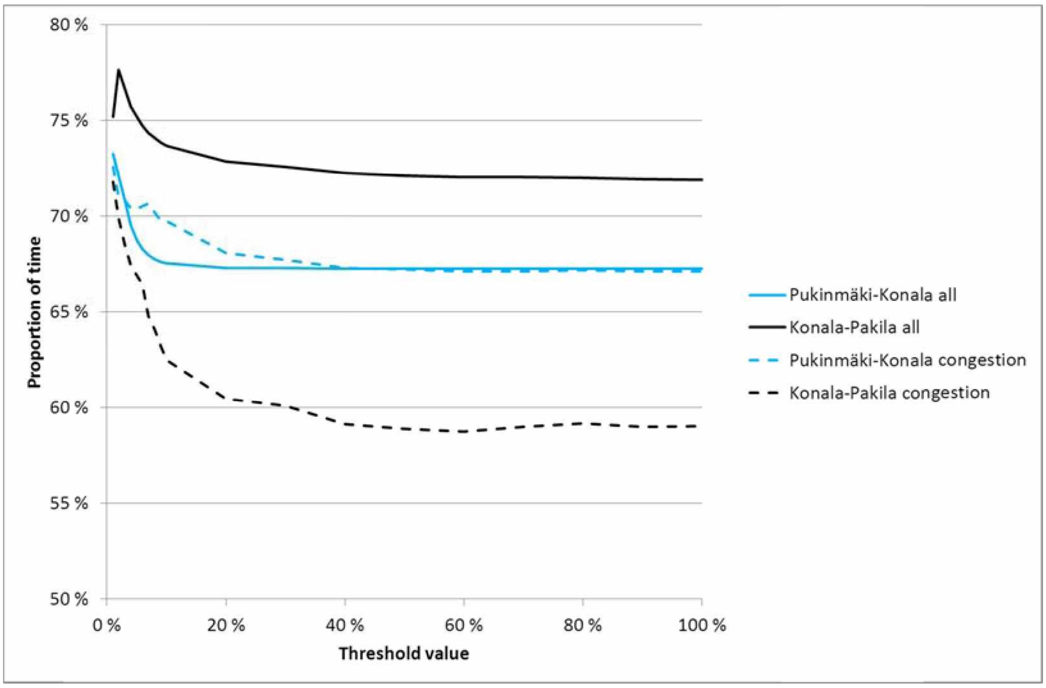
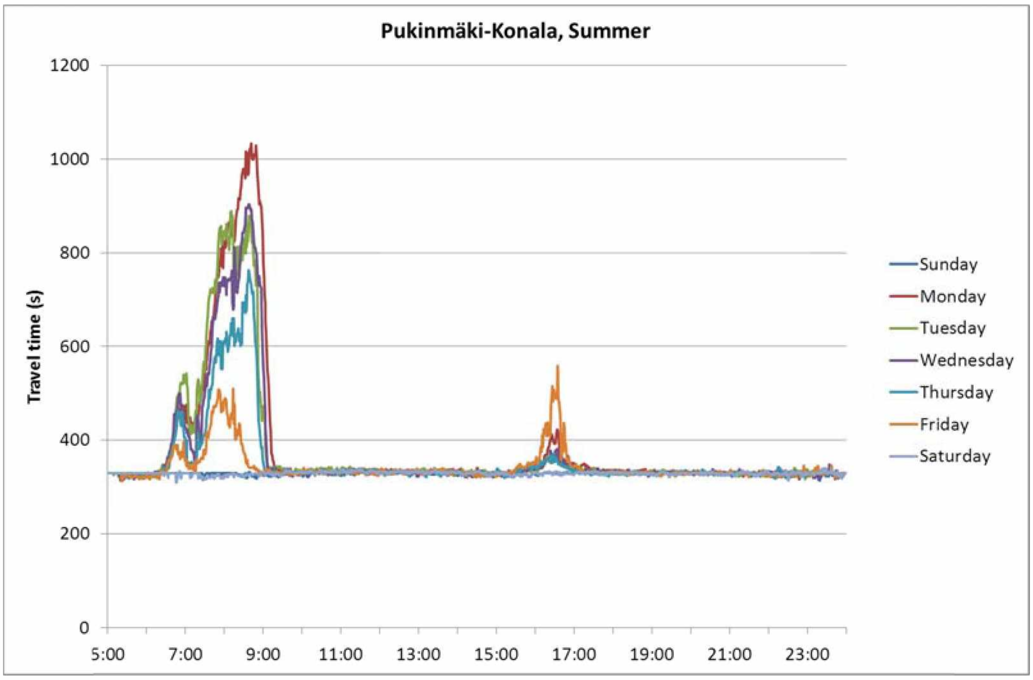


Figure 3. *Proportion of time when the historic median based forecast was better than the last measurement as a function of the threshold value for the difference of the last measurement from the corresponding historic value. Traffic was considered congested if the travel time was at least 10% longer than in free flow*

Seasonal models

Wintertime includes more varying road weather conditions than summer. In Finland, some roads also have lower speed limits during the winter season, but not our test road. Nevertheless, the model was divided into two parts: November–March as wintertime and April–October as summertime. Otherwise, the same principles were applied as with the basic model. The historic median curves show that although the timing of congestion was approximately the same for both seasons, there was a difference in the level of congestion (Figure 4 and Figure 5).



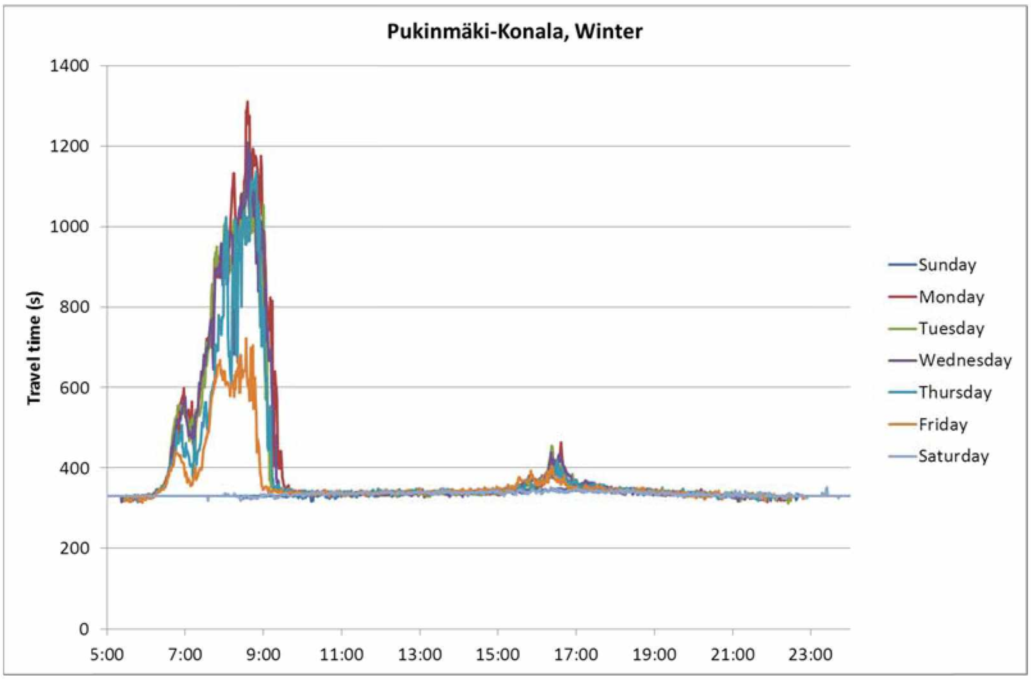


Figure 4. Seasonal models for the Pukinmäki–Konala link.

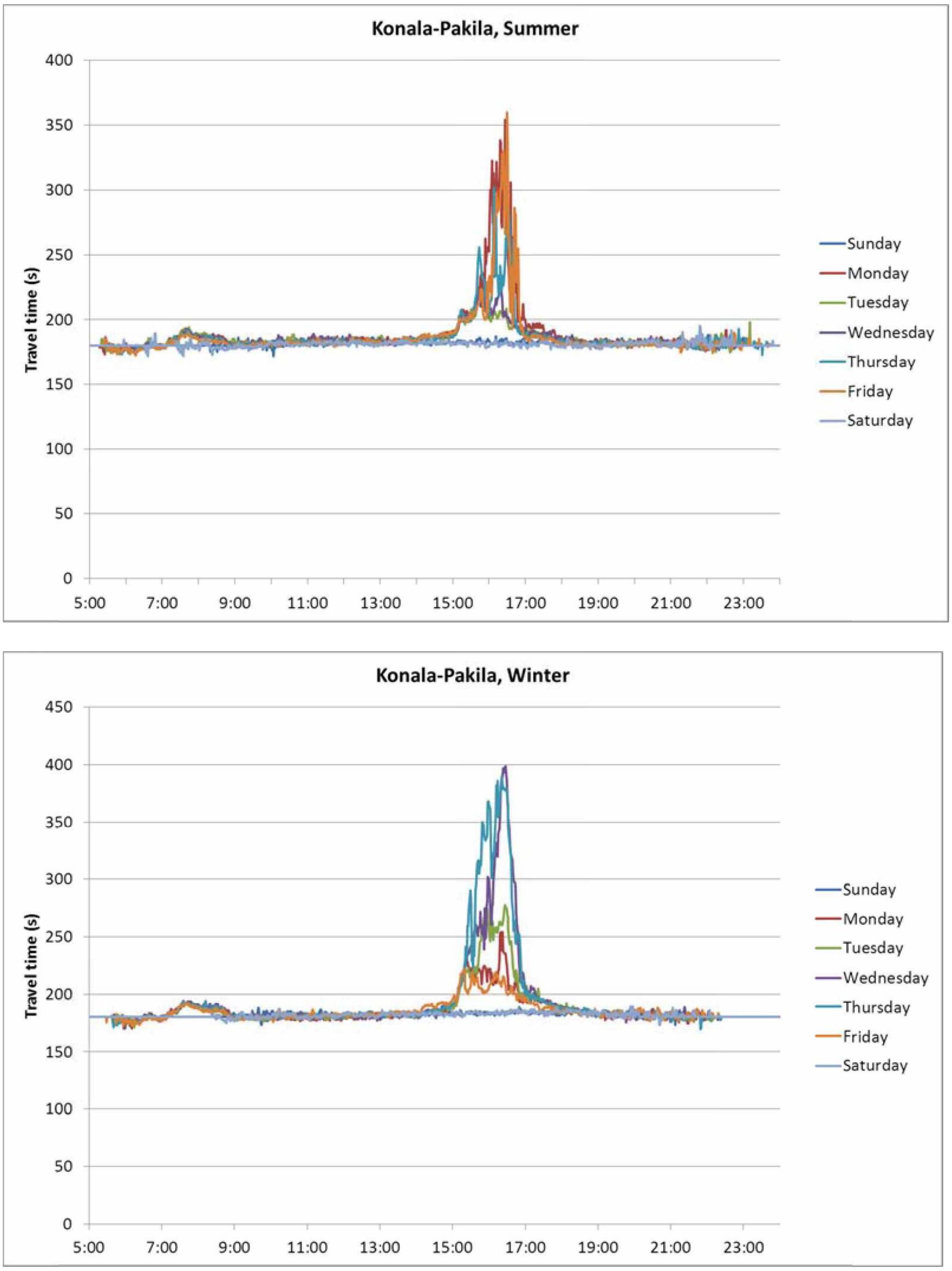


Figure 5. *Seasonal models for the Konala–Pakila link.*

The performance of the seasonal model (Table 6) for the Konala-Pakila link was slightly better than that of the basic model (Table 2) for all conditions, but slightly worse for congestion. On the Pukinmäki-Konala link, the seasonal model performed slightly worse both overall and for congested conditions. However, the differences between the models were small. The proportion of correct flow status classes was roughly equal to those of the basic model for the most fluent class on the Konala-Pakila link, and for the two most fluent flow status classes on the Pukinmäki-Konala link (Table 7). The same applies to the proportion of road status classes wrong by more than one class. In addition, the latter proportion was equal also for the most congested class. However, the seasonal model performed better in terms of the proportion of correctly predicted class where the travel time was 25-75% over the free flow travel time on the Konala-Pakila link, for the most congested class on the other link. The proportion of flow status classes wrong by more than one class was smaller in class travel time 75-90% over the free flow travel time on both links. The other indicators were worse for the seasonal model than for the basic model. Thus season has an effect on travel time patterns, but dividing the year into two seasons does not improve the modelling procedure because of the strong variation.

Table 6. Seasonal model test results based on 2012 data. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

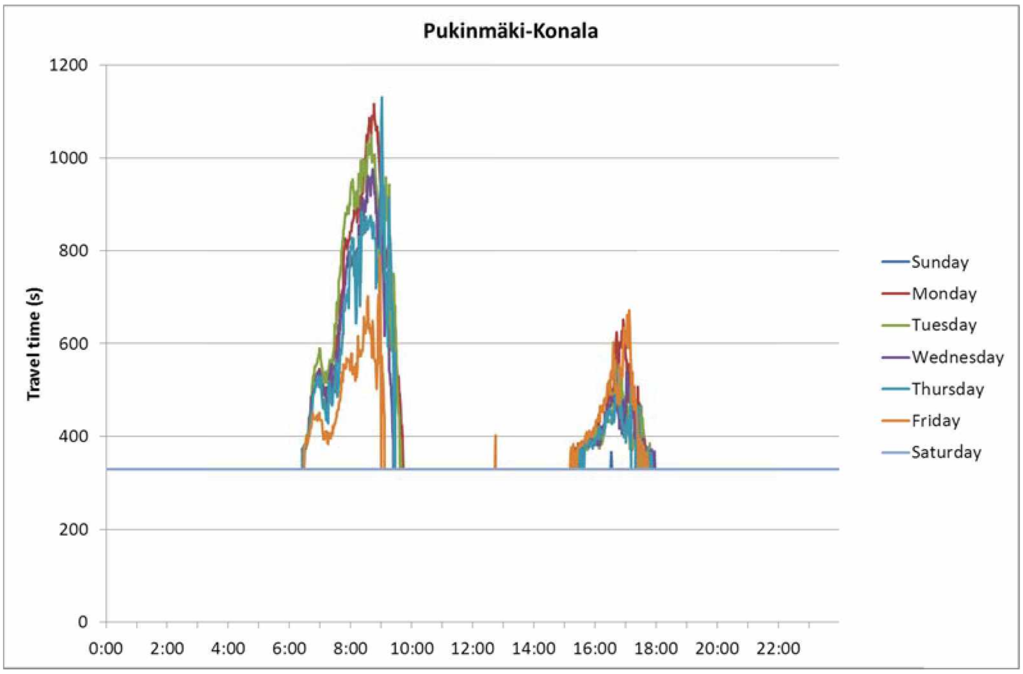
	Pukinmäki–Konala		Konala–Pakila	
	All	Congestion	All	Congestion
Average absolute value of relative error	4.2%	14.1%	3.3%	15.8%
Proportion of time when error <5%	81.0%	29.0%	89.5%	29.6%
Proportion of time when error <10%	91.3%	52.6%	95.9%	52.3%
Proportion of time when error <20%	96.0%	79.0%	97.8%	75.3%

Table 7. Test results of the seasonal model by correspondence of flow status classes.

		Measured output, % over free flow travel time				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Konala-Pakila link	Correct class	97.3%	41.8%	55.2%	9.5%	77.1%
	False by more than one class	0.7%	3.6%	15.4%	6.6%	13.9%
Pukinmäki-Konala link	Correct class	95.3%	37.2%	61.3%	17.0%	83.4%
	False by more than one class	1.4%	3.0%	16.2%	3.2%	11.0%

Model of exceptional conditions

The data appeared to be divided into free flow days and days with varying levels of congestion; thus models were built representing only those occasions when the median travel time exceeded the free flow travel time by at least 10% (Figure 6). The model covered the whole year using travel time medians based on at least five observations. The travel time was considered equal to free flow travel time if there were fewer than eight medians for the corresponding minute and day. The threshold was set higher here than for the other models, as with a smaller threshold there were lots of isolated peaks (single higher value), which is undesirable.



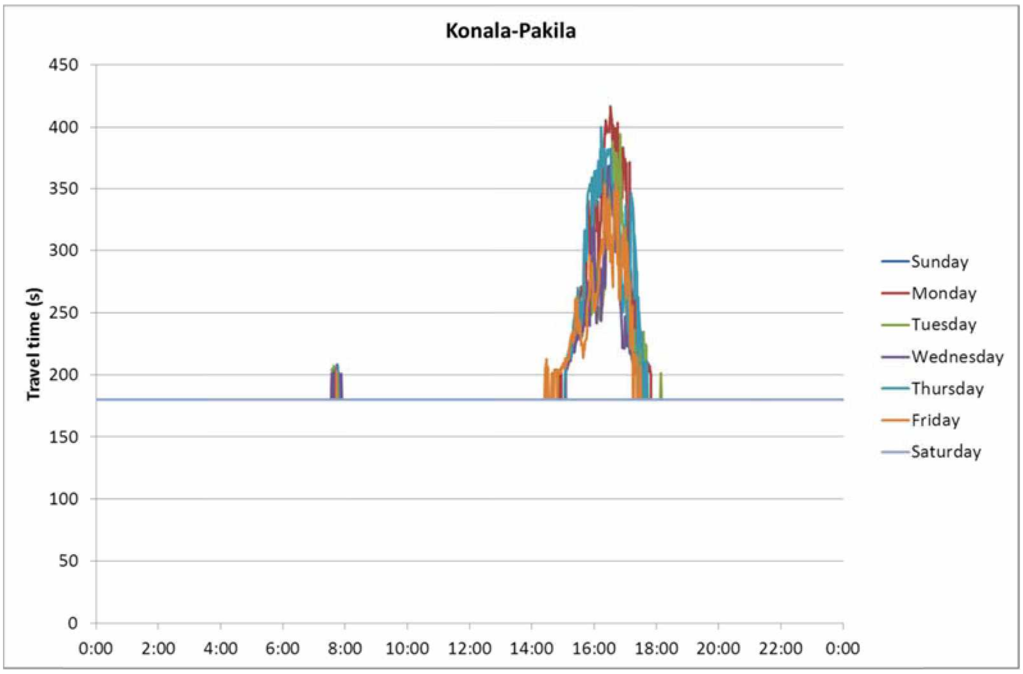


Figure 6. Model for exceptional conditions

The forecast was made for this model following the same principles as for the basic model if the current travel time was at least 10% higher than the free flow travel time. If it was less, the forecast was equal to the latest measurement.

The average absolute value of error was very similar to the basic model over all conditions, but surprisingly worse in congested conditions (Table 8). For the Pukinmäki–Konala link, the proportions of error of a certain magnitude were very similar to the basic model but slightly worse for the other link. In congested conditions, both models of exceptional situations performed worse than the basic model. When looking at the correspondence of flow status classes, the model of exceptional situations performed better in the most congested conditions than the basic model, equally in free flow conditions, and mostly worse in milder congestion (Table 9). It can be concluded that the prediction of free flow and exceptional conditions improved at the expense of performance in the prediction of milder congestion. Therefore, this model cannot be recommended for general use.

Table 8. Test results from the model of exceptional situations based on 2012 data. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		Konala–Pakila	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	4.3%	15.3%	3.5%	17.4%
Proportion of time when error <5%	82.0%	24.8%	86.4%	22.3%
Proportion of time when error <10%	91.2%	49.0%	92.7%	44.3%
Proportion of time when error <20%	95.8%	78.2%	96.3%	72.9%

Table 9. Test results from the Konala–Pakila model of exceptional situation by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	97.8%	17.5%	54.0%	13.7%	81.9%
	False by more than one class	0.9%	4.4%	27.7%	6.6%	12.8%
Pukinmäki-Konala link	**Correct class**	96.8%	15.3%	56.2%	20.4%	86.5%
	False by more than one class	1.5%	3.5%	30.0%	3.2%	8.3%

Forecasts for shorter prediction period

If a forecast accuracy of 15 minutes is not satisfactory, shorter prediction periods can be used. We therefore tested what the accuracy of forecasts would be if the prediction period was shorter: 10, 5 or 1 minute(s). The basic model was applied.

The result of the basic model for different prediction period lengths was clear: it improved with a shorter prediction period, as seen in a smaller average error, smaller proportion of large errors, bigger proportion of correct forecasts and smaller proportion of forecasts false by more than one class (Table 10 - Table 15 and Annex A).

Table 10. Test results from the basic model for a 10-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		**Konala–Pakila**	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	3.4%	10.9%	2.8%	12.1%
Proportion of time when error <5%	83.3 %	35.6%	87.6 %	33.0%
Proportion of time when error <10%	93.4 %	62.8%	94.6 %	58.8%
Proportion of time when error <20%	97.6 %	87.2%	97.8 %	83.5%

Table 11. Test results from the Konala–Pakila basic model for a 10-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	97.5%	43.6%	57.0%	15.0%	83.8%
	False by more than one class	0.5%	1.0%	10.5%	2.6%	8.4%
Pukinmäki-Konala link	**Correct class**	96.3%	42.3%	68.1%	25.5%	86.6%
	False by more than one class	0.8%	1.8%	9.7%	1.3%	7.1%

Table 12. Test results from the basic model for a 5-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		Konala–Pakila	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	2.8%	7.8%	2.2%	8.2%
Proportion of time when error <5%	85.4 %	44.5%	89.3 %	44.2%
Proportion of time when error <10%	95.6 %	74.6%	96.4 %	72.1%
Proportion of time when error <20%	99.0 %	94.1%	99.0 %	92.5%

Table 13. Test results from the Konala–Pakila basic model for a 5-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	97.6%	50.7%	71.5%	26.6%	90.6%
	False by more than one class	0.2%	0.3%	5.1%	2.5%	2.9%
Pukinmäki-Konala link	**Correct class**	97.1%	46.7%	77.3%	32.6%	90.9%
	False by more than one class	0.3%	0.3%	5.3%	0.1%	3.3%

Table 14. Test results from the basic model for a 1-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		**Konala–Pakila**	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	1.1%	3.0%	0.8%	2.6%
Proportion of time when error <5%	96.5%	82.4%	97.7%	86.0%
Proportion of time when error <10%	99.4%	95.9%	99.5%	96.4%
Proportion of time when error <20%	99.9%	99.6%	99.9%	99.6%

Table 15. Test results from the Konala–Pakila basic model for a 1-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	99.0%	79.0%	90.3%	67.2%	97.8%
	False by more than one class	0.0%	0.0%	0.4%	0.0%	0.4%
Pukinmäki-Konala link	**Correct class**	98.8%	77.0%	91.3%	61.8%	96.5%
	False by more than one class	0.0%	0.0%	0.7%	0.1%	0.5%

As shown above, the performance increases as the prediction period decreases. However, this is also true with the last measurement used as the forecast. Thus the suitability of the models is not certain despite better performance. Consequently, the same performance indicators were calculated for 10-minute, 5-minute and 1-minute prediction periods assuming that the forecast would have been equal to the latest measurement.

For the 15-minute model, the forecast based on historic median curve outperformed the last measurement. However, for the Pukinmäki-Konala link the historic median curve worked better than the last measurement, except for the 1-minute forecast where the last measurement was better (Table 16 - Table 21 and Annex A). For the Konala-Pakila link, the last measurement was more accurate than the historic median based for all prediction periods: 10 minutes, 5 minutes and 1 minute. Thus the use of a historic median based forecast can only be recommended for a 15-minute period.

Table 16. Test results from the latest measurement for a 10-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		**Konala–Pakila**	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	3.8%	13.7%	2.7%	11.7%
Proportion of time when error <5%	82.6%	26.2%	88.3%	34.8%
Proportion of time when error <10%	91.8%	51.0%	94.8%	60.3%
Proportion of time when error <20%	96.7%	82.1%	98.0%	84.6%

Table 17. Test results from the latest measurement for a 10-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	97.4%	44.4%	52.8%	16.7%	82.9%
	False by more than one class	0.4%	0.8%	12.7%	5.1%	8.4%
Pukinmäki-Konala link	**Correct class**	96.7%	31.0%	53.5%	20.8%	83.0%
	False by more than one class	1.0%	2.8%	18.7%	2.0%	9.2%

Table 18. Test results for the latest measurement for a 5-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

	Pukinmäki–Konala		**Konala–Pakila**	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	2.8%	8.5%	2.1%	7.5%
Proportion of time when error <5%	85.5%	40.2%	90.3%	46.4%
Proportion of time when error <10%	95.2%	71.1%	97.1%	77.4%
Proportion of time when error <20%	98.8%	93.1%	99.2%	93.8%

Table 19. Test results from the latest measurement for a 5-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	97.9%	53.7%	69.2%	28.7%	90.7%
	False by more than one class	0.1%	0.3%	4.5%	3.7%	2.3%
Pukinmäki-Konala link	**Correct class**	97.6%	41.6%	71.0%	32.2%	90.0%
	False by more than one class	0.3%	0.5%	7.2%	0.1%	3.2%

Table 20. Test results from the latest measurement for a 1-minute prediction period. Traffic was considered congested if the measured travel time for the prediction moment was at least 10% above the free flow median.

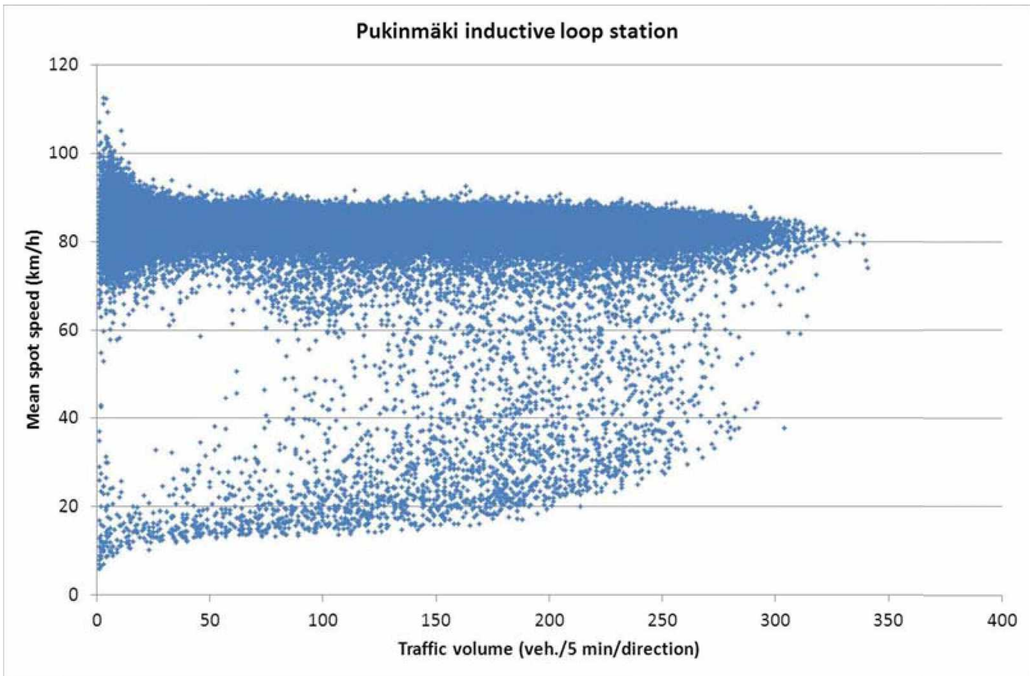
	Pukinmäki–Konala		Konala–Pakila	
	All	**Congestion**	**All**	**Congestion**
Average absolute value of relative error	0.9%	2.3%	0.7%	1.8%
Proportion of time when error <5%	97.3%	87.1%	98.6%	91.8%
Proportion of time when error <10%	99.5%	97.0%	99.8%	98.1%
Proportion of time when error <20%	99.9%	99.6%	100.0%	99.7%

Table 21. Test results from the latest measurement for a 1-minute prediction period by flow status class.

		Measured output, % over free flow travel time				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Konala-Pakila link	**Correct class**	99.3%	84.6%	92.5%	80.7%	98.1%
	False by more than one class	0.0%	0.0%	0.4%	0.0%	0.3%
Pukinmäki-Konala link	**Correct class**	99.2%	79.3%	92.4%	74.7%	97.2%
	False by more than one class	0.0%	0.0%	0.7%	0.1%	0.4%

Use of loop detector data

There are five inductive loop stations on the Pukinmäki–Konala link and three on the Konala–Pakila link. Basic traffic flow diagrams created for these cross-sections (examples in Figure 7) show that the traffic flow can have a free-flow speed of up to about 330–480 vehicles/5 minutes/direction depending on the cross-section (number of lanes). However, all measurement stations also include observations of saturated flow conditions down to almost zero volume with very low speed. Consequently, traffic volume alone does not describe the traffic condition nor can it be used (alone) to increase the prediction power.



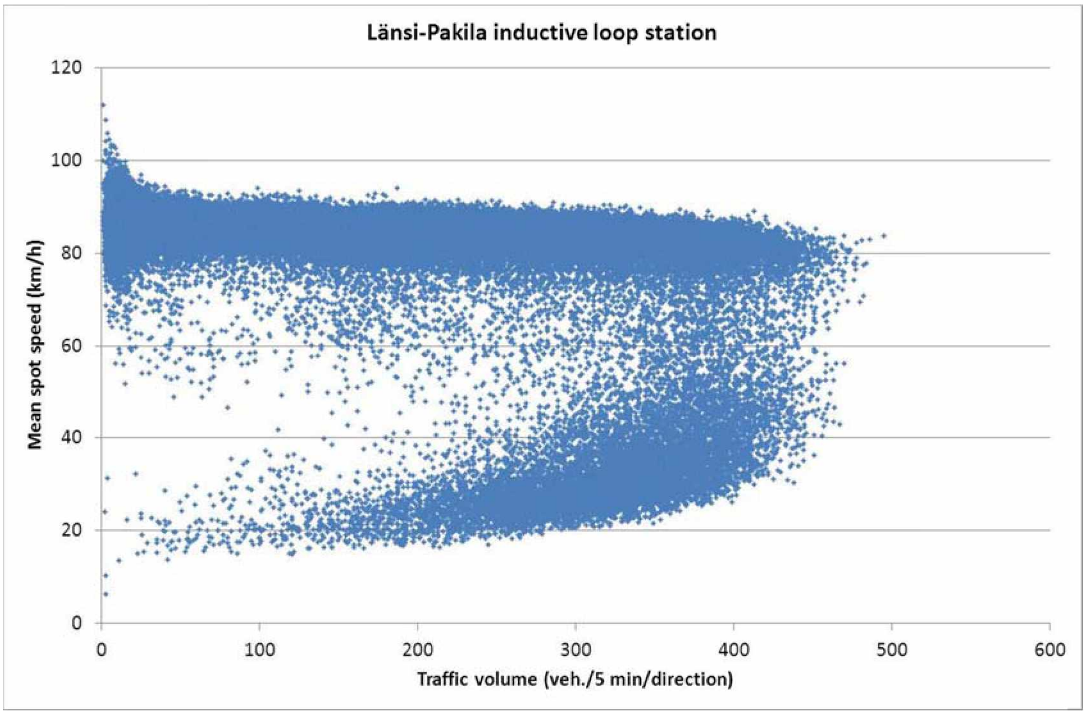


Figure 7. *Basic diagrams from westbound inductive loop detectors, based on 2011 and 2012 data*

Traffic intensity is a measure of the average occupancy of a facility (detector) during a specified period of time and defined as the ratio of the time during which a facility is occupied (continuously or cumulatively) to the time this facility is available for occupancy. Traffic intensity increases with traffic volume, but also with decreasing speed. In theory, the intensity speed curve is decreasing (like in Konala). However, in practice it may have two curves (like in Pukinmäki). The data processing system of the Finnish Transport Agency does not include intensity as a variable in its summaries, but this could be added.

The fusion of travel time and cross-section specific measures is not straightforward and requires further study.

2.1.4 Discussion and recommendations

Innamaa (2009) summarizes the literature on the impact of travel time information accuracy on benefits as follows: An increasing reliability of information results in higher compliance of e.g. route recommendations based on the information. The exact numeric definition for sufficient accuracy depends on the city and time of day. The net benefit from an advanced traveller information service was positive in studies included in the review only if the error in information provided by the service was below the range of 10–25%. Although a lower limit for the accuracy of information is critical, there is also an upper limit above which further improvements for the model are not necessary. Jung et al. (2003) noted that once a regional advanced traveller information system reaches a level of error near or below 5%, benefits from further improvements to service accuracy may be outweighed by the costs associated with these improvements.

The so-called basic model performed better than the model split by season (on the road without lowered winter speed limits) or a model concentrating on exceptional conditions. The difference when using the latest measurement as the forecast was small overall, but greater in congested conditions, where the prediction model performed better than the latest measurement.

Based on these findings, only the 1-minute basic model fulfilled the requirement of at most 10% error at least 95% of the time in congested conditions. The same model is the only one fulfilling the criterion if the error range is widened to 20%. However, then also the 5-minute model comes close to fulfilling the criterion, 92.5–94.1% of the time. With the proportion of time error less than 20% over all observations, all prediction period lengths fulfil the criterion. If the accepted error range is set to 10%, only the 5-minute and 1-minute models meet the criterion.

However, for the 10-minute, 5-minute and 1-minute prediction periods on the Konala-Pakila link, the latest measurement outperformed the historic median based forecast. On the Pukinmäki-Konala link this was the case only for the 1-minute prediction period. Therefore the recommendation for shorter period prediction models is questionable. For the 15-minute model the historic median based forecast was better than use of the last measurement. However, it did not fulfil the threshold of at most 10-25% error. Therefore the use of forecasts may not be beneficial. Nevertheless, if decisions must be made proactively, the use of this forecast although not perfect would lead to better decisions more often than when using just the latest measurement.

On road sections where the annual median is equal to the free flow travel time, the forecast would in practice be equal to the latest measurement, even if a historic median based forecast were used. Thus, the decision concerns only roads where the travel time increases frequently.

The travel time level alone does not describe how close the traffic flow is to getting saturated. The cross-section specific traffic volume alone does not describe the traffic condition, nor can it be used (alone) to increase the prediction power. The fusion of travel time and cross-section specific measures is not straightforward and requires further study.

If a prediction model is set up, a system collecting information on the circumstances (traffic, road weather) in which the model failed or was successful should be set up for further development of the model.

For setting up a model for a specific link the following procedure is recommended:

1. Collect travel time data for 1 year on links with no lowered winter speed limit and for 2 years on links with lowered winter speed limit.

2. Calculate the median travel time for 5-minute periods using a 1-minute interval.

3. Filter out all medians where the number of observations is smaller than five.

4. Determine the historic median for each minute of the day and day of the week based on the remaining medians from step 3. If the link has lowered winter speed limits, determine the historic median separately for the winter speed limit period and the summer speed limit period.

5. Use historic averages as a model. For night-time (00-05 am), use free flow travel time. Replace any historic average faster than the free flow travel time with the free flow travel time.

6. Update the model once a month.

7. Report the performance of the model once a month, analysing traffic and weather conditions when the model performed well and poorly.

The prediction procedure is shown in Figure 8.

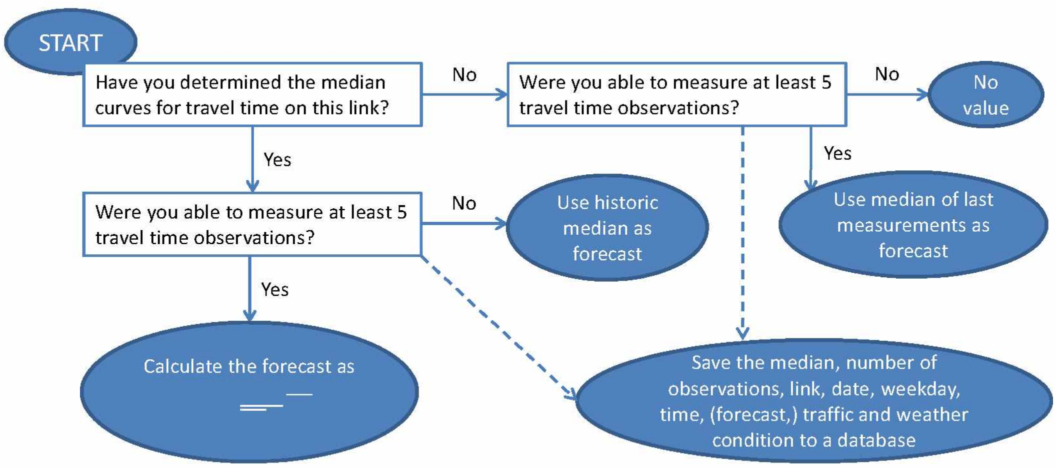


Figure 8. Recommended principles for making a forecast; however the given forecast should never indicate a travel time faster than free flow speed

If a prediction model is set up following the principles of this pilot, it must be acknowledged that the model works better the closer the traffic situation is to its median (or average) performance. When the traffic volume is smaller than normal due to e.g. a vacation period, or when a traffic accident or other incident takes place or the road weather condition is hazardous, the model most likely performs more poorly, and operator expertise on development of the traffic situation overrides it.

2.2 Other models found in the literature

The literature review of existing travel time prediction models focused on recently reported models that have shown good results in congested conditions and that have used real travel time data with relatively good results. In addition, models combining travel time data with other data sources were examined.

Bayesian inference-based dynamic linear model

A Bayesian inference-based dynamic linear model (DLM) developed by Fei et al. (2011) used the median of historical travel times, time-varying random variations, and a model evolution error to acquire an online prediction of short-term travel time on a stretch of freeway. The method looked at forecasting as a stochastic process and provided predicted travel times along with their associated confidence interval to account for the dynamics and uncertainty of traffic according to the concept of Bayesian inference.

Bayesian forecasting is a learning process that revises sequentially the state of *a priori* knowledge of travel time based on newly available information. To better track travel time fluctuations during non-recurrent congestion due to unforeseen events (e.g. incidents, accidents, or bad weather), the DLM was integrated into an adaptive control framework that can automatically learn and adjust the noise level of the system evolution. (Fei et al. 2011)

Fei et al. (2011) tested their model on an interstate segment in Northern Virginia, USA with an imbalanced traffic flow pattern, where the majority of commuting traffic in the morning peak hours flows eastbound to Washington, DC. The examined time periods were 5.00–11.00 and 14.00–20.00. The mean absolute error was found to be 0.8 minutes, whereas the mean absolute percentage error was close to 10%. Fei et al. found that the experiment results based on real loop detector data suggest that the proposed method is able to provide accurate and reliable travel time prediction under both recurrent and non-recurrent traffic conditions. They also thought that the proposed method could satisfactorily capture travel time fluctuations due to demand variations and capacity reduction.

Extended Kalman filter model

Van Lint (2008) developed an extended Kalman filter (EKF)-based online-learning approach which can be applied online and offers improvements over a delayed approach in which learning takes place only as actual travel time data is available. The approach relied on data-driven state-space neural networks (SSNN), and the source data consisted of spot mean speeds and vehicular flow per minute from dual inductive loops that were installed, on average, every 500 metres along a freeway stretch. As output, the method produced estimated travel times.

Van Lint (2008) tested the approach on a 7-km three-lane southbound freeway stretch between The Hague and Delft in the Netherlands. Data was chosen to represent regular congestion, which is why all congested weekday afternoon periods (between 14.00 and 20.00) in 2004 were chosen. Note that in all selected peak periods there were cases where the travel time during congestion was at least twice as high (i.e. >10 minutes) as the corresponding free-flow travel time (around 4 minutes). The reliability of the new approach was found to be significantly better than either instantaneous travel times or historic average. The root mean square errors (RMSE) for each of these approaches for the same data were: 100 seconds (SSNN), 167 seconds (instantaneous), and 250 seconds (historic)

Lane-by-lane tracing model

Li and Rose (2011) examined different kinds of travel time prediction methods in terms of how well they take into account the variability in travel times. Three models were examined, of which the first, called lane-by-lane tracing, relied on speed data from each lane to replicate the trajectories of relatively slow and relatively fast vehicles on the basis of speed differences across the lanes. The second model was based on the relationship between mean travel time (estimated using a neural network model) and driver-to-driver travel time variability. The third model was based on recent historic values.

Each of the models produced predictions of percentile travel times (10th and 90th percentiles) based on data collected from a toll road in Melbourne, Australia. The mean average percentage errors of the percentile travel times ranged from 6% to 9% and of mean travel times from 8% to 12%. The authors found that the results confirmed that the lane-by-lane tracing model can provide reliable estimates of the 90th and 10th percentile travel times when predicting up to 1 hour ahead. Since that model relies on nothing more than the speed information provided by inductive loop systems installed on most urban freeways today, it can be taken into use quite easily. (Li and Rose 2011)

Stochastic model

Hofleitner et al. (2012) developed a model especially for arterial traffic that includes a lot of turning traffic and signalised intersections. Their method estimated the probability distribution of travel times (rather than only the mean) between any two locations on the network. The stochastic model was based on traffic flow theory, and it learned parameters with a physical interpretation (such as fundamental diagram and signal parameters) and also learned turn movement probabilities within the arterial network. Using the learned parameters, real-time estimation and prediction of traffic conditions was performed using a customized particle filter.

The Hofleitner et al. model also leveraged historic data to estimate traffic conditions in real time throughout the network even where little or no real-time data was received. This is due to the model's ability to accurately track flows through the network as well as the relative recurrence of arterial traffic dynamics.

The data used as a basis of the model's estimations was collected as floating car data from taxicabs driving around the San Francisco street network. The mean absolute error of the estimations was found to be approximately 20 seconds, which translated into a mean absolute percentage error (MAPE) of around 38%. (Hofleitner et al. 2012)

Hybrid model of traffic flow and k-nearest neighbour

Lim and Lee (2011) developed a hybrid model using a fusion algorithm that simultaneously utilises data from both point and interval detection systems. The fusion algorithm was based on the traffic flow and k-nearest neighbourhood (k-NN) models. This method predicted future values by searching *k* data points in the past that were most similar to the current data, and then applying weighted mean values depending on the degree of similarity. The final predicted travel time was estimated by incorporating the predicted travel time variation into the travel time given by interval detection systems.

Lim and Lee (2011) tested their model on a 3.4 km-section of highway near Yangjae with three point detection systems measuring mean speeds (video image detectors) and two interval detection systems estimating travel times based on floating car data (DSRC). Both point and interval detection systems were installed at the starting and end points. One point detection system was additionally installed at an intermediate point. The test site is a continuous flow road of four lanes, and the test section includes two in-ramps and two outgoing ramps.

The mean average percentage error of the Lim and Lee model was found to be in the range of 11–19%. Travel time error caused by the time lag of interval detection systems was observed to be reduced by as much as 44%. Based on the results, the authors expect the proposed algorithm to have significant potential for real-time applications.

Hybrid model of historic pattern and Newell's traffic flow model

Tao et al. (2012) developed a hybrid traffic prediction model for congestion-prone corridors. This hybrid model consisted of two major prediction components: a historic pattern recognition model for predicting recurring congestion, and Newell's traffic flow model for predicting non-recurring congestion. For a congestion-prone corridor, when real-time traffic data is available, a model switcher is first used to decide which prediction module should be applied based on current and predicted non-recurring traffic condition data.

As input the model used information about the traffic network, sensor locations, sensor data (flow & speed), and incident, weather and work zone data. The outputs were link-based travel time estimates presented in visual form on an end-user portal. (Tao et al. 2012)

Travel time reliability was predicted ramp-to-ramp for the interstate portion of the trip only. Arterial street travel was excluded. Interstates 66 and 495 in Northern Virginia are the two busiest commute corridors in the region, connecting downtown Washington DC and surrounding residential areas in Northern Virginia. (Tao et al. 2012)

The "reliability-based" travel time information was well received by users, as compared to average travel time. As a result, users became aware of non-recurring events and the likely impact of these on their commute schedules. The difference between measured and predicted travel times ranged from 5 to 8 minutes (with 18 minutes being the longest total time). (Tao et al. 2012)

3 Incident risk assessment

3.1 Literature review

3.1.1 Incident duration estimation

A method developed by Khattak et al. (2012) analysed traffic incidents and presented an online tool (iMiT, incident Management integration Tool) that could dynamically predict the duration of incidents, the occurrence of secondary incidents and associated incident delays.

In related literature, variables that are positively associated with longer incident durations include longer response times, accidents (as opposed to other types of incidents), lane blockage, adverse weather, more heavy vehicles involved in an incident, injury or fatality, occurrence during peak hours, incidents located farther away from a traffic operations centre (partly resulting in longer response times), more vehicles responding from various agencies, and freeway facility damage. (Khattak et al. 2012)

Generally identified factors associated with the occurrence of a secondary incident include peak hours, weekdays, season, the clearance time of primary incidents, lane blockage duration of a primary incident, more vehicles involved in a primary incident, and primary vehicle rolling over. (Khattak et al. 2012)

The iMiT prediction tool was developed based on rigorous statistical models for incident duration and secondary incident occurrence – it uses a theoretically based deterministic queuing model to estimate associated delays. Ordinary least squares (OLS) regression models were estimated for incident duration with the following specification:

$$\begin{aligned}\text{Incident duration} = {} & \beta_0 + \beta_1(\text{TIMEOFDAY}) + \beta_2(\text{WEATHER}) + \\ & \beta_3(\text{LOCATION}) + \beta_4(\text{AVANNDAILYTRAFFIC}) + \beta_5(\text{DETECTION}) + \\ & \beta_6(\text{VEHICLES}) + \beta_7(\text{INCTYPE}) + \beta_8(\text{LANECLOSE}) + \beta_9(\text{EMS}) + \\ & \beta_{10}(\text{RTSHOULDERAFF}) + \beta_{11}(\text{RAMPAFF}) + \beta_{12}(\text{LFSHOULDERAFF}) + \varepsilon\end{aligned}$$

iMiT relies on available inputs about the roadway conditions, and incoming incident information including location, time of day and weather conditions. The main inputs to the dynamic incident delay prediction are incident severity, incident duration, traffic volume, and road geometry information. Output of the method and the iMiT tool is information about primary and secondary incidents: estimates for their clearance time, total delay and maximum queue length are provided. (Khattak et al. 2012)

The roadway inventory and traffic incident data was provided by the Hampton Roads Traffic Operations Center based on safety service patrol records. 37 934 incidents from the Hampton Roads Areas (100+ miles of roads) between January 2004 and June 2007 were analysed to identify primary, secondary and independent incidents using a method based on queue length calculations (with 15 minutes added to the clearance time of the primary incident when a lane is blocked by the incident, and there are no associated secondary incidents in the opposite direction). (Khattak et al. 2012)

The incident duration model estimated with 2006 incident data the incident durations in 2007. Both the mean average percentage error (MAPE) and root mean squared error (RMSE) are relatively low for incidents of average durations, i.e. incidents that lasted about 10–30 minutes (MAPE 37-47%, RMSE 8-13 minutes). However, both are quite large for substantially longer or shorter than average incidents. As is often the case, the duration model does not predict extreme values well. In particular, MAPE is largest when the incidents last less than 10 minutes. The largest RMSE are observed when incidents last very long, i.e. more than 2 hours. This indicates that the model does not perform adequately for predicting durations of extreme incident events. However, for incidents lasting 10–30 minutes, the model can provide realistic predictions. (Khattak et al. 2012)

Khattak et al. (2012) assessed that this kind of tool could be used in TMCs to help support decision-making. Although iMiT is currently calibrated using the Hampton Roads incident data, the methodology is likely transferable to other regions by using local data for the calibration.

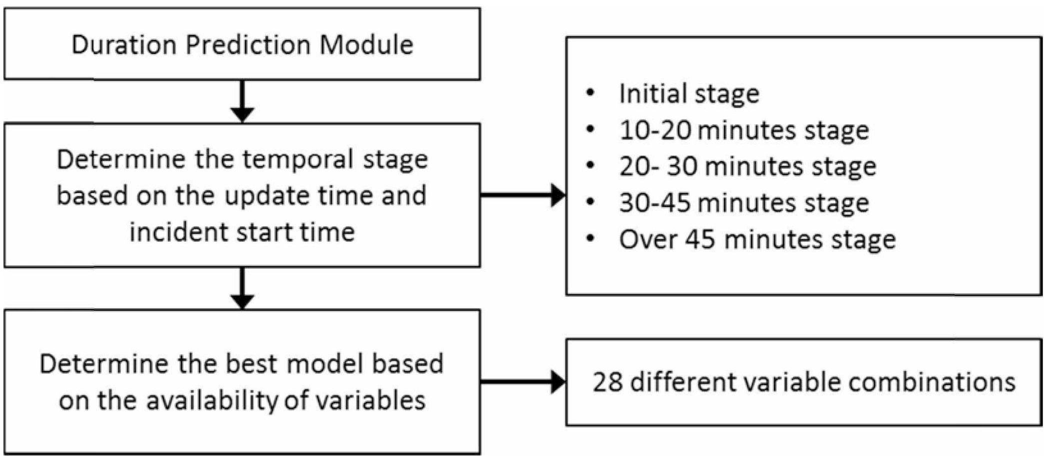


Figure 9. The methodology of iMiT (Khattak et al., 2011)

Hojati et al. (2012) have also investigated incident duration and identified contributing variables in Australian conditions. They presented a new framework for comprehensive traffic-incident data mining and analysis towards an incident delay model and travel-time reliability modelling.

Generally, the difficulty in recording incident data and its related variables at the required level of quality was one of the most important issues in analysing the characteristics of traffic incidents. In the creation of this framework, significant variables on incident duration were identified using an ANOVA test for each type of incident. The process involved cleaning the data. Next, all the sources were linked by referring to the coordinates, date, and time of the incidents. After this, further variables were calculated: e.g. duration of rainfall for each incident. (Hojati et al. 2012)

Incident data (4926 records for unplanned incidents in the cleaned data) was obtained from the Queensland Department of Transport and Main Roads' STREAMS Incident Management System (SIMS). The incident data was from urban freeways for South East Queensland (SEQ) for a one-year period from November 2009 to November 2010. (Hojati et al. 2012)

SIMS events were classified as traffic incidents, equipment faults or other events. Various types of incident information were recorded in SIMS including: priority, incident location, type, classification, start-time and end-time, request and arrival time of assistance, towing requirement, number of injuries and fatalities, medical attention required, and chemical spill. Weather data received from 10 weather stations included rainfall, temperature, humidity, and wind speed and wind direction for the same period as the incident data. In addition, information about the links and temporal effects were used as inputs. (Hojati et al. 2012)

Output of the process was initial data analysis and establishment of relationships between: traffic volume & weather conditions, incidents & weather conditions, and travel time & incidents & weather conditions. Based on these results, models were created for incident management and travel-time reliability monitoring. (Hojati et al. 2012)

Statistically significant differences were found for 22 possible independent variables for crashes. However, because of the correlation between some variables, only 15 possible variables were selected. A total number of 3251 incidents were recorded, giving an average frequency of two crashes, four hazards, and three stationary-vehicle incidents per day. The related incident durations were 43, 74 and 41 minutes respectively. The results showed that incident duration varied across the types of incident, time of day, and day/weekend of the week; however, no significant difference regarding month of the year, week of the month, and holiday/school holiday was observed. (Hojati et al. 2012)

The findings of Hojati et al. (2012) suggested that debris, breakdown and multiple-vehicle crashes were the major sources of incidents on freeways. Furthermore, freeway incident duration varied across the types of incident and time of day, and whether it was a week day or weekend day. However, there were no significant differences in relation to day, week or month of the year. In addition, the findings of the study of Hojati et al. revealed a high variance of incident duration within each incident type. A variety of probability distribution functions were employed to test the best model for the duration frequency distribution for each category of incident. Lognormal distribution was found to be more appropriate for crashes, but log-logistic distribution was more appropriate for hazards and stationary vehicle incidents.

The results of the analysis of Hojati et al. (2012) indicated that incident duration of crashes, hazards and stationary vehicles on freeways and freeway ramps were likely to be highly significantly different. Therefore, incidents on freeway ramps need to be analysed separately and this group of incidents was excluded from further analysis. No statistically significant differences were found for month of the year, week of the month, and day type (i.e. normal day or public/school holiday) to predict incident duration. Conversely, weekdays vs. weekend day incidents made a significant contribution to predicting incident duration.

In addition, the findings of Hojati et al. (2012) revealed that the variance in incident duration within each incident type was fairly large. The analysis of the effects of three weather conditions on traffic incident duration indicated that rain precipitation significantly affected incident duration for all three types of incidents, but air temperature only affected stationary-vehicle incidents. Moreover, the results indicated that distance from the nearest city's business district is a significant variable on crash and hazard incidents, but not on stationary-vehicle incidents. In addition, the volume-capacity ratio for the link in which an incident happened was found to be highly significant on incident duration in all three types of incidents.

3.1.2 Secondary incident risk estimation

Vlahogianni et al. (2012) introduced a neural network model approach to extract useful information on variables that are associated with the likelihood of secondary accidents. Specifically, traffic and weather conditions at the site of a primary incident were examined. To detect secondary incidents, a dynamic threshold methodology was used that considers real-time traffic information from loop detectors. Two sensitivity measures to evaluate the significance of the variables were used (mutual information and partial derivatives).

As input to the model of Vlahogianni et al. (2012), 3500 incident records between 2007 and 2010 were used. The data was from the Attica Tollway, a 65-km urban motorway connecting two major interurban motorways, Athens International Airport, and Athens city centre. This incident information was supported by traffic-related information including exact location, number of lanes blocked, total duration of the incident, vehicle type, and number of vehicles involved. Factors such as prevailing traffic conditions (speed and volume) and weather conditions (rainfall intensity) were also considered.

As output the Vlahogianni et al. model estimated the contribution of different variables to the likelihood of secondary incidents. In addition, the results showed that a multilayer perceptron with a supporting function acting as a general Logit model performed best among the different models.

The likelihood of the proposed model yielding incorrect classification of secondary incidents varied between 6% and 7%. The results suggested that traffic speed, duration of the primary accident, hourly volume, rainfall intensity, and the number of vehicles involved in the primary accident are the top five factors associated with secondary accident likelihood. However, changes in traffic speed and volume, number of vehicles involved, blocked lanes, and percentage of trucks and upstream geometry also significantly influence the probability of having a secondary incident. (Vlahogianni et al. 2012)

Vlahogianni et al. (2012) assessed that the proposed neural network approach is promising as a transport managerial tool for TMCs to support decision-making. It could potentially be extended to other transport applications as well.

3.1.3 Traffic flow prediction under atypical conditions

Castro-Neto et al. (2009) created an application of a supervised statistical learning technique called online support vector machine for regression (OL-SVR) for the prediction of short-term freeway traffic flow under both typical and atypical conditions. The OL-SVR model was compared with three well-known prediction models including Gaussian maximum likelihood (GML), Holt exponential smoothing, and artificial neural network models.

Input data used for testing the application was 5-minute loop detector data obtained from the California Freeway Performance Measurement System (PeMS). This system continuously collects 30-second loop detector data in real-time for more than 8100 freeway locations throughout the state of California. These data were then aggregated into 5-minute periods. The California Highway Patrol provided incident data in real-time with incident characteristics, including type of incident, starting time, location, and subsequent details about the incident. (Castro-Neto et al. 2009)

The performance of the OL-SVR application was evaluated using mean average percentage error (MAPE). For typical traffic conditions MAPE was 5.9%, and for atypical condition 13.1%. The resultant performance comparisons suggested that the GML method, which relies heavily on the recurring characteristics of day-to-day traffic, performed slightly better than other models under typical traffic conditions, as demonstrated by previous studies. However, the developed OL-SVR was the best performer under non-recurring atypical traffic conditions. (Castro-Neto et al. 2009)

Castro-Neto et al. (2009) suggested that future research regarding the OL-SVR model should look into multivariate time series models that incorporate spatial and temporal correlations among adjacent vehicle detection stations to improve prediction accuracy, especially when multi-step look-ahead forecasts are desired. In addition, future studies may evaluate the performance of OL-SVR for various look-back intervals, forecasting horizons, and data resolutions. Extension of this work may address the prediction of other short-term traffic parameters such as average speed and travel time.

3.1.4 The significance of traffic conditions

Ishak and Alecsandru (2005) performed an investigation of the characteristics of pre-incident, post-incident, and non-incident traffic conditions on freeways. The characteristics were defined by second-order statistical measures derived from spatiotemporal speed contour maps (Figure 10). Four performance measures were used to quantify properties such as smoothness, homogeneity, and randomness in traffic conditions in a manner similar to texture characterization of digital images.

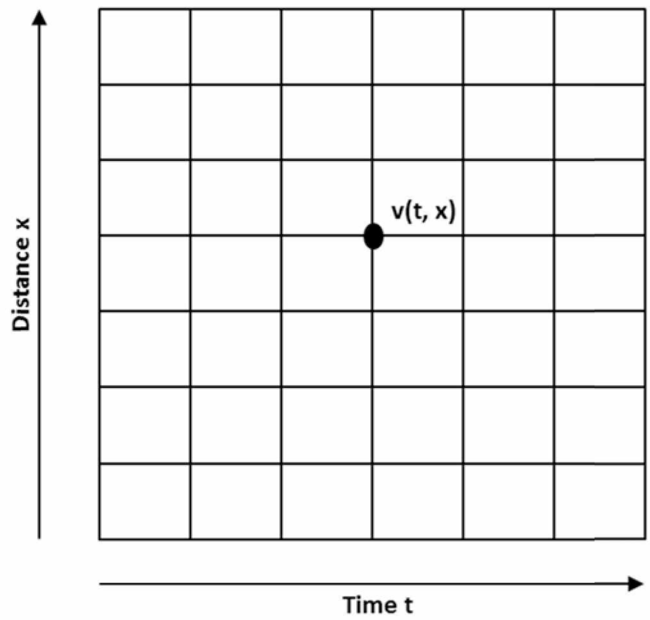


Figure 10. Example of a spatiotemporal speed contour map (Ishak and Alecsandru, 2005).

The study of Ishak and Alecsandru (2005) was conducted using data collected from the freeway corridor I-4 in Orlando, Florida. The study corridor was nearly 40 miles long and six lanes wide. The entire corridor was instrumented with 71 inductive dual-loop detectors or stations, spaced approximately half a mile apart. Each detector station collected three traffic parameters – traffic volume, lane occupancy, and speed – from each of the six lanes. The system supported data resolution of 30 seconds.

With real-world incident and traffic data sets, statistical analysis was conducted to seek distinctive characteristics of three groups of traffic operating conditions: pre-incident, post-incident, and non-incident. Incident data was also collected from various sources, and a total of 116 accidents, reported on different days, were selected for the analysis. Traffic conditions before and after the incident occurrence were separated into two groups: pre-incident conditions and post-incident conditions. Pre-incident conditions were restricted to observations that took up to 10 minutes before the incident happened, whereas post-incident conditions were collected from observations taken up to 10 minutes after the incident. The second-order statistical measures outlined earlier were computed for each group by using speed data collected from loop detectors. An arbitrarily selected time-space window of 5 minutes and three detector stations were used as the basis for calculation of each measure. In addition, non-incident traffic conditions were collected from a total of 5 weekdays in 2001 and used for comparative analysis. (Ishak and Alecsandru 2005)

The statistical analysis showed slight variations among the three groups (pre-, post-, and non-incident conditions) in terms of each of the four measures used. Although the nonparametric tests showed that the distribution of each measure within each group is different, a consistent pattern was not detected within the categories of each measure. Such inconsistency led to the conclusion that the pre-, post-, and non-incident traffic conditions may not be readily discernible from each other and that specific characteristics of precursory conditions to incidents may not be clearly identifiable. Such a conclusion, however, is driven by limited incident and traffic datasets and selected second-order traffic performance measures. Additionally, environmental factors such as inclement weather conditions were not accounted for in this study. (Ishak and Alecsandru 2005)

Ishak and Alecsandru (2005) suggested that further research should be conducted to include a broader sample of data and possibly more sophisticated measures and to account for factors such as weather conditions and possible inaccuracies in detector data.

3.1.5 Travel time estimation under incident conditions

Kamga et al. (2011) examined the distribution of travel time of origin–destination pairs on a transportation network under incident conditions using a transportation simulation dynamic traffic assignment (DTA) model. In the DTA model, incident on a transportation network was executed under normal conditions, under incident conditions without traveller information, and finally under incident conditions assuming that users had perfect knowledge of the incident conditions and could select paths to avoid the incident location. DTA models could estimate and predict time-dependent network conditions by capturing the temporal and spatial variations in dynamic traffic networks. DTA models produced the time–space trajectory of each individual vehicle from its origin to its destination. The used methodology provided insights into the usefulness of integrating a fully calibrated DTA model into the analysis tools of a traffic management centre.

The DTA model used by Kamga et al. had as its input the topology of the network in GIS format, the geometry of the roadway in question, traffic control data (signal timing, speed limit, lane movement designation, vehicle class prohibitions, ramp metering, signal pre-emption), bus routes, schedules and average dwelling time per bus stop, and the origin–destination matrices for each vehicle class (e.g. passenger cars, trucks, buses).

The area used for the simulation was part of the greater Chicago road network. The network configuration consisted of 123 nodes and 194 origin–destination pairs, thus allowing for alternative routes for origin–destination pairs. The total demand of the network during the 10 hours of the simulation assignment was 162,626 vehicles. (Kumga et al. 2011)

The results of Kumga et al. (2011) suggest that incidents have a different impact on different origin–destination pairs. The results confirm that an effective traveller information system has the potential to ease the impacts of incident conditions throughout the transportation network. In their conclusion, Kumga et al. stressed that the use of information may be detrimental to some origin–destination pairs while benefiting others. The impacts of incidents are not just on vehicles originating upstream or traversing the incident location; vehicles originating downstream or not traversing the incident location may also be negatively impacted by the incident.

3.2 Dutch incident management model

3.2.1 Long-term and short-term incident risk assessment

The Rijkswaterstaat Traffic Management Centre (TMC) carries out long-term incident risk assessment with annual and weekly forecasts (This chapter is based on van den Berg and van Wijngaarden, 2013). On an annual level, risk assessment is done by keeping a list of road works, big events etc. that are known to affect traffic for the following year. This list is done per area. This long-term forecast or situational picture is updated **on a monthly basis** and is used for traffic management and planning of road works as follows:

- Two road works are performed in the same direction of a certain road section simultaneously rather than in sequence.
- Road works are not performed on an alternative route or detour around other road work.

Every week, the items in the annual forecast are checked. The weather forecast is included and other issues are listed that potentially affect traffic, together with their estimated effects. This is done in a weekly meeting with traffic operators, traffic engineers, traffic inspectors, and those responsible for road works (project managers) to combine data and knowledge. The latter group is the best for estimating the effect of road works on traffic flow and timing of traffic jams. The aim of the weekly forecast is to specify for TMC which parts of road network need special attention. The meeting also addresses how to increase traffic flow fluency. This weekly rhythm provides adequate time to e.g. code an appropriate message to variable message signs.

The meeting also looks back on abnormal congestions of the previous week. The purpose is to determine the cause of the congestion and means to overcome such congestion in the future. For example, the infrastructure provider can paint a new solid line where merging is problematic, or build new overhead signalling or traffic lights for traffic management. Once a month all the challenges that could not be solved in weekly meetings are discussed again. These 'monthly' challenges are more complex and harder to solve. In the monthly meeting traffic engineers and specialists analyse the problem and propose solutions.

On a daily basis, traffic situation forecasts (maps) are prepared twice a day, for the morning and evening shifts. The same week of the previous year is chosen and serves as a forecast; if something exceptional happened then, the forecast is corrected to represent the average traffic situation. In addition, Easter and other holidays are treated separately. Previously, traffic flow status was allocated to 5-6 classes. However, traffic operators did not really use it, as they already knew the normal traffic situation. Therefore in the new system, only differences from normal are provided. These are of interest to traffic operators. The information is for internal use only, not for the public. In the future, the information should be based more on data than it is currently.

3.2.2 Proactive means to reduce incident risk

Rush lane

In the Netherlands there are two basic types of rush lanes: one on the left and one on the right (hard shoulder).

Left side rush lane: When the traffic volume nears capacity but the flow is still fluent, an extra rush lane is opened. The lane is narrower than the normal lane (like a hard shoulder but on the left); therefore a lower speed limit is imposed when it is open. When the traffic volume diminishes again, the rush lane is closed. It is important not to keep the rush lane open when normal lanes are enough, as it reduces throughput.

The threshold for opening or closing the rush lane also depends on the weather conditions, as the capacity is reduced in inclement weather.

If a certain road section suffers from capacity problems, the traffic engineer ensures that the traffic operators are aware of the problem and know how to manage traffic in the area (closer attention, faster reaction).

Road service vehicle at new road work sites

Utrecht TMC has noticed that new road works lead to a higher number of incidents than those that have already lasted longer. It may be that new road works come as a surprise to drivers. In addition, the building up phase of the work may be riskier than later phases.

To be able to react fast to potential incidents, a road service vehicle (road salvage team) is sent to the site proactively to provide immediate aid if an incident takes place. At the moment, this is done *ad hoc* but the TMC hopes to develop a more systematic approach to assessing the need for such proactive help.

In addition, TMC pays closer attention to the vicinity of a new road work than it normally would, adding further means of traffic control if necessary. In extreme cases the road work can be interrupted if the congestion it causes is too severe. For major road works, TMC can set up another desk for managing traffic in the vicinity of the construction site.

Road surface maintenance

The Dutch road network is paved with open asphalt, which dries fast after rain but is more susceptible to wear and tear. Prolific salting during the winter season is a further burden on the road surface.

Potholes appear on a daily basis, needing quick attention from road maintenance crews. They are repaired regularly at night to keep the road network safe for traffic. During small-scale night-time road works the corresponding lane is closed to traffic.

There are some 5000 minor road works per year in the area of Utrecht TMC, typically 60 per night, including both emergency repairs and proactive maintenance.

3.2.3 Incident detection

For the fast detection of incidents, Utrecht TMC has developed an incident detection algorithm of its own. This does not predict incidents but detects them very quickly. Earlier, incident detection was only dependent on phone calls to the emergency exchange. Emergency authorities informed TMC of incidents on roads, but the information came with some delay. There is no phone number for road user reports.

The method is based on relative differences in 1-minute traffic intensity and spot speeds at consecutive traffic inductive loop detector points (and over one point) installed every 400-500 metres. Drops in speed are identified, and set off an incident warning if the difference in speed and intensity between upstream and downstream measurement stations is sufficient.

When the system warns of a potential traffic incident, this is confirmed by observation cameras before incident management is initiated. The cameras are located approximately every 500 metres on the road network.

The method has been piloted on a 20 km two-lane road stretch. Although it is simple, it was proven to be efficient. Now the aim is to take expand it also to on multilane roads all over the Netherlands. In the multi-lane approach, an average is calculated over all lanes so that the data is similar to the two-lane approach. Monitoring the traffic situation per lane is also being considered, but this would complicate the model. Attempts are being made to improve the method in order to set off fewer false alarms.

3.2.4 Reactive means to minimise consequences of incidents

When an incident takes place, it is important to provide the right information at the right time. This applies to both TMC personnel and road users. There are several means of traffic control that TMC can employ upon detection of an incident, including lane control, variable speed limits and VMS messages. Once an incident is detected, the corresponding lane is closed with an X sign to guide traffic to other lanes. The effectiveness of the lane control is high and road users obey the signs, trusting that the lane has been closed for a valid purpose (rush lanes, road works, accidents).

Maintaining this trust is essential. The speed limit is also lowered to lane-specific variable speed limits.

VMS messages provide information on travel time (normal travel time + delay) and location of incident. There is a rerouting book with fixed messages programmed for VMS. If the incident is known about in advance (e.g. road work or big event), VMS messages can be tuned to fit the situation.

In the case of a traffic accident, an alternative route is recommended by VMS at a spot where the driver can still choose an alternative if he/she deems it necessary. It has been observed that if the congestion is visible from the VMS position, the proportion of drivers taking the detour is higher than when the congestion is further away.

When an incident has been detected, TMC monitors the development of traffic on the affected route and on any detour for a while before recommending the detour, to make sure the detour is helpful. VMS give the travel time on both routes and the cause of delay (road work, congestion, etc.) on the route with the incident.

In the current traffic monitoring system, the flow status is given in three classes: green (speed down to 70% of free flow speed), orange (a lot of traffic but still flowing), and red (congestion). A fourth class may be needed between green and orange to indicate where the risk of congestion is elevated. Usually the speed is monitored, but it is a very reactive measure. Intensity would be a better choice if proactive traffic management is targeted.

Earlier, speed limits were lowered for high traffic volume. Increase volume at an average speed level was expected to reduce the amount of shockwaves. However, traffic operators stopped using variable speed limits for this, as studies showed that the effect was negative or non-significant. In slippery conditions, speed limits are still lowered, but it is doubtful whether this is effective.

Closing one lane to improve merging downstream can be very effective in resolving minor congestion. This must be done at the right time and reopened at the right time.

3.3 Incident data analysis

3.3.1 Method

A small-scale study was conducted to obtain insight into to what extent accidents are connected with practically observable circumstances on the road. The study was based on registered accidents (from the accident records of the Finnish police) that took place on Ring-road I of the Helsinki Metropolitan Area between January 2011 and October 2012, totalling 450 accidents. This gave an average of 0.67 accidents per day.

In addition to accident data, the following data were used:

i. Traffic data from eight automatic traffic measurement stations (inductive loops) on Ring I during the study period

ii. Road weather data from a station located on highway 3 in Pirkkola, close to Ring I, during the study period.

The traffic data consisted of traffic volume and mean velocity measurements at 5-minute intervals. From volume Q (vehicles/5 min) and velocity V (km/h) an estimate of the traffic density was calculated as $D = 12Q/V$ vehicles/km. Passenger cars and heavy vehicles were counted separately, but in this study they were merged using the passenger car equivalent of 1.5 for heavy vehicles (HCM 1995).

The basic methodological idea was to compare the traffic and weather circumstances just before the accident with the Palm probability of the same circumstances. The notion of Palm probability comes from the theory of random point processes and means the probability distribution "seen" by a randomly selected point of the point process (in contrast to the stationary probability, which is the probability distribution seen at a random time point). In this case, Palm probability means the distribution of circumstances "seen by a randomly selected driver", and it was obtained by weighing the circumstance data items against the above-mentioned traffic density estimates.

If each car driver had a constant stochastic intensity of causing an accident, then the accident circumstances would follow the Palm distribution. Differences between the accident circumstance distribution and Palm distribution hint at effects of circumstances on accidents.

Both automatic traffic measurement and road weather station data had some gaps. The proportional share of missing records was about 2%, which is not much but not entirely negligible for the purpose. To obtain a complete time series of 5-minute intervals, the data of the nearest functioning station were copied to empty records (except for two instances where all stations where down). When needed, the artificial traffic records were distinguished by a dummy value in the station number field. The latest available weather record was associated to each 5-minute period.

Attention was restricted to the following characteristics:

- Traffic data: direction, volume, speed
- Weather data: surface temperature, rain consistency (liquid/crystal) and intensity, visibility, road surface conditions, warning level.

The space of possible circumstance combinations was high dimensional, even when only the above selected characteristics were chosen, while the accident data consisted of only 450 points. To make the point mass probabilities reasonably high and to enable a more meaningful treatment of the data, the numerical quantities were discretized with the following granularities:

- Traffic volume granularity 10: values 5, 15, 25,..., highest value about 300
- Traffic velocity granularity 5: values 2.5, 7.5, 12.5,..., highest value about 90
- Road temperature granularity 3: values ..., -4.5, -1.5, +1.5, +4.5,....

In the Finnish national road registry, Ring I is divided into eight road sections, numbered from the west end, with the lengths shown in Table 22. The locations of loop detectors are given in Table 23.

Table 22. Definition of road sections on Ring I, metres

	Road section							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Length	900	3990	972	3175	1931	2399	5198	4252
Start	0	900	4890	5862	9037	10968	13367	18565
End	900	4890	5862	9037	10968	13367	18565	22817

Table 23. Location of loop detectors

Station number	Station name	Road section	Position in section	Position on whole road
118	Keilalahti	1	490	490
116	Leppävaara	3	490	5380
126	Konala	4	2080	7942
145	Kannelmäki	5	1000	10037
146	Länsi-Pakila	6	700	11668
147	Pakila	6	2600	13568
148	Pukinmäki	7	1800	15167
149	Malmi	7	4000	17367

Thus, the automatic traffic measurement stations covered the road somewhat unevenly. Further causes for inaccuracy were:

- The accident data did not reveal in which road direction an accident happened; the direction was not always clear from the traffic data either, depending on the location of nearest detectors and the timing

- The weather data came from a single station that is not on Ring I itself (however, the accident records contain accurate descriptions of conditions).

3.3.2 Results

Annual and spatial distribution of accidents

First, a look was taken at the distribution of accidents during 1 year and spatially along Ring I. The following plot (Figure 11) shows density estimates of accidents for each year using a Gaussian kernel with height 1 and standard deviation parameter (in exponent only) of 1 day. The two annual pictures have striking similarities, which hint at more general patterns. There is a strong peak in mid-February, followed by a decrease until April, when it shoots up again. At the end of May it falls sharply and rises again only in September or October.

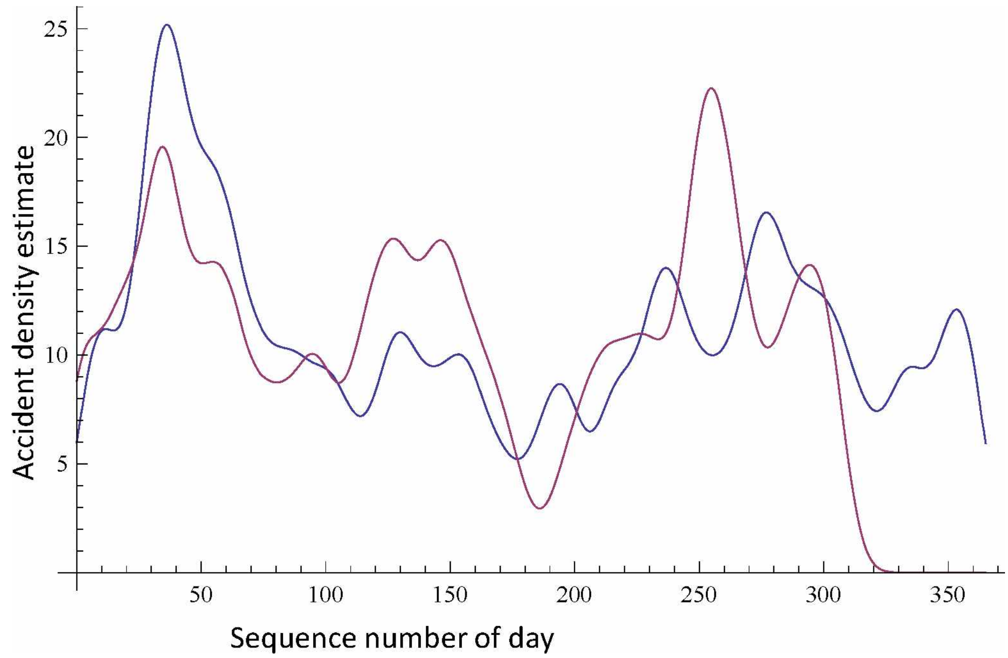


Figure 11. *Density estimates of accidents during each year using a Gaussian kernel with height 1 and standard deviation parameter (in exponent only) of 1 day. 2011 is shown in blue and 2012 in red.*

Second, the location of accidents was investigated using a Gaussian kernel with height 1 and standard deviation parameter (in exponent only) of 100 metres. Interestingly (though not surprisingly), the spatial distribution of accidents is far from uniform. In particular, it shows a very strong peak near the east end of the road. To confirm that this was not an artefact, the two years were plotted separately (Figure 12) and most of the peaks appeared in same places both years.

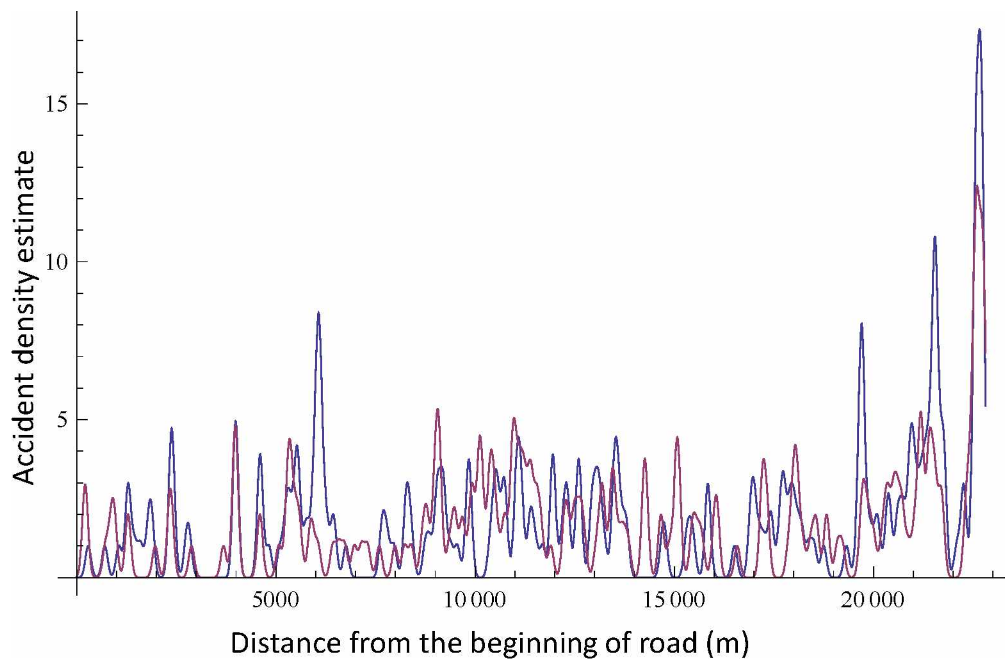


Figure 12. *Location of accidents (in metres from the western end of the road) using a Gaussian kernel with height 1 and standard deviation parameter (in exponent only) of 100 metres, 2011 in blue and 2012 in red.*

Time of day

It was then studied whether some times of day are more accident-prone than others. The following plot shows the relative density of the accident time distribution with respect to the Palm distribution. The time resolution was 15 minutes in Figure 13. Values above 1 indicate increased accident intensity per driver. Zero value means that no accident happened during the respective quarter hour. Since the quarter resolution was high compared with the size of accident data, the same quantities were also plotted at a resolution of 1 hour (Figure 14). The result shows that hours 15–16 and 16–17 have a higher accident intensity than the rest of the day. Also late night (after 2 a.m.) seems to have increased risk per driver.

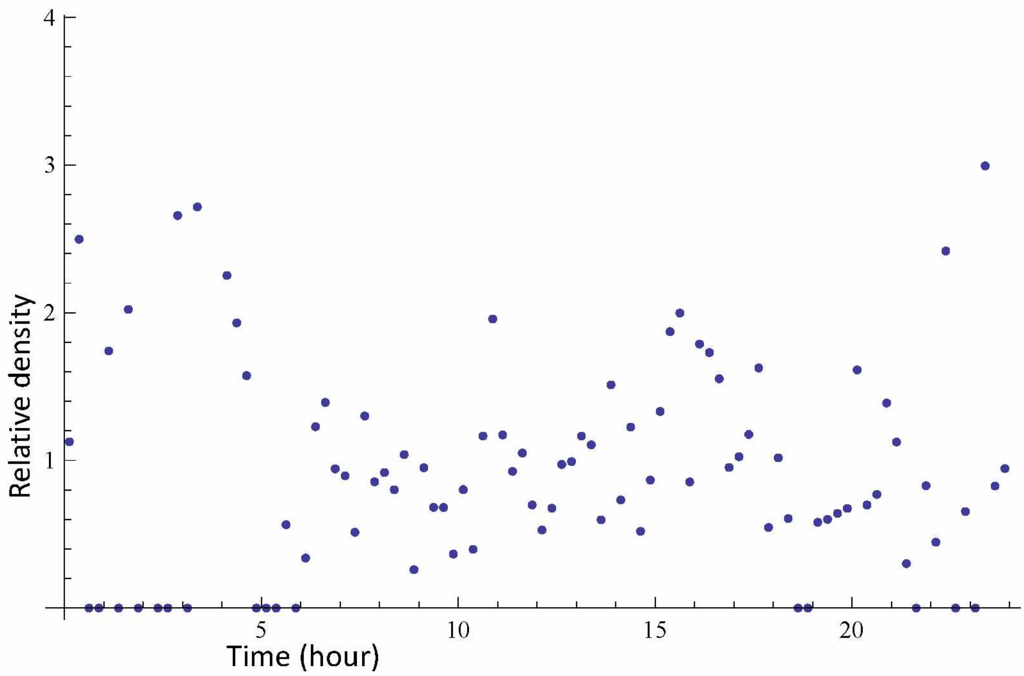


Figure 13. *Relative density of the accident time distribution with respect to the Palm distribution. Time resolution 15 minutes. Density is zero for classes without any observations.*

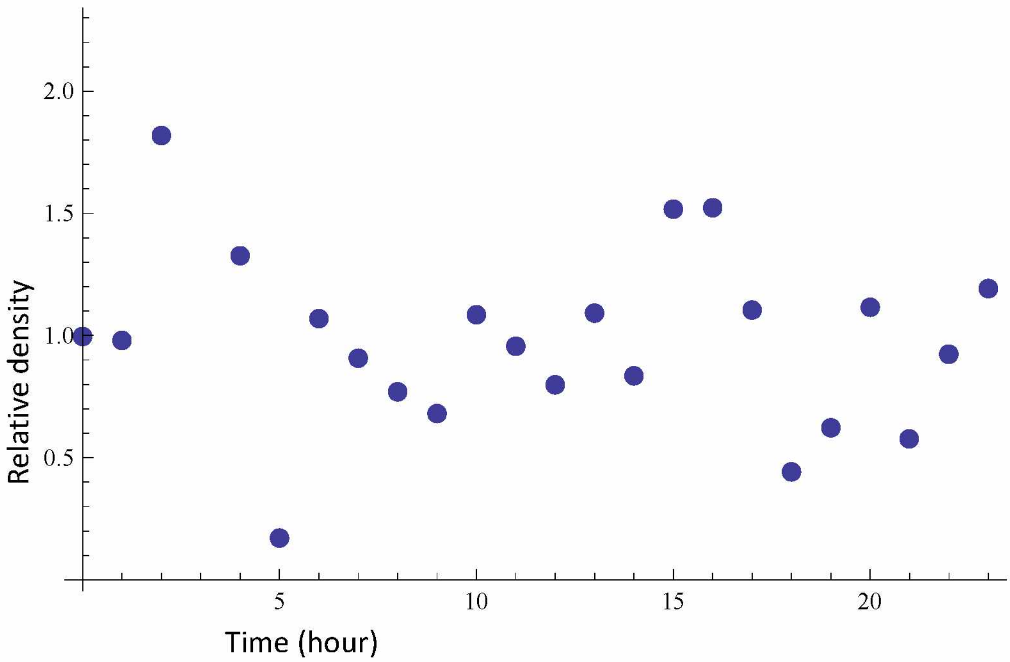


Figure 14. *Relative density of the accident time distribution with respect to the Palm distribution. Time resolution 1 hour.*

Traffic volume, velocity and density

Figure 15 compares the traffic volume measured by the nearest automatic traffic measurement station. The points are fairly evenly scattered around 1, except for extremely high and low volume levels, where the risk seems to be increased. The low densities appear at night.

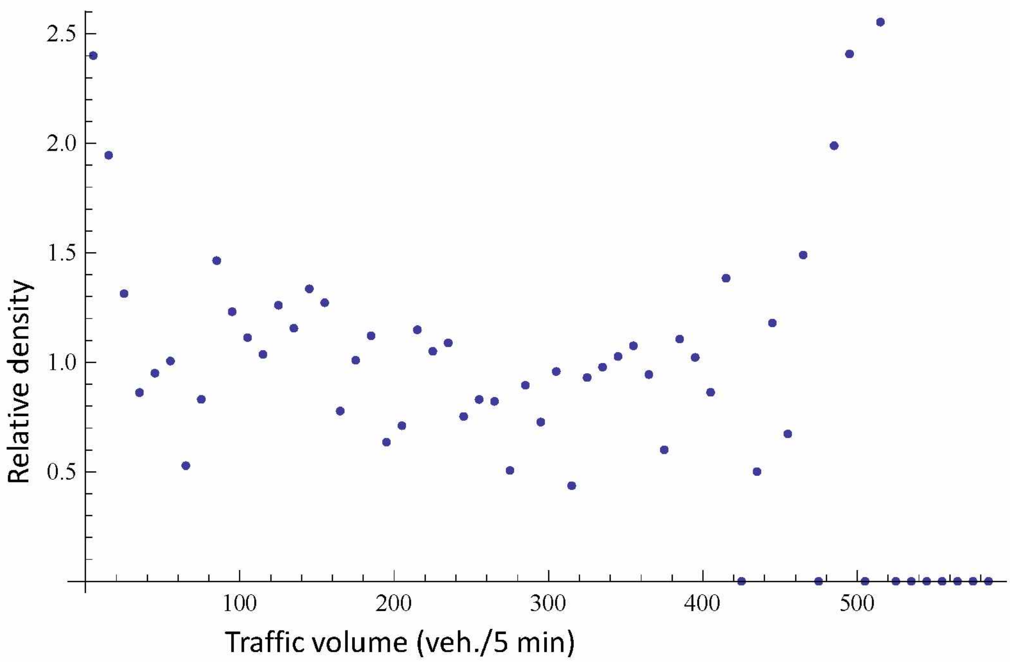


Figure 15. *Relative density of the traffic volume measured by the nearest automatic traffic measurement station. Density is zero for classes without any observations.*

Next, a corresponding look was taken at the role of speed. Figure 16 shows the Palm distribution of traffic and accident distribution of traffic speed at the nearest automatic traffic measurement station just before the accident. The bulk of accidents that occurred in normal speed conditions can be seen, but the accident risk is higher when the speed is unusually low. The ratios of the same distributions are presented in Figure 16 and Figure 17.

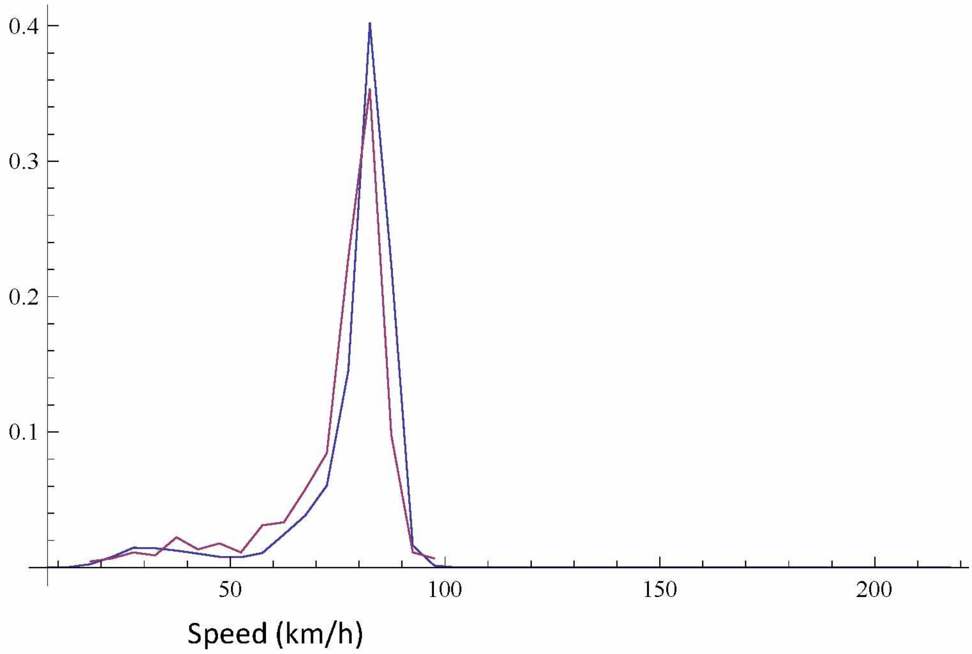


Figure 16. *Palm distribution (blue) of traffic (over all stations) and accident distribution (red) of traffic speed at the nearest automatic traffic measurement station just before the accident.*

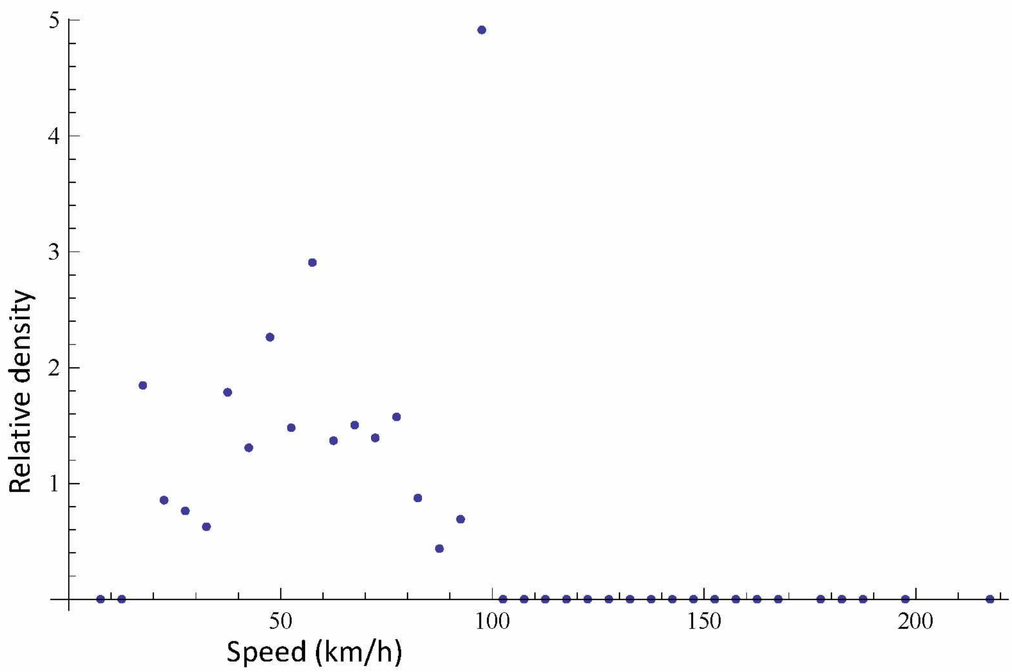


Figure 17. *Relative accident density of speed measured by the nearest automatic traffic measurement station. Density is zero for classes without any observations.*

Next, the accident density was studied as a function of the traffic density. The Palm and accident-time distributions are strikingly similar (Figure 18). Thus, somewhat surprisingly, the density alone seems to have no effect on accident intensity, except for the level 70-80 veh./km, where the risk seems to double (Figure 19). An overwhelming majority of accidents, however, occur independently of traffic density.

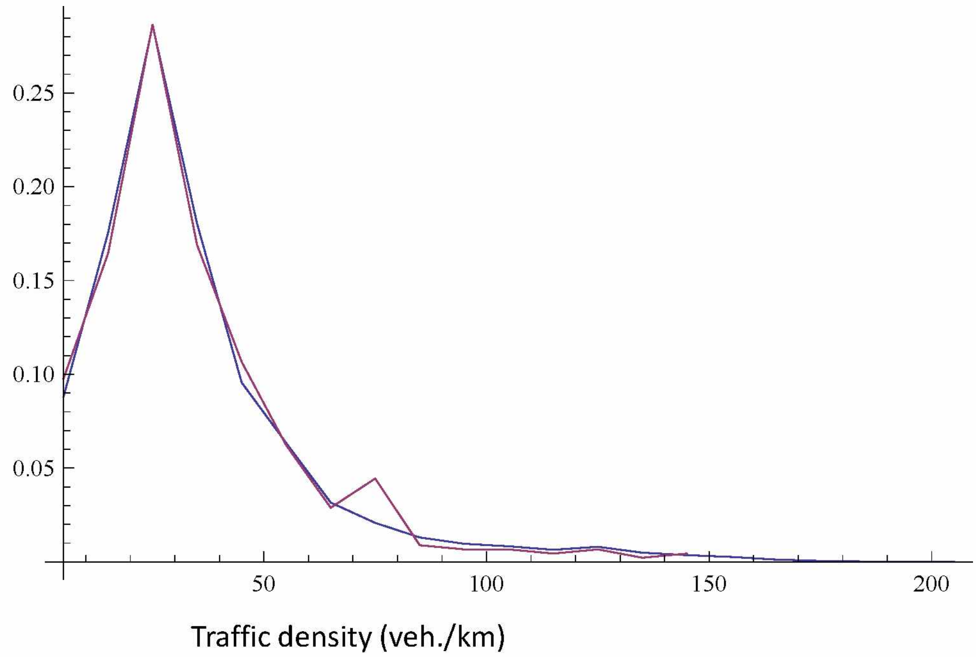


Figure 18. Palm distribution (blue) of traffic (over all stations) and accident distribution (red) of traffic density estimated based on the nearest automatic traffic measurement station data just before the accident.

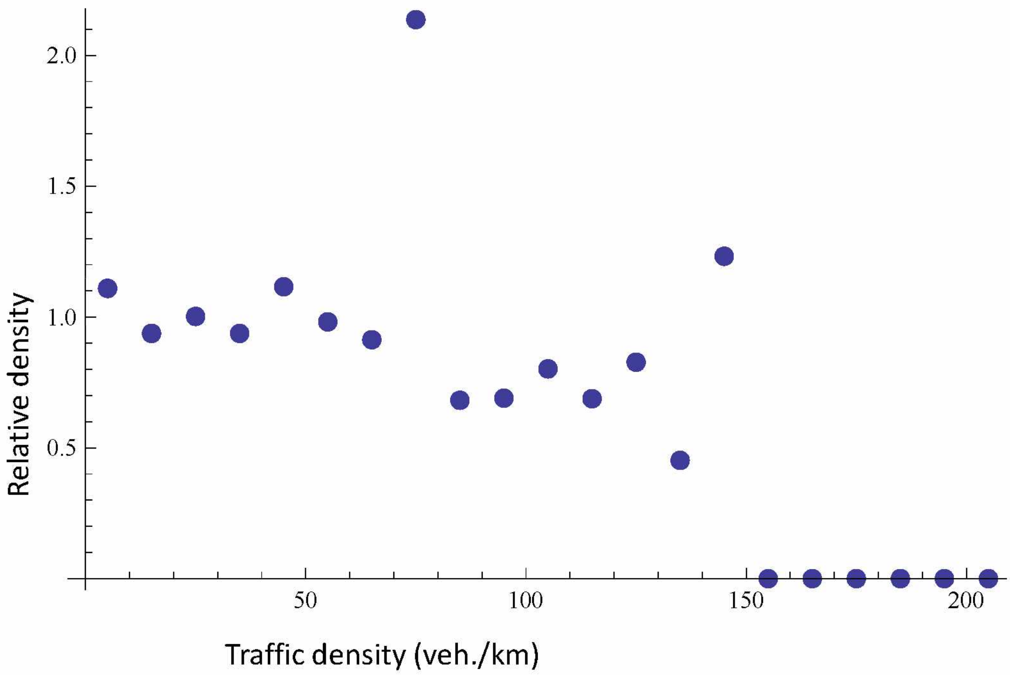


Figure 19. Relative accident density of traffic estimated based on the nearest automatic traffic measurement station data. Density is zero for classes without any observations.

Road surface temperature

Next, weather characteristics were studied. As mentioned above, the weather data do not directly concern Ring I, although general conditions can be expected to be roughly similar since the road where the station is located and Ring I belong to the same (highest priority) winter maintenance class.

The next pair of plots relates the Palm and accident-time road temperature distributions similarly as above (Figure 20). Not very surprisingly, the risk is clearly higher below zero degrees, roughly doubling below -5 (Figure 21). However, it is interesting that also road temperatures higher than 25 seem to bring about 1.5 times heightened risk.

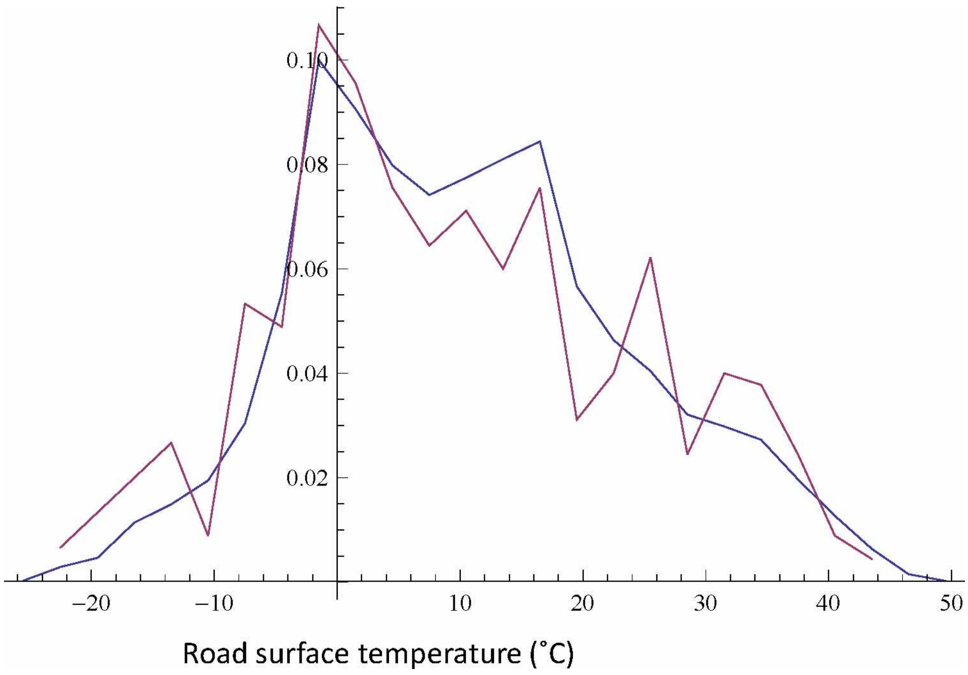


Figure 20. *Palm distribution (blue) and accident distribution (red) of road temperature*

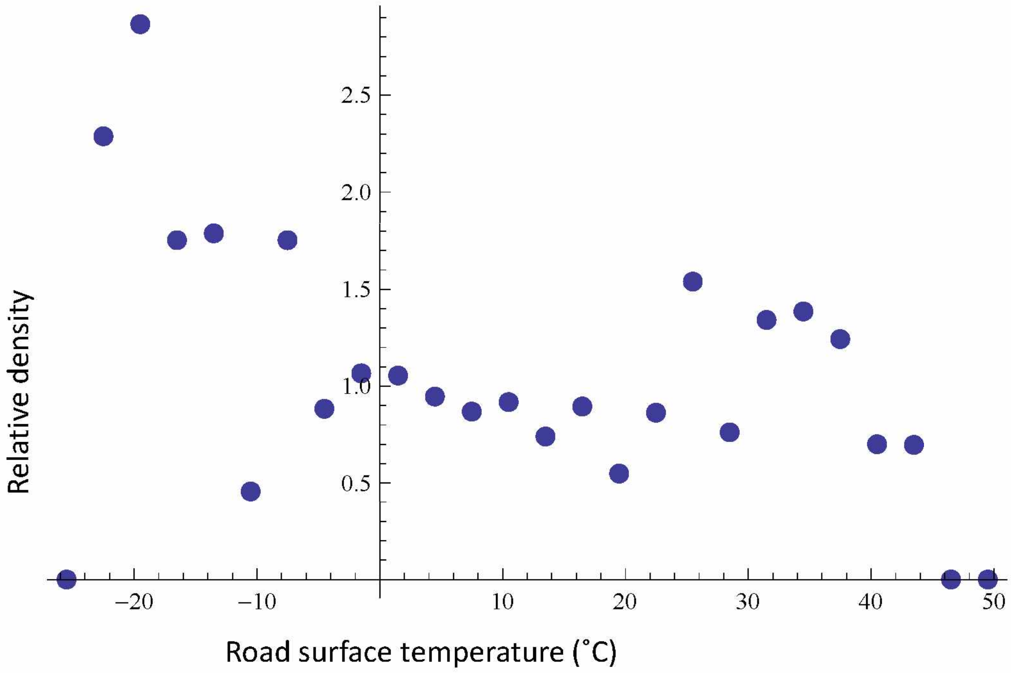


Figure 21. *Relative accident density of road temperature. Density is zero for classes without any observations.*

Rain consistency and intensity

The Palm distribution of rain consistency and intensity is presented in Table 24. The plot in Figure 22 shows the relative densities of accident conditions (the x-axis values correspond to those of the above table). It can be seen that all intensities of snowfall increase the risk, and already moderate snowfall makes it about six-fold in the present data. Since the overall probability of moderate or heavier snowfall is very low, the actual numbers should be treated with caution, but the result is qualitatively plausible. It is somewhat surprising that liquid rain does not increase accident risk at all.

Table 24. *Palm distribution of rain consistency and intensity*

1	2	3	4	5	6	7	8
No rain	Weak, liquid	Weak, crystal	Moderate, liquid	Moderate, crystal	Abundant, liquid	Abundant, crystal	Missing
84.7%	7.5%	6.6%	0.7%	0.2%	0.2%	0.02%	0.08%

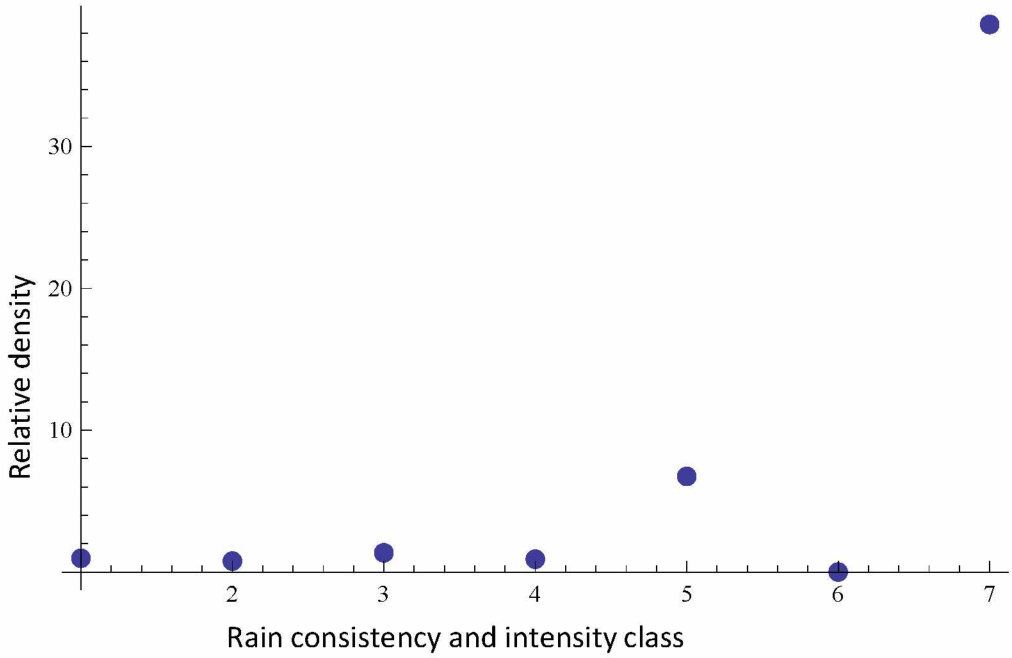


Figure 22. Relative accident density vs. rain consistency and intensity. X-axis values correspond to Table 24. Density is zero for classes without observations.

Visibility

The road weather station data includes visibility information; 97% of the time, visibility had a maximum value of "at least 2 km". The plot in Figure 23 of relative densities indicates that the weakest visibility (0.5 km) increases the accident risk considerably (no observations with visibility weaker than that). However, it should be noted that fog may be very local, and here the availability of only one road weather station may compromise the results.

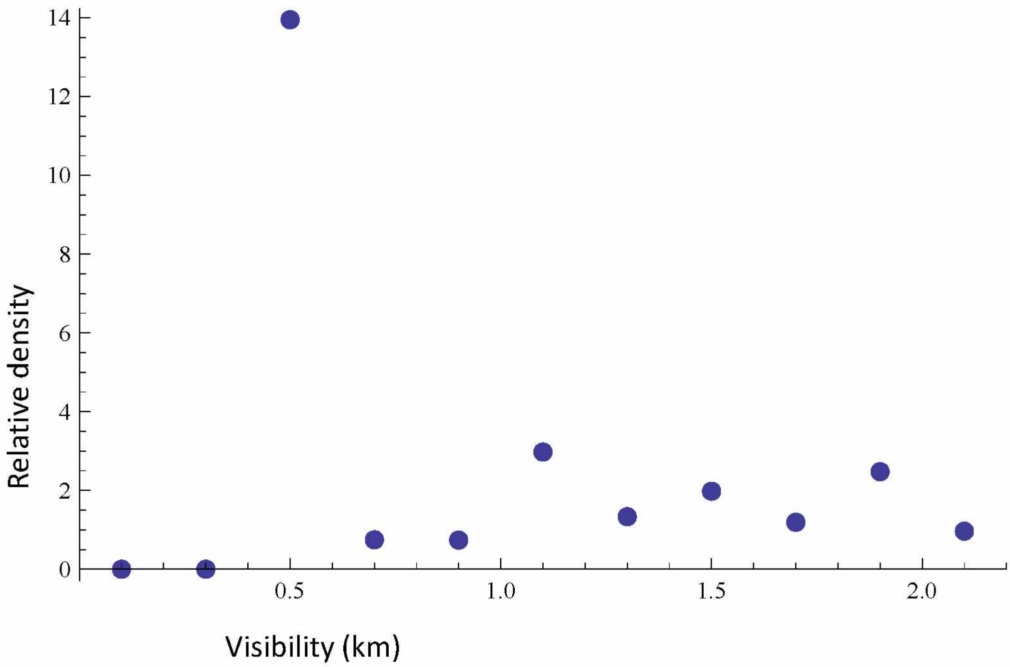


Figure 23. *Relative accident density vs. visibility. Density is zero for visibility classes without observations.*

Road surface conditions

The Palm distribution of road surface conditions is presented in Table 25. The relative density of their accident-time distribution shows that once again, snow and ice make a difference (Figure 24). Winter conditions are clearly a factor, as wet and salty conditions also result in elevated accident risk.

Table 25. *Palm distribution of road surface conditions*

1	2	3	4	5	6	7	8	9
Dry	Moist	Wet	Probably moist and salty	Wet and salty	Snow	Ice	Frost	Missing
58.5%	11.3%	11.0%	11.0%	4.2%	2.9%	1.1%	10^{-6} %	10^{-3} %

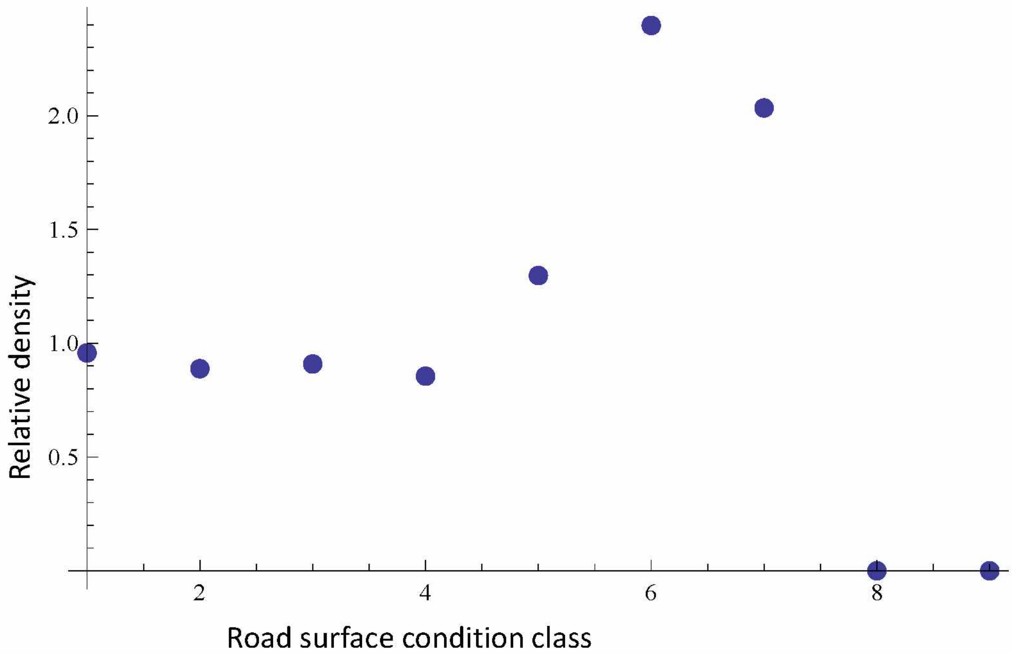


Figure 24. *Relative accident density of road conditions. X-axis values correspond to Table 25. Density is zero for classes without observations.*

Warning level

Finally, the weather data included a warning level indicator distributed (in the Palm sense) as shown in Table 26. A look at the relative densities indicates that the alarm conditions were well motivated (Figure 25). Frost does not appear here to be a factor increasing accident intensity.

Table 26. Palm distribution of warning level indicator

1	2	3	4	5	6
OK	Rain	Frost	Warning	Alarm	Missing
85.6%	7.4%	3.5%	2.8%	0.6%	0.1%

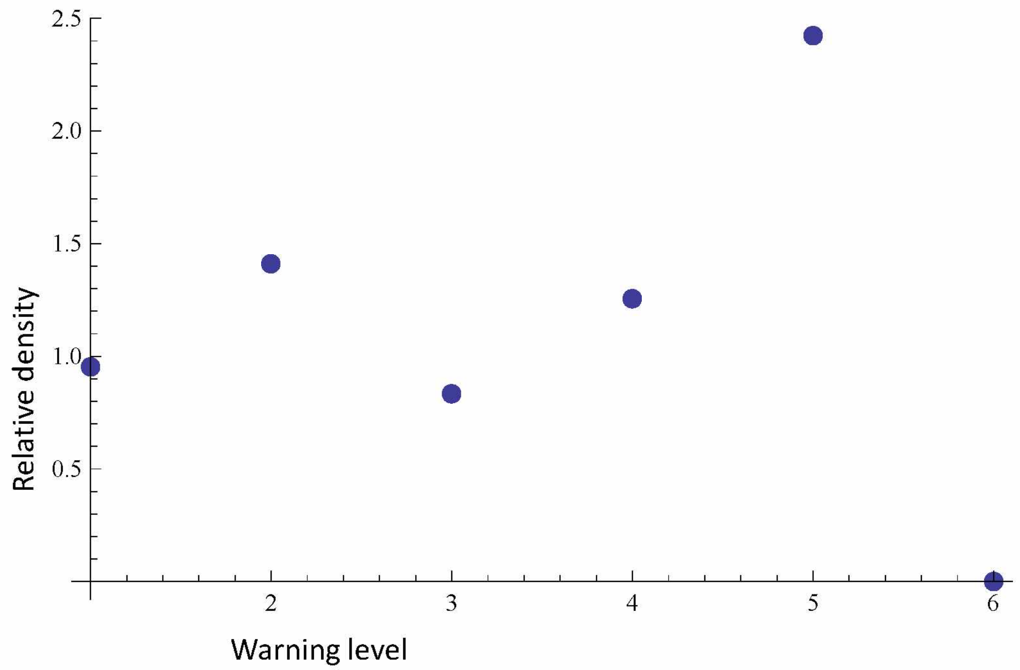


Figure 25. Relative accident density of road conditions. X-axis values correspond to Table 26. Density is zero for classes without observations.

3.3.3 Discussion

The methodical idea of comparing the Palm distribution of traffic and weather characteristics (defined as their distribution weighted by traffic density) with their distribution at accident times seems indeed to give insight into the predictability of accidents on the basis of general traffic and weather conditions.

The preliminary conclusions of this study are the following:

- The distribution of the spatial location of accidents is far from uniform and shows several strong peaks. This information should be borne in mind when considering means for preventing accidents.
- The distribution of accidents during 1 year also shows some clear patterns, but the reasons have not yet been analysed.
- The afternoon rush hour (15-17) has a higher accident risk than the morning rush hour.
- The accident risk is relatively high at night (with respect to the low traffic density).
- The traffic density, taken alone, has no effect on accidents.

- Conditions with unusually low traffic velocity have increased risk.
- Snowfall increases the risk clearly, but liquid rain has hardly any effect.
- Ice and snow on the road increase risk.
- Lowered visibility increases the risk.

The statistical significance of the results above has not been studied.

This work could be continued as follows:

- Make similar one-dimensional comparisons on the effect of traffic velocity and density changes, e.g. within the last 15 or 30 minutes before each accident
- Have a look at the accident types occurring at the identified risky locations and circumstances
- The studies of subsection 3.3.2 were one-dimensional. Could the data suggest something about the effects of combinations?
- Develop the method for assessing the statistical significance of observations like those discussed above.

3.4 Incident clusters

When studying traffic incident clusters, two types of incidents were included: regular congestion and traffic accidents.

3.4.1 Regular congestion

First, locations where traffic regularly becomes congested were identified. A link was considered to be regularly congested if travel time differed from the annual median by at least 20% during at least 150 hours per year, and severely congested if the difference was at least 50%. Congested links were determined based on the Transport Agency's travel time data collected during 2012. Road sections that fulfilled the set criteria, but where the traffic volume was <7,500 vehicles/day on one-carriageway roads and <15,000 vehicles/day on two-carriageway roads, were excluded. Reasons for longer travel times include road works etc. If there was a short road section that almost fulfilled the criteria and it was situated between two road sections that did fulfil the criteria, that road section was included. Road sections where the travel time measurement was not working sufficiently to produce the necessary data were excluded. The resulting road sections are presented for whole of Finland in Figure 26 and for the Uusimaa region in Figure 27. A detailed description of links is given in Annex B.

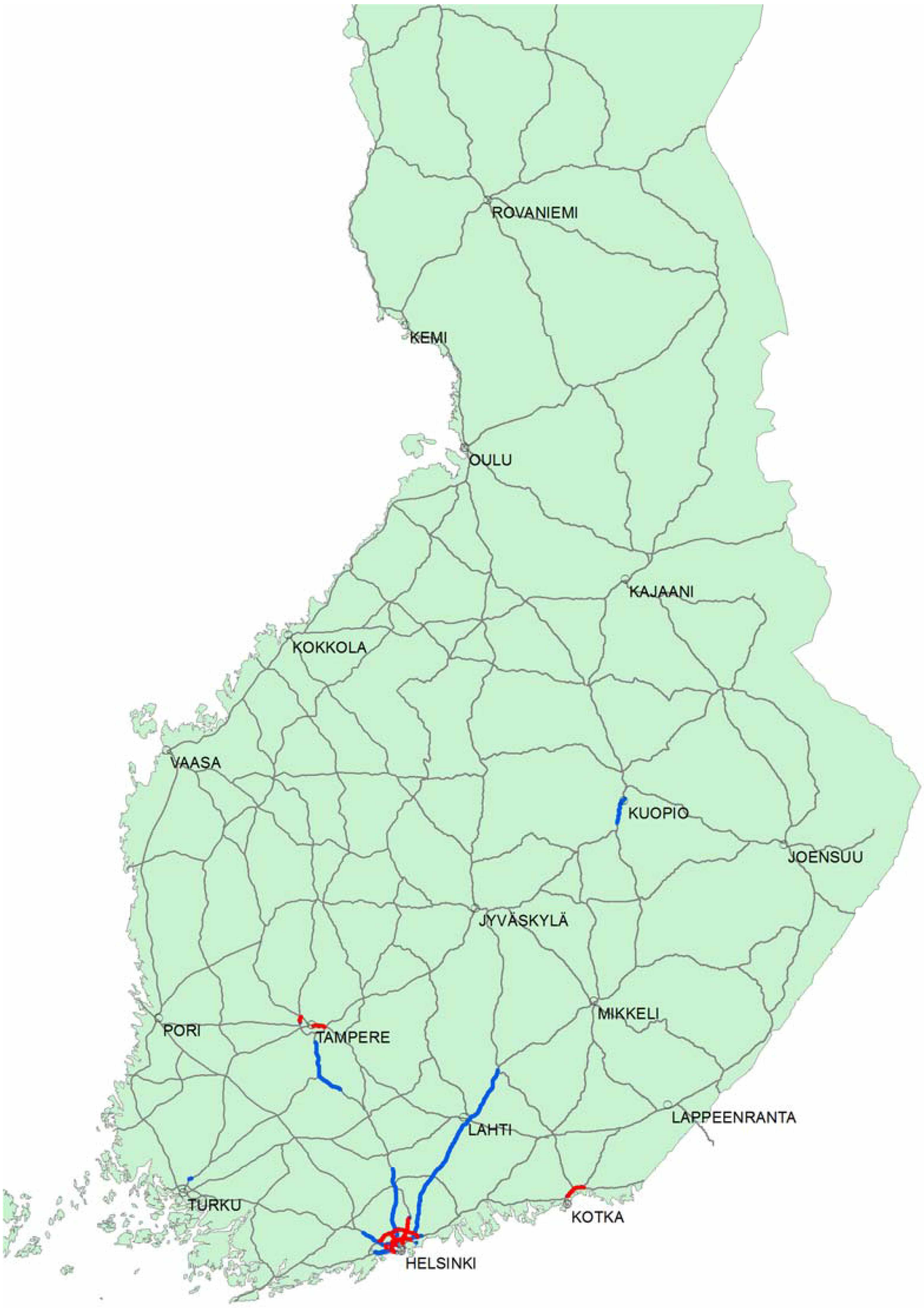


Figure 26. Regularly congested road sections in Finland. Blue indicates an increase of at least 20% in travel time at least 150 h per year; red shows an increase of at least 50%

Figure 27. *Regularly congested road sections in the Uusimaa region. Blue indicates an increase of at least 20% in travel time at least 150 h per year; red shows an increase of at least 50%*

3.4.2 Traffic accidents

The second type of incident studied was traffic accidents. All traffic accidents that were included in the police database and took place during 2007–2011 on roads 1–999 (main roads and secondary roads) were included. These accidents totalled 56,400.

Accidents were clustered based on their location. Accidents were considered clustered if they were situated within a 100 m road stretch starting from every single accident. Different accident types were given different weights based on their impact on traffic flow: fatal accidents had weight 3, injury accidents 2 and other accidents 1. The sum of these weights was calculated for the next 100 m road stretch starting from every accident location. If the total was greater than or equal to 20, the location was considered an accident cluster. If a cluster overlapped with another cluster, they were combined. This procedure resulted in 162 accident clusters as shown in Figure 28 and detailed in Annex C.

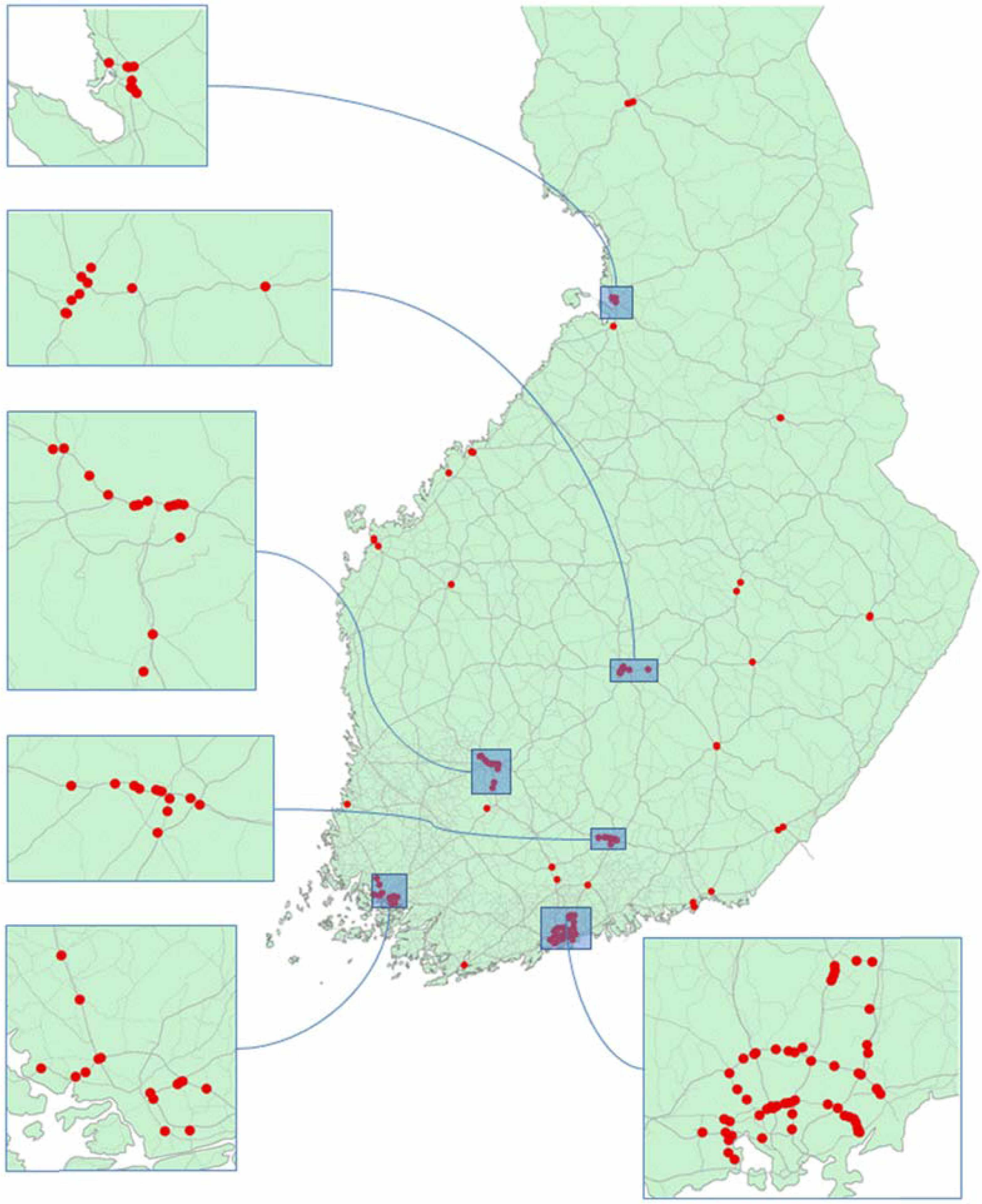


Figure 28. Accident clusters with weights 1, 2 and 3 and minimum weighted total of 20 on a 100 m road section.

3.5 Incident information in traffic management centres

3.5.1 Current incident information system messages

The Incident Information System is used as the Transport Agency's centralised storage and tool for managing traffic-related incident information (Finnish Transport Agency, no date). The Incident Information System manages information about traffic incidents gathered from a variety of sources and collates it in such a way that the information can be used to create incident advisories (both for public consumption and for the use of maintenance contractors and operators).

The Incident Information System uses the XML-based DATEX II standard version 1.0 as its data model, which means that all the system's messages are formatted using the DATEX II v1.0 schema (European Commission 2009). Each DATEX II message is associated with a specific location that the message deals with. This location can be defined with several different location referencing systems, and it can correspond to the road network or to an area. (European Commission 2006)

The DATEX II standard offers hundreds of different traffic related messages, but only a selected subset of them is in use in traffic management centres. The number of different public messages currently in use at the Finnish Transport Agency is 197, and messages used to communicate with maintenance operators include 162 different options (Setälä 2013).

The public messages in use include messages for road surface conditions, general obstructions, frost damage, transit information, network management, abnormal traffic conditions, visibility, accidents, poor road infrastructure, road works, vehicle obstructions, and activities. (Setälä 2013)

'Road surface condition' messages can provide information on e.g. hazardous conditions, packed snow, risk of skidding, icy road, icy patches of road, and risk of aquaplaning. 'General obstruction' messages can be used to inform about animals, objects, obstructions or fallen trees or power cables on the road. 'Frost damage' messages can be used where roadways have been severely damaged by frost.

'Transit information' messages are used to provide information about ferry operations (e.g. service delays and resumptions). 'Network management' messages are used to inform about restrictions on the traffic network including road and lane closings, stoppages and temporary lane reorganisations. 'Abnormal traffic' messages are used when traffic conditions become congested or are returning back to normal.

'Visibility' messages can convey changes in visibility or environmental conditions in cases of fog, windstorms, sleet, and dense snow or rainfall, for example. 'Accident' messages provide information about the type of accident that has taken place (e.g. several vehicles, bus, truck, hazardous materials involved) and about the progress of recovery operations ('in progress' or 'finished').

'Poor road infrastructure' messages can be used to inform about problems with traffic lights or variable message signs. 'Road works' messages can provide a variety of different information about the type of road works taking place (e.g. cable, bridge, surface repair, temporary traffic lights).

'Vehicle obstruction' messages can inform about broken down or dangerous vehicles on the road. 'Activity' messages are used in cases of major public events that can cause disruption to traffic (e.g. running event, fair, demonstration, sports event).

3.5.2 Analysis of coverage of incident information system messages

In the literature review on incident risk assessment (Chapter 3.1), several factors were found to influence both the duration of an incident and the likelihood of secondary incidents. Studies have shown that debris, breakdowns and multiple-vehicle crashes are the major sources of incidents on freeways.

Factors contributing to the longer duration of an incident included longer response times, accidents, lane blockages, adverse weather conditions (especially rain precipitation), heavy vehicles involved in an incident, injuries or fatalities, occurrence during peak hours, incidents located farther away from a traffic operations centre, more vehicles responding from various agencies, and freeway facility damage.

Factors associated with the increased likelihood of occurrence of a secondary incident included peak hours, weekdays, rainfall intensity, clearance time of primary incidents, duration of primary incident, larger number of involved vehicles in primary incident, and rolling over of primary vehicle.

When examining how well the messages currently used by the Incident Information System in traffic management centres cover these contributing factors, the overall coverage seems quite good. Information about accidents that have been found to be major sources of incidents is all covered (debris on the road, broken down vehicles, and crashes involving multiple vehicles).

Factors contributing to longer incident duration are also quite well covered. The effect of rainfall intensity can be communicated using visibility messages, and location information can be used to convey distances. Information about whether a vehicle has rolled over in an accident can only be conveyed for heavy vehicles (overturnedHeavyLorry message), not for other types of vehicles. It could be useful to take into use the more general overturnedVehicle message from the same Accident class.

As precipitation intensity was found to be a contributing factor both to the duration of an incident and to the likelihood of a secondary incident, more detailed information about precipitation conditions should perhaps be provided. This could be accomplished by taking into use the PrecipitationInformation and PrecipitationDetail messages available as part of the DATEX II standard. They could be used to provide information about the depth of rain or snow on the ground and about the intensity of precipitation. This information could be acquired from the Finnish Road Weather Information System, for example using DigiTraffic interfaces. A summary of suggested additions is given in Table 27.

Table 27. Factors found to contribute to longer duration of an incident and to the likelihood of secondary incidents, and their coverage in the current Incident Management System

Factor	**Status**
Factors contributing to longer duration of an incident	
Longer response times	Ok
Accidents	Ok
Lane blockages	Ok
Adverse weather conditions (especially rain precipitation)	More detailed information on precipitation intensity suggested, i.e. use of PrecipitationInformation and PrecipitationDetail messages in DATEX II
Heavy vehicles involved	Ok
Injuries or fatalities	Ok
Occurrence during peak hours	Ok
Incidents located farther away from a traffic operations centre	Ok
More vehicles responding from various agencies	Ok
Freeway facility damage	Ok
Factors influencing the likelihood of secondary incidents	
Peak hours	Ok
Weekdays	Ok
Rainfall intensity	More detailed information on precipitation intensity suggested, i.e. use of PrecipitationInformation and PrecipitationDetail messages in DATEX II
Clearance time of primary incidents	Ok
Duration of primary incident	Ok
Larger number of involved vehicles in primary incident	Ok
Rolling over of primary vehicle	Conveyed for heavy vehicles (overturnedHeavyLorry message), not for other types of vehicles; More general overturnedVehicle message from the same Accident class suggested

3.6 Use of road user made incident notifications

Road users report traffic incidents to the Transport Agency in addition to radio stations. So far these road user notifications have been only for information within the traffic centre and only official incident notifications have been published.

As traffic-monitoring systems do not cover all the roads and the detector network is not designed for fast detection of incidents, a road user notification can be the first indication of an incident. As reaction time is critical both in minimisation of consequences including secondary accidents, the asset of road user notifications should be exploited.

However, incident notifications made by road users are not always reliable. Some may involve misunderstanding of a situation, others intentional disruption. Therefore a protocol should be developed to confirm the notification before any incident management or information provision steps are taken. Alternative means of confirmation could include:

- Detection of incident consequences from the Transport Agency's traffic monitoring systems or road surveillance cameras
- Sufficient number of sequential notifications of the same incident (e.g. by at least three persons)
- Notification made by a road user registered with a system for incident notification
- Visual proof sent by the road user (e.g. MMS from a mobile phone) together with GPS coordinates

If the Transport Agency decides to allow road user notifications as a basis for traffic announcements to the public, such announcements should specify the origin, and stress that the public authorities have yet to confirm the incident. Thus it would be up to service providers to decide whether or not to use announcements of this type in their system.

4 Traffic monitoring system

4.1 Monitoring system overview

A travel time prediction model would require as input a stable indicator for travel time that would be measured with a sufficient number of observations in all conditions (except night time). Information about the traffic flow state (volume and speed) might indicate the risk of oversaturation better than travel time alone.

Travel time is a reactive measure as it can be measured only with delay. Therefore it is recommended that in areas with regular congestion, the traffic flow should be monitored using sufficiently densely spaced cross-section specific detectors that are capable of monitoring reliably at least the traffic volume and speed. Travel time (or speed) remains at roughly same level as traffic volume increases, and finally when the volume reaches a critical value (capacity), travel time (or speed) suddenly drops. The vicinity of this critical point cannot be estimated by travel time information alone. With detectors capable of detecting traffic volume in addition to speed, the level of congestion (risk of oversaturation) could be monitored also before the travel time decreases. In addition, the delays in monitoring would be significantly shorter than with travel time information. With a dense cross-section based detector network, the development of the congested area (slowly travelling queues) could be defined.

The distance between consecutive cross-sections is approximately 500 metres in countries like the Netherlands, which has much more traffic than the Helsinki Metropolitan area (or Finland in general). Dutch traffic operators seem satisfied with their detector density. Therefore it can be used as recommendation for Finnish conditions as well.

In the future, with widespread use of satellite-based tracking, vehicle trajectory information will partly fulfil the need for detailed traffic status information along the road. However, it cannot totally replace cross-section based monitoring for providing accurate traffic volume data.

In areas where congestion does not take place on a weekly basis, traffic monitoring serves incident management and traffic information (e.g. media). In such areas, cross-section specific monitoring would be too expensive if sufficient coverage were targeted. However, travel time monitoring indicates the consequences of incidents and the level of congestions on an overall level, and suits this kind of purpose where a delay in getting information is not so critical. In addition to travel time monitoring, a system capable of measuring traffic volume should exist for statistical purposes and forecasting of holiday season traffic.

4.2 Flow status classification

In Finland, traffic flow status is categorized in five classes (Table 28) based on drivers' perception of the traffic situation (Kiljunen and Summala 1996).

Table 28. Definition of flow status classes used by the Finnish Transport Agency (Kiljunen and Summala 1996)

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

All other Nordic countries use a three-step classification for traffic flow status: green, yellow and red. However, the definition of classes varies between countries. The Danish classification is based on a speed indicator and the Norwegian classification on a travel time indicator (Table 29). The green and yellow classes are larger in Denmark than in Norway, and correspondingly the red class is larger in Norway than in Denmark.

Table 29. Definition of flow status classes in the Nordic countries (Bjerkeholt 2013, Egemalm 2013 and Eskedal 2013).

Country	**Green**	**Yellow**	**Red**
Denmark	Speed is more than 80% of the posted speed limit	Speed is less than 40–80% of the posted speed limit	Speed is less than 40% of the posted speed limit
Norway	Travel time is less than 15% longer than in free flow (corresponds to more than 87% of free flow speeds)	Travel time is 15–50% longer than in free flow (corresponds to 67–87% of free flow speeds)	Travel time is more than 50% longer than in free flow (corresponds to less than 67% of free flow speeds)
Sweden	Delay is less than 30 sec/km	Delay is 30–60 sec/km	Delay is more than 60 sec/km

The Swedish classification with fixed delays (Table 29) provides very different percentage differences in travel time or speed depending on the speed level on the road. In areas with a speed limit of 120 km/h, the 30 sec/km delay corresponds to 50% of the speed limit speed and 60 sec/km delay to 33% of the speed limit speed. In the 80 km/h speed limit area, the corresponding proportions are 60% and 43% and in the 50 km/h speed limit area 71% and 55%.

In the Rijkswaterstaat Traffic Management Centre's traffic monitoring system, the flow status is also given in three classes: green (speed down to 70% of free flow speed), orange (a lot of traffic but still flowing) and red (congestion). However, they assess that a fourth class may be needed between green and orange to indicate where the risk of congestion is elevated.

If the Finnish traffic flow status classification is used mostly with travel time data, it would make sense to define classes based on the travel time indicator instead of speed. The limits set in Norway seem suitable also for Finland, thus their use is recommended.

5 Discussion

5.1 Overall discussion

The goal of the project was to find methods for creating an accurate overall understanding of the current status of the transport system and to predict changes in traffic conditions. The most important task in achieving this was travel time prediction. Another goal was to find methods for assessing incident risk. In addition, an overall assessment of the monitoring system was performed considering the needs of short-term prediction and incident risk assessment.

Best practices were sought and found among other road operators, in the literature and from small data pilots. Existing applications in use by the Finnish Transport Agency were evaluated based on theory and practice found in the literature and in the data pilot studies.

5.2 Conclusions related to the travel time prediction model

A slightly modified version of the dynRP travel time prediction model of the Danish Road Directorate was piloted on Ring I of the Helsinki Metropolitan Area. The piloted model was based on median values of direct travel time measurements. It included annual historic median values for all minutes of all weekdays separately. The forecast was interpolated or extrapolated based on the latest measurement and the historic median curve.

The main results showed that the 15-minute prediction model gave better travel time estimates than just using the latest measurement, especially in congested conditions. Specifically, the model predicted the travel time correctly 77–82% of the time in congested conditions when the acceptable error was 20%. The corresponding proportion was 71–76% with the latest measurement. The model did not fulfil the threshold of keeping maximum errors between 10% and 25% that was prevalent in the literature. Therefore the use of this forecast may not be beneficial. Nevertheless, if decisions must be made proactively, although not perfect the forecast would lead to better decisions more often than just using the latest measurement. Therefore the use of model can be recommended. *Recommendation: the Finnish Transport Agency starts the definition of functional requirements for the prediction model. The requirements of the Finnish Transport Agency (2013) can be used as the starting point.*

Furthermore, shorter-than-15-minute prediction models provided more accurate estimates than the 15-minute model. However, with the shorter prediction period length also the latest measurement served better as an estimate, and the difference from the prediction model was small if any, or even negative. Therefore, the use of these shorter-term models cannot be recommended. If shorter-term prediction is needed, it is recommended to use the latest measurement as the forecast.

The best models found in the literature had an average percentage error of approximately 10%. These models outperform the dynRP model in congested conditions with a 13–15% average error. However, a clear benefit of the dynRP model is that its estimation and updating procedure can be fully automated without the need for neural network estimation or other special methods or for manual work. If a more accurate model is targeted, it is recommended to implement a self-adapting model. Although it needs to be set up manually for each link, there is no, or at least less, need for manual updating as the model adapts itself. Such a self-adapting traffic flow status prediction model was successfully piloted earlier on Ring I (Innamaa 2009). The model ran for years at the traffic management centre of the Finnish Transport Agency.

For setting up a travel time prediction model, the following principles are recommended: The model should be based on 1 year of data on links without lowered speed limits in wintertime, and on 2 years of data on links with lowered winter speed limits. 5-minute medians are calculated with a 1-minute update interval. Only those travel time medians are included that are based on at least five observations. Historic median curves are determined separately for each weekday. On links with lowered winter speed limits, the curves should be determined separately for the winter and summer speed limit periods. At night, free flow speed is forecast. Travel times should not be forecast as shorter than those corresponding to the speed limit. It is recommended that the model is updated once a month (this can be automated) and that the performance of the model is validated on a regular basis. To overcome smoothly the impact of changes in the physical infrastructure (e.g. large roadwork or opening of a new lane), the application should include a feature that allows the user to set a date after which, or a period during which the source data is valid. The traffic operator should also always have the option to choose latest measurement instead of forecasts. In addition, the possibility to manually adjust the historic median curve used for making the forecast to correspond to the current situation facilitates use of the model also during the period when travel time data is collected for updating the model. *Recommendation: The Finnish Transport Agency sets up a process to get winter speed limits and the dates of speed limit change automatically fed into the DigiTraffic system.*

A model made with the principles described above works better the closer the traffic situation is to its median (or average) performance. When the traffic volume is smaller than normal due to e.g. a vacation period, or when a traffic accident or other incident takes place or when the road weather condition is hazardous, the model most likely performs more poorly, and operator expertise on the development of traffic situations overrides it. For days with unusually high traffic demand (e.g. holiday seasons), separate prediction models should be made and applied. The models should be based on previous years, and modified to take into account the weekday and week when e.g. a holiday occurred during the base year and current year, incidents (of the base year), road works (of the base year and current year), trends and weather.

5.3 Conclusions related to incident risk assessment

The Rijkswaterstaat Traffic Management Centre had several procedures that can be considered best practice in incident risk assessment and management. It is recommended that a procedure to systematically collect and use information on events (e.g. sports events, music festivals, road works) that affect traffic be set up. Once a month the annual traffic forecast should be updated indicating the timing and location of such events and their foreseen impact on local traffic. It is recommended that these annual forecasts be studied in a meeting once a week to identify abnormalities of traffic during the coming week and to find solutions for (proactively) operating the traffic in such conditions. In the meetings, the success of the previous week's operation should be evaluated in order to perform better next time. The annual traffic forecast can also be used in the planning of timing of road works. *Recommendation: The Finnish Transport Agency sets up a process to collect information on events that affect traffic and provides it as open data.*

If a dense cross-section based traffic-monitoring network (e.g. loop detectors) is set up, it is recommended that a simple incident detection system like the one developed at the Rijkswaterstaat Traffic Management Centre be set up for fast detection of accidents and other traffic incidents.

When an incident takes place, it is important to provide the right information at the right time. One of the assets of the Rijkswaterstaat Traffic Management Centre is the use of road patrols e.g. proactively located in the vicinity of new road works prone to incidents. One common cause of delays also on the Finnish road network is the presence of broken-down vehicles by the roadside, even when outside the carriageway. Towing these vehicles more promptly than at present would have societal advantages by reducing time spent on the road for all road users. *Recommendation: The Finnish Transport Agency examines the possibility to draw up a framework agreement with towing companies for prompt clearance of broken-down vehicles on a regularly congested road network (Figure 26).*

When variable message signs are used to inform road users of an incident ahead, it is recommended that the travel time be given as normal travel time + delay. This has been found to be successful in the Netherlands. Whenever possible, also the cause of the delay (e.g. accident or road work) should be indicated on the sign.

Ishak and Alecsandru (2005) concluded that pre-, post-, and non-incident traffic conditions may not be readily discernible from each other and that specific characteristics of precursory conditions to incidents may not be clearly identifiable. Such a conclusion, however, was driven by limited incident and traffic datasets and selected second-order traffic performance measures. Additionally, environmental factors such as inclement weather conditions were not accounted for in this study.

Incident data analysis of Ring I included the road weather conditions in addition to traffic flow status information. The results indicate that some circumstances do indeed have a higher incident risk than others, like the evening rush hour, reduced visibility, and moderate or abundant snowfall. However, the statistical significance of the results could not be studied with the amount of data used and the resources available in this project. Nevertheless, this should be studied further with a larger dataset. The target could also be to determine an iMit type of prediction tool for incident duration and secondary incident occurrence on the basis of information provided by the incident information form.

An incident detection system could be supplemented by incident notifications made by road users, which could help minimise delays in incident management. However, to guarantee the reliability of these notifications, it is recommended that a confirmation protocol be set up. Confirmation could be made based on e.g. traffic monitoring equipment in the area, number of notifications in sequence to each other, registering volunteers to give these notifications, or visual proof of the situation accompanied by a GPS position. If such notification(s) lead to an official traffic announcement, it should include the information that the incident has not yet confirmed by the public authorities. *Recommendation: The Finnish Transport Agency sets up the organisation and resource allocation for a road user line.*

Factors contributing to longer incident duration are also quite well covered in the current Incident Management System of the Finnish Transport Agency. Nevertheless, the inclusion of the general overturnedVehicle message and the PrecipitationInformation and PrecipitationDetail messages are suggested. As incident management involves also other authorities than the Finnish Transport Agency, the use of new measures should be commonly agreed. *Recommendation: The Finnish Transport Agency starts the promotion of these new measures as part of incident message services.*

5.4 Conclusions related to traffic monitoring

Travel time is a reactive measure, as it can be measured only with delay. Therefore it is recommended that in areas with regular congestion, the traffic flow should be monitored using sufficiently densely spaced cross-section specific detectors that are capable of monitoring reliably at least the traffic volume and speed. A distance of 500 metres can be recommended based on experiences abroad. The Rijkswaterstaat Traffic Centre recommends the use of traffic intensity instead of speed (or travel time) if proactive traffic management is intended. In addition, information on traffic volume and speed might indicate the risk of oversaturation better than travel time alone. The road network selected for intensive management should consist of a regularly congested road section (Figure 26). It is assumed that the best cost-benefit ratio for an intensive monitoring system can be achieved there.

In the future, with widespread use of satellite-based tracking, vehicle trajectory information can partly fulfil the need for detailed traffic status information along the road. However, it cannot totally replace cross-section based monitoring, which provides accurate traffic volume data.

In areas where congestion does not take place on a weekly basis, traffic monitoring assists in incident management and information (e.g. media). In such areas, travel time monitoring would be sufficient to indicate the consequences of incidents and the levels of congestion. The system could be supplemented by road user notifications. In addition, a system capable of measuring traffic volume should exist for statistical purposes and forecasting of holiday season traffic.

Problems at accident cluster locations (Figure 28) outside normally congested areas (Figure 26) most likely will not be solved by monitoring or traffic management, but rather by enhancing the physical infrastructure and layout of the site.

A travel time prediction model would require as input a stable indicator for travel time that would be measured with a sufficient number of observations in all conditions. Thus the reliability of the travel time monitoring system is fundamental for further use of the information.

A three-step classification is recommended for traffic flow status. For travel time information, the classification should be as follows:

- Green: Travel time less than 15% longer than in free flow (travel time corresponding to the speed limit)
- Yellow: Travel time 15–50% longer than in free flow
- Red: Travel time more than 50% longer than in free flow

Recommendation: The Finnish Transport Agency promotes the use of the three-step classification of the traffic flow status and implements it for all systems.

References

van den Berg JM, van Wijngaarden B (2013). Interview of operational traffic team leader Jan Maarten van den Berg and road office leader Bart van Wijngaarden of Rijkswaterstaat TMC in Utrecht, the Netherlands. February 5, 2013.

Bjerkeholt B (2013). Email message from Bo Bjerkeholt, Swedish Transport Agency, to Satu Innamaa, VTT, on May 22, 2013.

Castro-Neto M, Jeong Y, Jeong M, Han LD (2009). Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions. Expert Systems With Applications. 2009;36:6164-6173.

Danish Road Directorate (no date). dynRP – rejsetidsprognose. Notes. 5 p.

Egemalm Å (2013). Email message from Åke Egemalm, Danish Road Directorate, to Satu Innamaa, VTT, on May 22, 2013.

Eskedal TG (2013). Email message from Thor Gunnar Eskedal, Norwegian Road Administration, to Satu Innamaa, VTT, on May 22, 2013.

European Commission (2006). Datex II v 1.0 User Guide. 22 December. Directorate General for Transport and Energy. Available at: http://www.datex2.eu/sites/www.datex2.eu/files/sites/test.datex2.eu/files/DATEXIIv1.0-UserGuide_v1.0.pdf [accessed 18 April 2013].

European Commission (2009). Datex II v1.0 Data Model. Available at: http://www.datex2.eu/content/datex-ii-v10-data-model [accessed 17 April 2013].

Fei X, Lu CC, Liu Ke (2011). A bayesian dynamic linear model approach for real-time short-term freeway travel time prediction. Transportation Research Part C 19 (2011) pp. 1306-1318.

Finnish Transport Agency (no date). Manual of the Incident Information System [Häiriötietojärjestelmän käyttöohje]. 28 p.

Finnish Transport Agency (2013). Liikenneviraston matka-ajan ennustemalli, Toiminnalliset määrittelyt. Memo. 3 p.

HCM (1995). Highway Capacity Manual. Transportation Research Board.

Hofleitner A, Herring R, Bayen A (2012). Arterial travel time forecast with streaming data: A hybrid approach of flow modeling and machine learning. Transportation Research Part B 46 (2012) 1097–1122.

Hojati A, Ferreira L, Charles P, bin Kabit M (2012). Analysing freeway traffic-incident duration using an Australian data set. ROAD & TRANSPORT RESEARCH. 2012;21:19-31.

Hu TY, Tong CC, Liao TY, Ho WM (2012). Simulation-Assignment-Based Travel Time Prediction Model for Traffic Corridors. IEEE Transactions on Intelligent Transportation Systems, Vol. 13, Iss. 3, pp. 1277-1286.

Innamaa S (2009). Short-term prediction of traffic flow status for online driver information. Doctoral dissertation. VTT Publication 708, VTT Technical Research Centre of Finland, Espoo. 79 + 90 p.

Innamaa S, Silla A (2006). Tanskan tielaitoksen käyttämän matka-aikaennustemallin soveltuvuus Suomeen. [Suitability of the travel time prediction model used by the Danish Road Administration in Finland] Finnish National Road Administration. Finnra Reports 26/2006, Helsinki. 42 p. + app. 27 p.

Ishak S, Alecsandru C (2005). Analysis of freeway traffic incident conditions by using second-order spatiotemporal traffic performance measures. In: WASHINGTON: TRANSPORTATION RESEARCH BOARD NATL RESEARCH COUNCIL; 2005:20-28.

Kamga CN, Mouskos KC, Paaswell RE (2011). A methodology to estimate travel time using dynamic traffic assignment (DTA) under incident conditions. Transportation Research Part C. 2011;19:1215-1224.

Khattak A, Wang X, Zhang H (2012). Incident management integration tool: dynamically predicting incident durations, secondary incident occurrence and incident delays. IET INTELLIGENT TRANSPORT SYSTEMS. 2012;6:204-214.

Kiljunen M, Summala H (1996). Ruuhkaisuuden kokeminen ja liikennetilanne-tiedottaminen. Tienkäyttäjätutkimus kaksikaistaisilla teillä. (Perception of traffic conditions, and traffic information – a road user survey on two lane roads). Finnra reports 25/1996, Finnish National Road Administration, Helsinki. 77 + 5 p.

Li R, Rose G (2011). Incorporating uncertainty into short-term travel time predictions. Transportation Research Part C 19 (2011) pp. 1006-1018.

Lim S, Lee C (2011). Data fusion algorithm improves travel time predictions. IET Intelligent Transport Systems. doi: 10.1049/iet-its.2011.0014.

van Lint JWC (2008). Online Learning Solutions for Freeway Travel Time Prediction. IEEE Transactions on Intelligent Transportation Systems, Vol. 9, No. 1, March 2008.

Setälä, H (2013). Interview. E-mail, 4 April 2013.

Tao Z, Spotts J, Lu B, Zhou X, Xing T (2012). Forecasting and Delivery of Highway Travel Time Reliability Information. Final Report for SHRP 2 Reliability IDEA Project L-15A. November 2012.

Vlahogianni E, Karlaftis M, Orfanou F (2012). Modeling the Effects of Weather and Traffic on the Risk of Secondary Incidents. JOURNAL OF INTELLIGENT TRANSPORTATION SYSTEMS. 2012;16:109-117.

Annex A – Correspondence of traffic flow status classes on Ring I pilot links

15-minute models

Basic model, 15 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	43 932	846	61	12	25
	10-25%	933	1 129	500	6	6
	25-75%	298	543	714	80	120
	75-90%	5	31	94	30	118
	Over 90%	24	39	145	83	996
Correct class		97.2%	43.6%	47.2%	14.2%	78.7%
False by more than one class		0.7%	2.7%	13.6%	8.5%	11.9%

Basic model, 15 min forecast, Pukinmäki–Konala link

		Measured output				
		1	**2**	**3**	**4**	**5**
Forecast	1	128 184	2 617	333	10	41
	2	4 128	2 386	1 119	42	39
	3	1 433	1 172	4 260	589	580
	4	84	52	506	242	420
	5	244	120	556	390	4 932
Correct class		95.6%	37.6%	62.9%	19.0%	82.0%
False by more than one class		1.3%	2.7%	13.1%	4.1%	11.0%

Last measurement, 15 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	43802	1065	215	13	22
	10-25%	1080	1037	455	12	15
	25-75%	274	420	651	95	137
	75-90%	11	25	66	19	114
	Over 90%	25	41	127	72	977
Correct class		96.9%	40.1%	43.0%	9.0%	77.2%
False by more than one class		0.7%	2.6%	22.6%	11.8%	13.8%

Last measurement, 15 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	128680	3493	1183	16	46
	10-25%	3229	1627	1586	82	45
	25-75%	1597	951	2788	657	832
	75-90%	146	73	382	186	500
	Over 90%	421	203	835	332	4589
Correct class		96.0%	25.6%	41.2%	14.6%	76.3%
False by more than one class		1.6%	4.3%	29.8%	7.7%	15.4%

Seasonal model, 15 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	43 957	886	79	12	25
	10-25%	933	1 082	351	2	6
	25-75%	267	527	836	94	145
	75-90%	9	41	94	20	114
	Over 90%	26	52	154	83	975
Correct class		97.3%	41.8%	55.2%	9.5%	77.1%
False by more than one class		0.7%	3.6%	15.4%	6.6%	13.9%

Seasonal model, 15 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	127 731	2 505	349	5	45
	10-25%	4 466	2 359	995	36	33
	25-75%	1 586	1 292	4152	554	581
	75-90%	80	57	527	217	336
	Over 90%	210	134	751	461	5 017
Correct class		95.3%	37.2%	61.3%	17.0%	83.4%
False by more than one class		1.4%	3.0%	16.2%	3.2%	11.0%

Model of exceptional conditions, 15 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	44 214	1 383	259	13	22
	10-25%	556	453	169	1	13
	25-75%	369	637	817	91	127
	75-90%	17	57	109	29	67
	Over 90%	36	58	160	77	1 036
Correct class		97.8%	17.5%	54.0%	13.7%	81.9%
False by more than one class		0.9%	4.4%	27.7%	6.6%	12.8%

Model of exceptional conditions, 15 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	129 726	3 795	1 249	19	52
	10-25%	2 269	968	409	22	19
	25-75%	1 661	1 359	3 809	517	427
	75-90%	132	75	522	260	315
	Over 90%	285	150	785	455	5 199
Correct class		96.8%	15.3%	56.2%	20.4%	86.5%
False by more than one class		1.5%	3.5%	30.0%	3.2%	8.3%

Basic models for shorter prediction periods

Basic model, 10 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	44 741	936	67	6	18
	10-25%	925	1 162	410	0	6
	25-75%	202	540	882	96	84
	75-90%	3	15	93	35	99
	Over 90%	15	11	96	97	1 073
Correct class		97.5%	43.6%	57.0%	15.0%	83.8%
False by more than one class		0.5%	1.0%	10.5%	2.6%	8.4%

Basic model, 10 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	130 302	2 533	197	5	31
	10-25%	3 974	2 763	1 050	13	6
	25-75%	916	1 121	4 714	607	398
	75-90%	30	43	484	344	393
	Over 90%	90	72	473	382	5 341
Correct class		96.3%	42.3%	68.1%	25.5%	86.6%
False by more than one class		0.8%	1.8%	9.7%	1.3%	7.1%

Basic model, 5 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	45570	877	36	4	8
	10-25%	1000	1361	292	2	0
	25-75%	99	437	1141	84	30
	75-90%	1	2	81	65	83
	Over 90%	2	5	45	89	1170
Correct class		97.6%	50.7%	71.5%	26.6%	90.6%
False by more than one class		0.2%	0.3%	5.1%	2.5%	2.9%

Basic model, 5 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	134151	2516	84	1	22
	10-25%	3579	3151	796	1	2
	25-75%	356	1056	5570	549	193
	75-90%	5	11	460	465	376
	Over 90%	25	12	297	411	5953
Correct class		97.1%	46.7%	77.3%	32.6%	90.9%
False by more than one class		0.3%	0.3%	5.3%	0.1%	3.3%

Basic model, 1 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	52572	424	3	0	3
	10-25%	549	2377	134	0	0
	25-75%	5	207	1642	33	3
	75-90%	0	0	34	174	26
	Over 90%	1	0	5	52	1417
Correct class		99.0%	79.0%	90.3%	67.2%	97.8%
False by more than one class		0.0%	0.0%	0.4%	0.0%	0.4%

Basic model, 1 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	150 475	1 228	15	1	13
	10-25%	1 718	5 683	349	0	1
	25-75%	21	468	7 147	321	26
	75-90%	1	0	279	982	219
	Over 90%	13	0	37	285	7 083
Correct class		98.8%	77.0%	91.3%	61.8%	96.5%
False by more than one class		0.0%	0.0%	0.7%	0.1%	0.5%

Last measurement, 10 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	44 715	1027	102	6	18
	10-25%	984	1184	461	6	7
	25-75%	167	431	818	100	82
	75-90%	5	9	72	39	112
	Over 90%	15	13	95	83	1061
Correct class		97.4%	44.4%	52.8%	16.7%	82.9%
False by more than one class		0.4%	0.8%	12.7%	5.1%	8.4%

Last measurement, 10 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	130 898	3 343	598	6	33
	10-25%	3 094	2 023	1 450	21	8
	25-75%	1 130	980	3 700	663	527
	75-90%	70	59	475	281	482
	Over 90%	120	127	695	380	5 119
Correct class		96.7%	31.0%	53.5%	20.8%	83.0%
False by more than one class		1.0%	2.8%	18.7%	2.0%	9.2%

Last measurement, 5 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	45694	867	28	4	8
	10-25%	911	1440	354	5	0
	25-75%	64	368	1104	85	22
	75-90%	1	2	65	70	90
	Over 90%	2	5	44	80	1171
Correct class		97.9%	53.7%	69.2%	28.7%	90.7%
False by more than one class		0.1%	0.3%	4.5%	3.7%	2.3%

Last measurement, 5 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	**10-25%**	**25-75%**	**75-90%**	**Over 90%**
Forecast	**0-10%**	134759	2962	136	1	22
	10-25%	2899	2803	1082	1	2
	25-75%	428	949	5116	576	184
	75-90%	5	15	487	459	445
	Over 90%	25	17	386	390	5893
Correct class		97.6%	41.6%	71.0%	32.2%	90.0%
False by more than one class		0.3%	0.5%	7.2%	0.1%	3.2%

Last measurement, 1 min forecast, Konala–Pakila link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	52746	346	3	0	3
	10-25%	378	2544	105	0	0
	25-75%	2	118	1681	24	2
	75-90%	0	0	24	209	23
	Over 90%	1	0	5	26	1421
Correct class		99.3%	84.6%	92.5%	80.7%	98.1%
False by more than one class		0.0%	0.0%	0.4%	0.0%	0.3%

Last measurement, 1 min forecast, Pukinmäki–Konala link

Over free-flow travel time		Measured output				
		0-10%	10-25%	25-75%	75-90%	Over 90%
Forecast	0-10%	150951	1190	16	1	13
	10-25%	1240	5848	322	0	1
	25-75%	23	341	7229	215	14
	75-90%	1	0	222	1187	175
	Over 90%	13	0	38	186	7139
Correct class		99.2%	79.3%	92.4%	74.7%	97.2%
False by more than one class		0.0%	0.0%	0.7%	0.1%	0.4%

Annex B – Regularly congested road sections

Table 30. Regularly congested road sections, 20% increase from median hour travel time at least 150 hours per year

Regularly congested road sections	Start point			End point			
	Road	Road section	Distance	Road	Road section	Distance	Direction
Ring I - Ring III	1	4	705	1	5	5993	1
Ämmässuo - Veikkola	1	7	0	1	8	0	1
Veikkola - Munkkiniemi	1	8	0	1	3	503	2
Kaivoksela - Klaukkala	3	101	8744	3	104	0	1
Myllypuro - Soppeenmäki	3	139	1823	3	139	5575	2
Sääksjärvi - Iittala	3	134	5161	3	120	1059	2
Herajoki - Kaivoksela	3	110	6240	3	101	8744	2
Järvenpää - Ahtiala	4	108	3381	4	202	3045	1
Lusi - Tattarisuo	4	210	1625	4	103	1312	2
Vehmasmäki - Päiväranta	5	156	2980	5	201	3335	1
Päiväranta - Vehmasmäki	5	201	3335	5	156	2980	2
Kesälahti - Parikkala	6	332	5177	6	323	2085	2
Kotka - Hamina	7	29	1486	7	33	1260	1
Östersundom - Länsimäentie	7	3	0	7	1	2689	2
Moisio - Jäkärlä	9	103	10	9	103	2170	1
Jäkärlä - Moisio	9	103	2170	9	103	10	2
Amuri - Alasjärvi	12	127	2401	12	201	3202	1
Alasjärvi - Amuri	12	201	3202	12	127	2401	2
Käpylä - Riihikallio	45	1	3715	45	4	1412	1
Riihikallio - Käpylä	45	4	1412	45	1	3715	2
Muurala - Länsisalmi	50	2	4474	50	8	2490	1
Länsisalmi - Muurala	50	8	2490	50	2	4474	2
Matinkylä - Sundsberg	51	5	110	51	7	2972	1
Espoonlahti - Katajaharju	51	6	2400	51	2	1378	2
Keilaniemi - Pukinmäki	101	1	590	101	7	2103	1
Pukinmäki - Keilaniemi	101	7	2103	101	1	590	2
Olari - Kauniainen	102	1	970	102	3	2660	1
Pitäjänmäki - Varisto	120	2	60	120	3	5260	1

Regularly congested road sections	Start point			End point			
	Road	Road section	Distance	Road	Road section	Distance	Direction
Varisto - Pitäjänmäki	120	3	5260	120	2	60	2
Vartioharju - Mellunmäki	170	3	1090	170	3	4165	1
Itäsalmi - Vartioharju	170	5	2570	170	3	1090	2

Table 31. Regularly congested road sections, 50% increase from median hour travel time at least 150 hours per year

Regularly congested road sections	Start point			End point			
	Road	Road section	Distance	Road	Road section	Distance	Direction
Ring I - Munkkiniemi	1	4	705	1	3	503	2
Myllypuro - Soppeenmäki	3	139	1823	3	139	5575	1
Kotka - Hamina	7	29	1486	7	33	1260	1
Amuri - Alasjärvi	12	127	2401	12	201	3202	1
Alasjärvi - Amuri	12	201	3202	12	127	2401	2
Veromies - Käpylä	45	3	430	45	1	3715	2
Muurala - Länsisalmi	50	2	4474	50	8	2490	1
Länsisalmi - Muurala	50	8	2490	50	2	4474	2
Westend - Katajaharju	51	4	300	51	2	1378	2
Otaniemi - Konala	101	2	741	101	6	1713	1
Pukinmäki - Otaniemi	101	7	2103	101	2	741	2
Olari - Kauniainen	102	1	970	102	3	2660	1
Pitäjänmäki - Varisto	120	2	60	120	3	5260	1
Konala - Pitäjänmäki	120	3	680	120	2	60	2
Vartioharju - Mellunmäki	170	3	1090	170	3	4165	1
Mellunmäki - Vartioharju	170	3	4165	170	3	1090	2

Annex C – Accident clusters

Road	Start point		End point	
	Road section	Distance	Road section	Distance
1	3	0	3	105
1	4	702	4	850
1	36	1720	36	1820
1	36	2520	36	2620
3	101	5476	101	5576
3	101	5693	101	5793
3	102	3499	103	100
3	126	4039	134	64
3	203	1310	203	1426
4	103	0	103	100
4	104	160	104	260
4	104	3732	105	18
4	232	1700	232	1847
4	232	2366	233	100
4	301	486	301	586
4	307	6049	308	100
4	362	6913	363	81
4	401	770	401	920
4	448	7831	449	83
4	449	1653	449	1769
4	449	2600	449	2789
5	201	0	201	100
6	349	4887	350	99
6	401	10	401	110
6	401	343	401	517
6	401	580	401	732
6	401	1486	401	1680
7	29	305	29	405
8	104	2300	104	2400
8	105	2907	105	3007

Road	Start point		End point	
	Road section	Distance	Road section	Distance
8	239	321	239	421
8	302	3995	303	100
8	401	228	401	329
8	401	1185	401	1353
9	124	2151	124	2251
9	205	0	205	100
9	235	5165	235	5323
9	235	6280	235	6493
9	306	0	306	100
10	1	4294	1	4394
10	1	4624	1	4755
10	1	5000	1	5100
12	102	130	102	230
12	127	2837	127	3027
12	127	3236	127	3336
12	127	3395	127	3565
12	127	4572	127	4730
12	201	492	201	716
12	201	1200	201	1350
12	201	1697	201	1830
12	201	2293	201	2410
12	201	4080	202	100
12	221	4333	221	4461
12	222	0	222	100
12	222	2374	222	2477
12	222	3069	222	3169
12	222	5160	222	5322
12	222	5533	222	5656
12	222	5815	223	102
12	223	3525	223	3625
13	101	862	101	969
13	220	906	220	1006

Road	Start point		End point	
	Road section	Distance	Road section	Distance
13	220	1682	220	1782
13	220	2486	221	95
13	239	194	239	294
15	1	2698	1	2915
15	7	7547	8	13
18	50	8140	50	8275
18	50	8377	50	8477
19	8	1098	9	20
20	1	2232	1	2339
20	1	2423	1	2528
20	1	2990	1	3090
20	1	3871	3	99
22	1	1603	1	1703
22	2	163	2	263
22	2	807	2	946
23	317	2224	317	2324
25	9	3682	11	100
40	1	1536	1	1636
40	2	2878	2	3000
40	2	4195	2	4313
40	2	4426	3	178
40	3	225	3	369
40	5	4524	5	4624
45	1	3689	1	3789
45	2	0	2	100
45	2	1695	2	1795
45	2	7000	3	100
45	4	994	4	1111
45	4	1149	4	1283
45	4	1706	4	1806
45	4	2274	4	2374
45	4	2855	4	2983

Road	Start point		End point	
	Road section	Distance	Road section	Distance
45	5	145	5	300
50	5	2250	5	2350
50	5	3576	6	513
50	6	2614	6	2820
50	6	4090	6	4330
50	6	4860	6	5040
50	7	2797	7	2897
50	7	5868	7	6009
50	8	2446	8	2615
50	8	2626	8	2726
54	11	877	11	977
65	1	616	1	760
65	1	3983	1	4083
65	2	434	2	544
68	38	5490	38	5590
76	3	3799	3	3899
76	3	3990	3	4090
76	3	4158	3	4258
78	224	3400	224	3581
101	2	399	2	499
101	2	1452	2	1573
101	2	3028	2	3188
101	2	3703	2	3803
101	5	1480	5	1580
101	6	101	6	201
101	6	570	6	670
101	6	1615	6	1736
101	6	1958	6	2064
101	6	2306	6	2406
101	7	4060	7	4333
101	8	1080	8	1308
101	8	1748	8	1848

Road	Start point		End point	
	Road section	Distance	Road section	Distance
101	8	2279	8	2379
101	8	2903	8	3064
101	8	3590	8	3690
101	8	3714	8	3814
101	8	3930	8	4252
103	1	178	1	278
110	1	4956	3	97
110	3	765	3	865
110	36	3207	36	3330
114	1	391	1	491
120	2	671	2	800
120	3	1326	3	1469
120	3	2988	3	3166
120	3	5153	3	5330
135	1	848	1	1003
140	4	2974	4	3095
140	12	1016	12	1116
143	1	1925	1	2047
148	1	2359	1	2482
148	2	482	2	620
152	1	5840	1	5970
167	1	2687	1	2800
167	1	4314	1	4414
167	2	0	2	100
170	3	0	3	114
170	3	2978	3	3078
180	1	429	1	530
190	4	1444	4	1544
312	1	810	1	910
371	1	2777	1	2877
390	2	548	2	648
553	3	4589	3	4689

Road	Start point		End point	
	Road section	**Distance**	**Road section**	**Distance**
637	1	0	1	105
637	1	1576	1	1728
724	1	2053	1	2153
724	2	0	2	100

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